Economic Development According to Chandler*

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Abstract

Business historian Alfred Chandler showed that firms in the Second Industrial Revolution had to adopt managerial capitalism to benefit fully from new technologies that leveraged economies of scale or scope and raised productivity. We show that the same forces are relevant for understanding economic development today. Large firms around the world use white-collar labor more intensively. Developing countries have low shares of white-collar workers, accounted for entirely by low skill levels. Motivated by these facts, we develop a multi-sector general equilibrium model of the link between skills and the adoption of managerial capitalism. The model extends the occupational choice model of Lucas (1978) by allowing entrepreneurs to decide the share of administrative tasks performed by hired professionals. Professionalizing a higher share of tasks brings the firm closer to constant returns to scale and leads to larger firm size. We calibrate the model to replicate joint patterns of education, firm size, sectoral choices, and occupational choices in the average middle-income country. Our counterfactuals show that growth in the supply of skills can help explain the adoption of managerial capitalism, whereas structural transformation by itself cannot.

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1 Introduction

In a seminal contribution, Chandler (1977) documents that the transition to managerial capitalism played a central role in unlocking the Second Industrial Revolution in the United States. Innovation yielded new technologies that leveraged economies of scale and scope to raise productivity in select industries. Firms that adopted these new technologies became large and encountered logistical challenges in terms of sourcing a constant supply of inputs, coordinating a high volume of production across establishments, and marketing and selling outputs. They solved these challenges by recruiting and training a hierarchy of white-collar workers, such as managers, accountants, purchasing agents, and clerks.[1]

The main contribution of this paper is to show that this same interplay among adoption of productive technologies, growth in firm size, and use of white-collar labor is relevant for understanding development and structural transformation today. We start by using representative data sets drawing on nearly one hundred countries around the world to show the continuing relevance of Chandler's insights. We show that larger firms use white-collar labor more intensively around the world. Development is associated with a shift towards white-collar-intensive production in manufacturing and low-skill service sectors, which are precisely those emphasized by Chandler's historical work.

We then document two new facts about the relationship between human capital and the rise of managerial capitalism. First, we show that the share of white-collar workers varies systematically with development, ranging from ten percent in the poorest countries to sixty percent in the richest. We provide new evidence that this large gap can be almost entirely accounted for by differences in aggregate skills. This fact reflects that there are large differences in the share of white-collar workers across education levels, ranging from ten percent for workers without primary schooling to ninety percent for workers with tertiary education. At the same time, workers of a given education level are equally likely to choose white-collar work in developing and developed countries alike. Second, we show that development is associated with a transformation in the organization of production. Even the least educated workers shift from own-account work to work in firms as income levels increase.

These facts motivate us to develop a model that captures the interaction between human capital and the rise of managerial capitalism. The model features a continuum of workers with heterogeneous skills. Workers make an occupational and a sectoral choice.

[1] See also Kuznets (1973) for a broad overview of this economic transition and Chandler (1990) for a comparative history of the rise of managerial capitalism and economic development in the United States, Germany, and Great Britain.

In terms of occupations, they can become entrepreneurs, laborers, or professionals. Laborers and professionals supply their labor to firms in competitive markets. Similar to Lucas (1978), entrepreneurs hire workers, pay them a wage, and receive firm profits as their income.

The main novel feature is that entrepreneurs also decide whether and how intensively to adopt managerial capitalism. We model this choice by assuming that there is a continuum of administrative tasks that are inputs to the production process. For each task, the entrepreneur decides whether to hire dedicated white-collar professionals to perform the task. We show the entrepreneur's problem is equivalent to one where she operates a decreasing returns Cobb-Douglas production function with laborers and professionals as inputs. In addition to choosing how much of each type of labor to hire, the entrepreneur also chooses the share of tasks to professionalize, if any, which gives us a notion of both an intensive and extensive margin of the adoption of managerial capitalism. An increase in the share of tasks that are professionalized brings the firm closer to constant returns to scale, similar to the managerial delegation model of Akcigit, Alp and Peters (2021), and also increases the factor share of white-collar labor.

The model has multiple sectors that vary in the potential costs and benefits of adopting managerial capitalism. We close the model by allowing consumers to have preferences over the outputs of the different sectors represented by an indirect demand curve consistent with structural transformation as in Comin, Lashkari and Mestieri (2021).

We provide several analytical results to help characterize the model. We show that occupational choices satisfy a cutoff rule in the worker's skill. Workers with low levels of skills either become laborers or become entrepreneurs who run small, traditional firms. Workers with higher levels of skills become professionals or entrepreneurs who run large, modern firms that adopt managerial capitalism. The endogenous allocation of workers to different types of firms has the same spirit as Banerjee and Newman (1993), although the underlying model mechanism is very different. Our model features that among entrepreneurs, those with higher skills professionalize more tasks, operate larger firms with more workers, and earn higher profits.

We use a simplified version of the model to provide analytical results that build intuition about the forces that can explain the adoption of managerial capitalism. Standard forces that generate structural transformation, such as differential growth in sectoral productivities (Ngai and Pissarides, 2007) or non-homothetic preferences (Kongsamut, Rebelo and Xie, 2001), cannot. Instead we show that an expansion in the aggregate supply of skills leads to both adoption and expansion of managerial capitalism in a manner that is qualitatively consistent with the data.

We then use a quantitative version of the model to explore these forces further.

We calibrate the model primarily to fit a rich set of cross-sectional moments on 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 over-identified, it provides a good fit to the moments we consider.

We use the model as a laboratory to evaluate the forces that can generate a shift towards managerial capitalism that is quantitatively consistent with the data. Our first counterfactual assesses whether it might be a natural consequence of structural transformation. We force the model to replicate the sectoral reallocation of labor that is associated with moving from the average middle-income to the average high-income country. Structural transformation generates a re-organization of production within sectors that goes in the wrong direction, towards *smaller* firms that use white-collar labor *less* intensively. The reason is that high-income countries have a much larger high-skill service sector. The high-skill service sector is the most skill-intensive sector in the economy, so its growth requires the other sectors to economize on the use of skilled, white-collar labor and hence leads them to operate smaller firms – contrary to the data.

Our second counterfactual instead gives middle-income countries the educational distribution of the average high-income country. We show that this generates a re-organization of production within sectors that is consistent with the data. The model generates small changes in relative wages and occupational choices conditional on education and mostly works through composition effects, consistent with the stylized facts that we document. The model also generates a quantitatively insignificant structural transformation, again re-emphasizing that structural transformation and re-organization of production are distinct phenomena.

Our work is most directly related to an earlier historical literature that takes a wide-ranging perspective on the broad changes that accompanied economic development. This literature emphasizes, for example, the joint importance of technology adoption, re-organization of production, and shifts of economic activity across sectors (Kuznets, 1973; Chandler, 1977). We show that skills are also an important component of this story and bring to bear new microdata as well as quantitative modeling to explore the complementary importance of these factors.

Our paper is also related to a growing recent literature that documents the empirical importance of skills for occupational choices or structural transformation. See Gottlieb, Grobovšek and Monge-Naranjo (2023) for evidence on skills and occupational choice; Gottlieb, Poschke and Tueting (2024) for evidence on skills and firm size; Amaral and Rivera-Padilla (2024) for evidence on skills, technology adoption, and firm size; and

Herrendorf and Schoellman (2018), Buera et al. (2022) and Porzio, Rossi and Santangelo (2022) for evidence on skills and structural transformation. We provide evidence and theory that ties together many of these transitions through the rise of managerial capitalism. A growing body of work uses plausibly exogenous policy-induced expansions of schooling to show that it has a causal effect on structural transformation and the growth of large firms (Porzio, Rossi and Santangelo, 2022; Coelli et al., 2023; Nimier-David, 2023; Russell, Yu and Andrews, forthcoming; Cox, 2023). We validate our model using evidence from this literature.

Our paper also touches on the literature that documents the importance of management (Bloom and Van Reenen, 2010; Bloom et al., 2013; Hjort, Malmberg and Schoellman, 2023). We develop a theory where entrepreneurs endogenously decide whether to professionalize administrative tasks; this is related to providing a theory of management quality as in Akcigit, Alp and Peters (2021). Empirically, we take a broader view and relate our findings to the overall adoption of a hierarchy of white-collar workers, including also finance officers, bookkeepers, and clerks.

2 Motivating Evidence

This section documents several facts that motivate our model and analysis. First, we use representative data sets drawing on nearly one hundred countries around the world to show the relevance of Chandler's insights today. We show that larger firms use white-collar labor more intensively around the world and that development is associated with a shift towards white-collar-intensive production, particularly in the manufacturing and low-skilled service sectors. Second, we document new facts about how human capital interacts with the insights of Chandler. We show that human capital accounts for essentially all cross-country variation in the share of white-collar workers. We also show that development is associated with a transformation in the organization of production that affects even the least-educated workers.

2.1 Managerial Capitalism Across Countries

We build on two essential insights of Chandler's historical work covering the Second Industrial Revolution in the United States (Chandler, 1977). First, 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.[2] Second, the productivity advantages conferred by the modern business enterprise 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.[3]

These insights remain important for understanding the organization of production around the world today. We start by showing the importance of white-collar workers for large firms. For this analysis we use the database of labor force surveys from Donovan, Lu and Schoellman (2023). The database includes a representative sample of people aged 16–65 living in urban areas of 49 countries with a wide range of income levels. We measure occupational choices using data classified according to the International Standardized Classification of Occupations (ISCO) scheme. The ISCO has undergone several revisions, but the codes are reasonably comparable at the 1-digit level for the two most recent revisions (1988 and 2008). Throughout this section, we use data with either classification. 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).

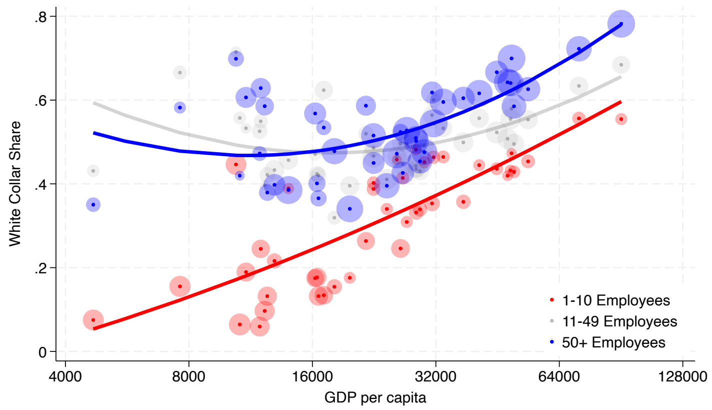
The main advantage of labor force surveys is that they frequently ask workers about how many employees work in their firm. The responses are coded into categories that vary across countries, but we can consistently compare results for workers in three categories: small firms with 1–10 employees, medium-sized firms with 11-49 employees, and large firms with 50 or more employees. We compute the share of white-collar workers in each firm size bin for each country in the database.

Figure 1 plots the share of white-collar workers by firm size category in each country against the country's PPP GDP per capita, taken from Penn World Tables 10.01 (Feenstra, Inklaar and Timmer, 2015). Each marker in this figure captures a country × firm size category, with the three firm size categories plotted using different colors. In this and subsequent figures, we scale the size of each marker in proportion to the employment share of the relevant category in the country as a whole and include quadratic

[2] 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).

[3] 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 1: WHITE-COLLAR SHARE AND FIRM SIZE



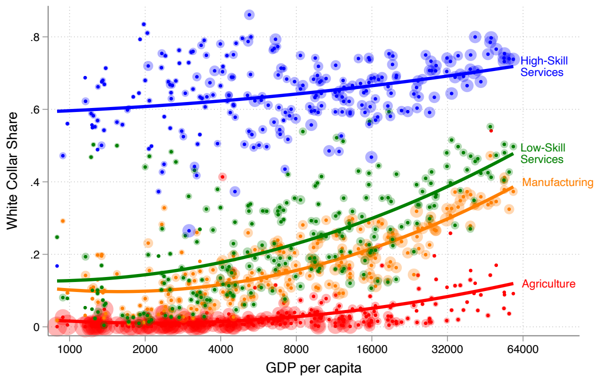
best fit lines for reference. There are large differences in the employment share of white-collar workers across firm size categories. These differences are particularly pronounced in developing countries, where there is a large gap between small as compared to medium or large firms. Medium and large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

We also find that the share of white-collar workers varies systematically by sector and level of development. To document this, we turn to microdata from Minnesota Population Center (2020), which collects and harmonizes censuses from around the world. While censuses lack information on firm size, they are more broadly available; this dataset provides information on 233 cross-sections from 77 different countries spanning six decades and covering most of the global income distribution. We measure white-collar work based on occupation codes in the same fashion as for labor force surveys. 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.[4]

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 $\times$ 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,

[4]High-skill services includes industries whose workers have on average 13 or more years of schooling in the United States, which includes education; financial services and insurance; health; public administration; other services; real estate and business services; and utilities. Low-skill services includes service industries with less education, which consists of hotels and restaurants; private household services; communication and transportation; and wholesale and retail trade. Manufacturing includes also construction and mining.

FIGURE 2: SECTORS AND WHITE-COLLAR LABOR



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. Figure A.1 in the Appendix shows results for more detailed sectors that generally support the idea that production becomes more white-collar-intensive mostly within the industries emphasized by Chandler.

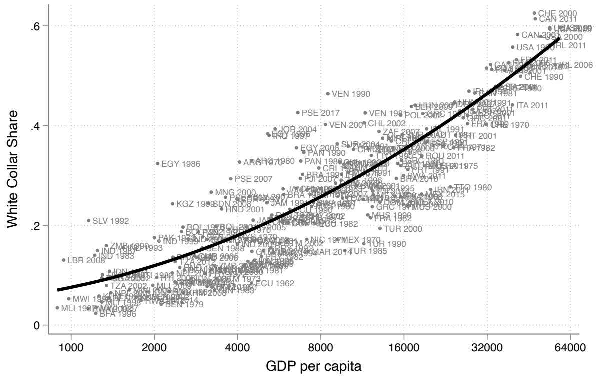
2.2 Human Capital and Managerial Capitalism

In the previous section we showed that two of Chandler's key insights about the importance of white-collar workers for U.S. development are also relevant for understanding cross-country patterns today. In this section we document two novel facts about the role of human capital for the adoption of managerial capitalism discussed by Chandler.

As a starting point, we note that developing countries generally have few white-collar workers. We compute the share of white-collar workers for each country × year using international census data and plot it against PPP GDP per capita in Figure 3. The share rises from roughly 10 percent in the poorest countries to 60 percent in the richest.

Our first novel finding is that human capital accounts for essentially all of this aggregate trend. 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 4a 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. The patterns are strikingly different from Figure 3. While there are large differences in the share of white-collar workers between education groups, there is essentially no relationship between the share

FIGURE 3: WHITE-COLLAR WORK AND DEVELOPMENT



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 4: EDUCATION AND WHITE-COLLAR OCCUPATIONS

(a) White-Collar Share by Education (b) Estimated Propensities

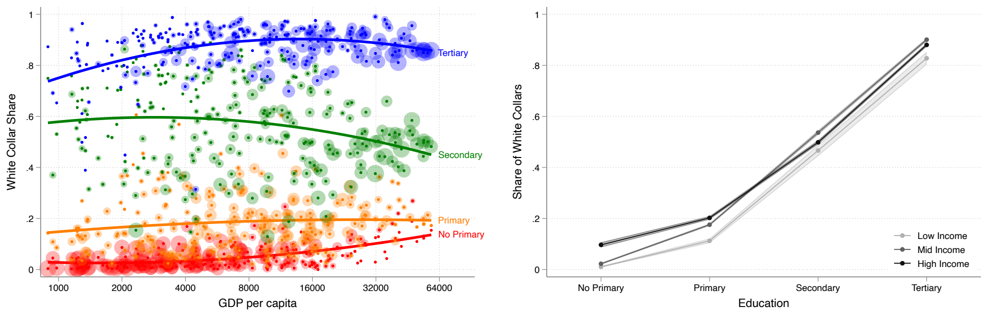


Figure 4b provides an alternative way to visualize this fact. It plots the average share of white-collar workers by education level for countries in three income groups: low-income, middle-income, and high-income countries. These income groups are based on official World Bank classifications and are used throughout the paper. The main finding again is that the white-collar share conditional on educational attainment is nearly the same in low-, middle-, and high-income countries.

A direct implication of these findings is that differences in aggregate human capital account for almost all of the cross-country variation in the share of white-collar workers. We formalize this idea using shift-share accounting in Appendix A.4 and show that the exact figure is that education accounts for 90 percent of the variation.[5]

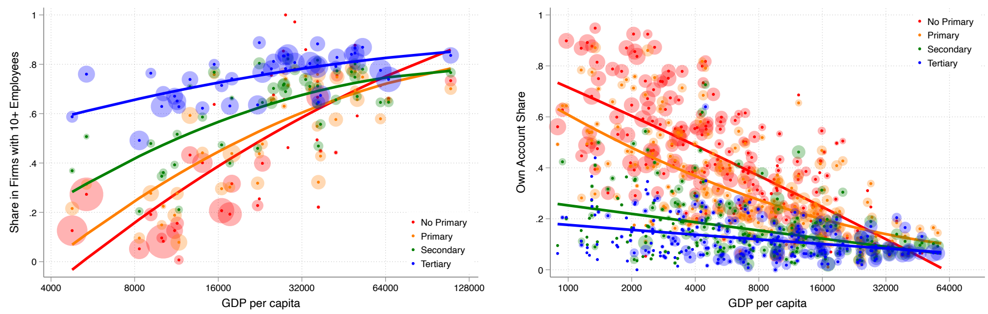
This strong accounting relationship turns out to be extremely robust. Table A.1 in

[5]An implication of our findings is that large firms also use educated workers more intensively around the world, which is consistent with contemporaneous work by Gottlieb, Poschke and Tueting (2024).

the Appendix summarizes the results from a number of robustness checks and shows that the implied accounting share for human capital ranges from 84–105 percent. For example, Appendix A.2 shows that the results are similarly large if we instead focus on the time series for countries we can track for long periods. Appendix A.3 shows that it also holds using alternative measures of human capital such as childhood or adult test scores. This analysis is motivated by the concern that licensure or credentialism may generate a mechanical relationship between educational attainment and occupational choices. We find that the results are actually stronger when using test scores than when using educational attainment. Overall, the strength and robustness of these results motivate us to model a link between a worker's skills and their occupational choices.

FIGURE 5: EDUCATION AND THE ORGANIZATION OF PRODUCTION

(a) Medium and Large Firms (b) Own Account



Our second novel empirical result is that the adoption of managerial capitalism affects the organization of production for workers of all education levels. We compute two moments related to the organization of production conditional on education, both shown in Figure 5. Figure 5a plots the relationship between the share of workers in medium and large firms and development, estimated using labor force survey data. Each marker in this figure captures a country × education level, with the four education levels plotted using different colors. Figure 5b plots the relationship between the share of workers engaged in own account work and development, estimated using international census data. Each marker in this figure captures a country × year × education level, with the four education levels plotted using different colors.

Figure 5 shows that tertiary-educated workers are highly likely to work in large firms and rarely engage in own account work in all countries in our data set. These facts follow naturally from the finding that tertiary-educated workers are highly likely to choose white-collar work and that white-collar workers are used intensively in large firms. The potentially more surprising finding is that 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 the organization of production for primary-educated workers. Whereas in the poorest countries in the world more than half of primary-educated workers are engaged in own account work, in the richest countries roughly three-quarters of the are employed in medium- and large-sized firms. Similar results apply for workers with no primary education.

Taking stock, we have documented two sets of motivating facts that inform our model in the next section. The first set of facts relates to firms and shows the importance of Chandler's insights for understanding cross-country data today. We show that it is still the case that large firms use white-collar labor much more intensively than small ones. In particular, even in the poorest countries of the world, large firms have a very high share of white-collar workers. Further, we show that while there are large differences in the white-collar intensity between sectors, development is associated with a large shift in the white-collar intensity within the sectors emphasized by Chandler. Our model generates an endogenous relationship between firm size and white-collar intensity as well as a re-organization of production within select sectors induced by the adoption of managerial capitalism.

The second set of motivating facts relates to the relationship between human capital and the rise of managerial capitalism. We show that cross-country differences in the share of white-collar workers can be accounted for by differences in aggregate human capital. This finding motivates us to think about skills as being an important driving force for the rise of managerial capitalism. We also find that development pulls less-educated workers out of own account work and into large firms, which is a consequence of the rise of managerial capitalism in our model.

3 Model

These motivating facts lead us to develop a model that captures the importance of skills and the adoption of managerial capitalism for growth and structural transformation. The model features a continuum of workers with heterogeneous skills who make occupational and sectoral choices. Workers who become entrepreneurs also choose whether to adopt managerial capitalism, which we model as a decision about whether to hire professional white-collar workers to perform administrative tasks. This section develops the model, while Section 4 characterizes optimal choices and develops useful analytical results. Proofs for this section and the next are in Appendix B.

3.1 Environment

We model the long-run (static) equilibrium of an economy with one factor of production, labor, and many sectors.

Agents and Preferences. 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 $G(z)$. Workers have log preferences over their income and are endowed with a vector of idiosyncratic relative preferences for working in sector j that is drawn from a type-I extreme value distribution with shape parameter ν.

Choices of Sectors and Occupations. Each worker chooses a sector j and an occupation. The available occupations include starting a firm (entrepreneurship) or working for a firm as a professional or a laborer. A worker with skill z who works in sector j earns income $\pi_j(z)$ as an entrepreneur, $w_{p,j}z^{\rho_j}$ as a professional, and $w_{\ell,j}z^{\chi_j}$ as a laborer. As we describe below, $\pi_j(z)$ is the outcome of profit maximization, while $w_{p,j}$ and $w_{\ell,j}$ are the equilibrium wages per efficiency unit. ρ_j and χ_j are parameters that modulate the intensity with which professionals and laborers use skills in sector j.

Within a sector, each worker chooses the occupation that maximizes income:

$$\underbrace{\phi_j(z)}_{\text{Income in Sector } j} = \max \left\{ \underbrace{w_{\ell,j}z^{\chi_j}}_{\text{Laborer}}, \underbrace{w_{p,j}z^{\rho_j}}_{\text{Professional}}, \underbrace{\pi_j(z)}_{\text{Entrepreneur}} \right\}. \tag{1}$$

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

Given the properties of the extreme value distribution, the share of workers with skill level z that choose sector j is then given by

$$\sigma_j(z) = \frac{\phi_j(z)^\nu}{\sum_{k\in J}\phi_k(z)^\nu}. \tag{2}$$

The endogenous distribution of skills in sector j satisfies

$$G_j(z) = \frac{1}{\overline{G}_j}\int_0^z \sigma_j(\tilde{z})dG(\tilde{z}), \tag{3}$$

where we have defined $\overline{G}_j \equiv G_j(\overline{z})$ as the overall share of employment in sector j.

Entrepreneur's Problem and Production Function. 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 classic span of control model of Lucas (1978). The production process uses two types of task inputs. First, there is a single production task that can only be accomplished by hiring laborers, which captures 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 $z^{\lambda_j} a_j(i) n_p(i)$ units of task output. The term $a_j(i)$ captures the relative productivity of professionalizing task i in sector j. The entrepreneur's ability enters the task output modulated by the parameter λ_j, which captures that the entrepreneur sets overall firm strategy and that her skill in doing so is particularly complementary to the labor input of professionals. 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 $\gamma_{p,j}$ and $\gamma_{\ell,j}$. 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 in a sector j solves

$$\pi_j(z) = \max_{\{n_p(i)\}_{i\in[0,1]}, n_\ell} \tilde{\tau}(\{n_p(i)\}) \left\{ z^{\mu_j} p_j A_j \exp\left(\int_0^1 \log \tilde{n}(i)^{\gamma_{p,j}} di \right) n_\ell^{\gamma_{\ell,j}} - w_{p,j} \int_0^1 n_p(i) di - w_{\ell,j} n_\ell \right\} \quad (4)$$

s.t.

$$\tilde{n}(i) = \max\left\{1, z^{\lambda_j} a_j(i) n_p(i)\right\}$$

$$n_p(i) \geqslant 0 \quad \text{for} \quad i \in [0,1] \qquad \text{and} \qquad n_\ell \geqslant 0$$

Without loss of generality, we order tasks in descending order by their relative productivity $a_j(i)$. We assume that the size-dependent wedge depends only on the share of tasks that are professionalized: $\tilde{\tau}(\{n_p(i)\}) = \tilde{\tau}\left(\int_0^1 \mathbb{I}_{n_p(i)>0} di\right)$. Under these assumptions, Lemma 1 shows that the multi-dimensional problem (4) 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 (4) 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:*

$$\pi(z) = \max_{q\in[0,1],n_p\geqslant 0,n_\ell\geqslant 0} \tilde{\tau}(q)\left\{z^{\mu+q\lambda\gamma_p} p\tilde{A}(q)\left[n_p^{\alpha(q)} n_\ell^{1-\alpha(q)}\right]^{\eta(q)} - q w_p n_p - w_\ell n_\ell\right\} \tag{5}$$

where

$$\tilde{A}(q) \equiv A \times \left(\exp \frac{1}{q}\int_0^q \log a(i)^{\gamma_p} di\right)^q$$

$$\eta(q) \equiv q\gamma_p + \gamma_\ell$$

$$\alpha(q) \equiv \frac{q\gamma_p}{\eta(q)}$$

To ease notation, we have omitted the j subscript, but the Lemma 1 applies for each sector. 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, which in turn implicitly affects the firm's productivity $\tilde{A}(q)$, the factor share of professionals $\alpha(q)$, and the extent of decreasing returns to scale in production $\eta(q)$. This observation implies that we can interpret q as a choice of the organization of production as described in Chandler (1977). We return to this point when we characterize the optimal choices of q for different types of entrepreneurs in Section 4.1. Finally, we define $y_j(z)$ to be the optimally chosen output by an entrepreneur with productivity z in sector j, which solves problem 5.

Closing the model. To close the model, we need to describe how the relative prices of each sector are determined. We follow Comin, Lashkari and Mestieri (2021) and postulate that, given a base sector b with the normalization $p_b = 1$, the price for each sector j satisfies

$$\log p_j = -\frac{1}{\sigma}\log\frac{Y_j}{Y_b} + (\varepsilon_j - 1)\left(\log\frac{Y_b^{\frac{1}{\sigma}}}{Y}\right) + \log \mathbb{P}_j \tag{6}$$

where σ is the elasticity of substitution across goods, ε_j controls the relative income elasticity of demand of sector j, $Y_j = \int y_j(z)dG_j(z)$ is the total output in sector j, and $Y = \sum_{j\in J} p_j Y_j$ is the total income in the economy. The terms $\log \mathbb{P}_j$, which are kept constant across counterfactuals, capture differences (up to a normalization) in the level of demand for each good.[6]

3.2 Equilibrium

We define an equilibrium in our setting, which requires that agents' occupational and sectoral 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 in each sector j, ($w_{p,j}$, $w_{\ell,j}$); ii. the share of tasks to professionalize, hired labor input of professionals and laborers, and profits for each entrepreneur z in each sector j, ($q_j(z)$, $n_{p,j}(z)$, $n_{\ell,j}(z)$, $\pi_j(z)$); iii. shares of individuals in each sector and occupation ($\sigma_j(z)$, $\omega_{\pi,j}(z)$, $\omega_{p,j}(z)$, $\omega_{\ell,j}(z)$); iv. distribution of skills z in each sector j, ($G_j(z)$); v. sectoral prices ($\{p_j\}_{j\in J}$) such that:*

1. *entrepreneurs maximize firm profits solving (4);*

2. *$\omega_{\pi,j}(z)$, $\omega_{p,j}(z)$, $\omega_{\ell,j}(z)$ satisfy the occupational choice (1), that is,*

$$\begin{aligned} \omega_{\pi,j}(z) > 0 \quad &\textit{iff} \quad \phi_j(z) = \pi_j(z) \\ \omega_{p,j}(z) > 0 \quad &\textit{iff} \quad \phi_j(z) = w_{p,j} z^{\rho_j} \\ \omega_{\ell,j}(z) > 0 \quad &\textit{iff} \quad \phi_j(z) = w_{\ell,j} z^{\chi_j}; \end{aligned}$$

[6] We impose equation (6) rather than derive it from a non-homothetic CES preference system as in Comin, Lashkari and Mestieri (2021) to avoid the challenge of integrating non-homothetic demands across heterogeneous workers. Equation (6) would follow from non-homothetic CES preferences if workers engage in ex-ante risk sharing arrangements that lead them to all consume an equal share of aggregate income.

3. the markets for professionals and laborers clear in each sector j:

$$\int q_j(z) n_{p,j}(z)\omega_{\pi,j}(z)dG_j(z) = \int z^{\rho_j}\omega_{p,j}(z)dG_j(z)$$
$$\int n_{\ell,j}(z)\omega_{\pi,j}(z)dG_j(z) = \int z^{\chi_j}\omega_{\ell,j}(z)dG_j(z);$$

4. skill distributions in each sector are consistent with individual choices (2)–(3)*;*

5. prices satisfy (6).

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 then provide an analytical result that helps build intuition for the interaction between human capital and the adoption of managerial capitalism.

4.1 Characterization

In general, the entrepreneurial problem is well-behaved when profits are a concave function of the share of professionalized tasks q. For the remainder of the paper we restrict attention to a parametric function for $a_j(i)$ that makes it straightforward to impose concavity and that also yields convenient analytical solutions.

ASSUMPTION **1.** The relative productivity of professionalizing task i in sector j is given by the product of a sector-specific constant and a decreasing function of i: $\log a_j(i) = \frac{1}{\gamma_{p,j}}(\log \beta_j + \log \vartheta \log(1-i))$.

Intuitively, $\log \vartheta > 0$ implies that the relative productivity of professionalizing tasks decreases as i rises, with log relative productivity being a decreasing and concave function of i with $\lim_{i\to 1} \log(a_j(i)) = -\infty$, while β_j encodes the productivity of professionalization. This property makes it straightforward for us to derive conditions on ϑ that guarantee a concave problem with an interior solution in the next section. Under this assumption, the endogenous component of TFP becomes

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

Note that $\lim_{q\to 0}\tilde{A}_j(q) = A$ while $\lim_{q\to 1}\tilde{A}_j(q) = A\frac{\beta_j}{\vartheta}$.

We also assume a convenient functional form for the size-dependent distortions.

ASSUMPTION **2.** The wedge $\tilde{\tau}(q)$ takes the following functional form: $\tilde{\tau}(q) = \left(\frac{1-\eta(q)}{1-\eta(0)}\right)^{\tau}$.

The parameter τ modulates the extent of the size-dependent distortions: when $\tau = 0$ there is no distortion, while if τ is positive, a higher q reduces the share of profits the entrepreneur receives.

Second, it is useful to define two important objects that are central in the characterization of the equilibrium.

DEFINITION **1.** The *skill premium* in sector j is $\mathbb{W}_j \equiv \log \frac{w_{p,j}\gamma_{\ell,j}}{w_{\ell,j}\gamma_{p,j}}$.

DEFINITION **2.** The *scalability* in sector j is $\mathbb{A}_j \equiv \frac{1}{\gamma_{p,j}} \log \beta_j$.

The skill premium is related to the wage per efficiency unit in a sector (which is different from the observed wage). The scalability of the sector is the potential productivity gains from professionalizing administrative tasks in the sector, which in turn is informative about the benefits from adopting managerial capitalism. We now characterize the solutions to the worker's problem.

Entrepreneurial Problem

We start by characterizing the entrepreneur's problem. 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. We drop subscript j to ease notation. 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:

$$\tilde{\pi}(z;q) = \tilde{\tau}(q)(1-\eta(q))z^{\mu+q\lambda\gamma_p}p\tilde{A}(q)\left[\tilde{n}_p(z;q)^{\alpha(q)}\tilde{n}_\ell(z;q)^{1-\alpha(q)}\right]^{\eta(q)}, \quad (7)$$

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

$$\tilde{n}_p(z;q)^{\alpha(q)}\tilde{n}_\ell(z;q)^{1-\alpha(q)} = \left[z^{\mu+q\lambda\gamma_p}p\tilde{A}(q)\left(\frac{\gamma_p}{w_p}\right)^{\alpha(q)}\left(\frac{\gamma_\ell}{w_l}\right)^{1-\alpha(q)}\right]^{\frac{1}{1-\eta(q)}}. \quad (8)$$

Equations (7) and (8) show that the expressions for labor utilization and profits are similar to their counterparts in standard span of control models (Lucas, 1978).[7] The main novel feature of these expressions 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 (for $\lambda > 0$).

We use equation (7) 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.[8]

LEMMA **2** (Optimal Organization of Production)**.** *Let* $\log \vartheta > \max_j \{\frac{\gamma_{p,j}^2}{1-\gamma_{\ell,j}}\}$*. Then each sector admits a cutoff value* $\log \hat{z}_{q,j}$ *given by*

$$\log \hat{z}_{q,j} = \frac{1-\gamma_{\ell,j}}{\left(1-\gamma_{\ell,k}\right)\lambda_j + \mu_j} \left[1 + \tau + \mathbb{W}_j - \mathbb{A}_j - \frac{\log \left(p_j A_j \frac{\gamma_{\ell,j}}{w_{\ell,j}} \right)}{1-\gamma_{\ell,j}} \right].$$

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

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

The relationship between the optimal firm scale (in terms of output) and the entrepreneur's skills z *satisfies*

$$\frac{\partial \log y_j(z)}{\partial \log z} = \begin{cases} \frac{\mu_j}{1-\gamma_{\ell,j}} & \text{if } z \leqslant \hat{z}_{q,j} \\ \frac{\mu_j + q_j(z)\lambda_j\gamma_{p,j} + \gamma_{p,j}\frac{dq_j(z)}{d\log z}}{1-\eta_j(q_j(z))} & \text{if } z > \hat{z}_{q,j}. \end{cases}$$

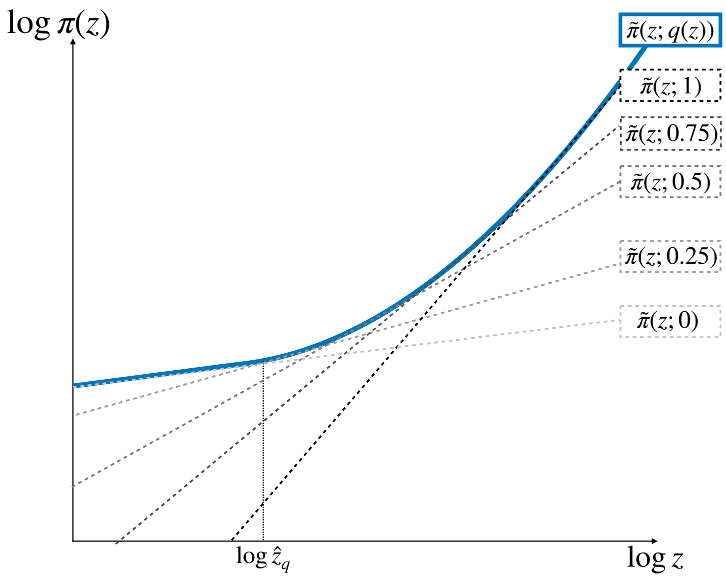
Figure 6 provides a graphical representation of the results of Lemma 2. Each gray line shows profits as a function of entrepreneurial skill z for a given choice of q (e.g., $\tilde{\pi}(z,q)$). As q increases, the profit functions become less concave and eventually turn convex in z. This reflects that a higher q reduces the degree of diminishing returns,

[7]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.

[8]Conversely, if ϑ is low, the entrepreneur's problem instead 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.

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.

FIGURE 6: TECHNOLOGY CHOICE AND FIRM PROFITS



Lemma 2 and Figure 6 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 $\eta_j(0) = \gamma_{\ell,j}$) and so operate small firms in equilibrium. The elasticity of output with respect to skill is $\frac{\mu_j}{1-\gamma_{\ell,j}}$, 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. (2023).

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.[9] The elasticity of output with respect to the entrepreneur's skill is larger than the standard $\frac{\mu_j}{1-\gamma_{\ell,j}}$ 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 firms that adopt managerial capitalism and refer to the entrepreneurs of such firms as modern entrepreneurs.

At this point we have characterized the optimal organization of production for workers who choose to become entrepreneurs conditional on z. In the next section we solve

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

for optimal occupational choice, which informs us about which workers actually choose entrepreneurship.

Occupational Choice and Equilibrium within Sector

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

ASSUMPTION **3.** The parameters $\chi_j, \mu_j, \rho_j, \lambda_j$ satisfy

$$\underbrace{\chi_j}_{\text{Laborers}} = \underbrace{\frac{\mu_j}{1-\gamma_{\ell,j}}}_{\text{Traditional Entrepreneurs}} < \underbrace{\rho_j}_{\text{Professionals}} < \underbrace{\frac{\mu_j + \lambda_j \gamma_{p,j}}{1-\gamma_{p,j}-\gamma_{\ell,j}}}_{\text{Modern Entrepreneurs}} .$$

Note that the elasticity for modern entrepreneurs applies for an 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)**.** *For each sector j for which Assumption 3 holds, 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*

   - $w_{\ell,j} z^{\chi_j} \geqslant \tilde{\pi}_j(z, 0)$ *with equality if and only if* $\omega_{\pi,j}(z)\mathbb{I}_{z \leqslant \hat{z}_{q,j}} > 0$
   - *if* $\hat{z}_0 = \hat{z}_1 : w_{\ell,j} z^{\chi_j} = w_{p,j} \hat{z}_{1,j}^{\rho_j}$*,* $w_p \hat{z}_{2,j}^{\rho_j} = \pi(\hat{z}_{2,j})$*;*
   - *if* $\hat{z}_0 < \hat{z}_1 : w_{\ell,j} z^{\chi_j} = \pi(\hat{z}_{0,j})$*,* $\pi(\hat{z}_{1,j}) = w_{p,j} \hat{z}_{1,j}^{\rho_j}$*,* $w_p \hat{z}_{2,j}^{\rho_j} = \pi(\hat{z}_{2,j})$*;*

3. *there are traditional entrepreneurs – i.e.* $\omega_{\pi,j}(z)\mathbb{I}_{z\leqslant\hat{z}_{q,j}} > 0$ *– if and only if:*

$$G(\hat{z}_{0,j}) > \int_{\underline{z}}^{\hat{z}_{0,j}} n_\ell(x)\omega_{\pi,j}dG(x) + \int_{\hat{z}_{0,j}}^{\hat{z}_{1,j}} n_\ell(x)dG(x) + \int_{\hat{z}_{2,j}}^{\infty} n_\ell(x)dG(x).$$

Lemma 3 describes two possible equilibria, both of which arise in our quantitative exercises. Figure 7 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.7 in the Appendix shows the case where $\hat{z}_0 < \hat{z}_1$. Figure 7a 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 λ_j. Finally, the blue line shows the profit of entrepreneurs (both traditional and modern), which take into account the optimal choice of technology q.

FIGURE 7: OCCUPATIONAL CHOICE AND ENDOGENOUS DUALITY

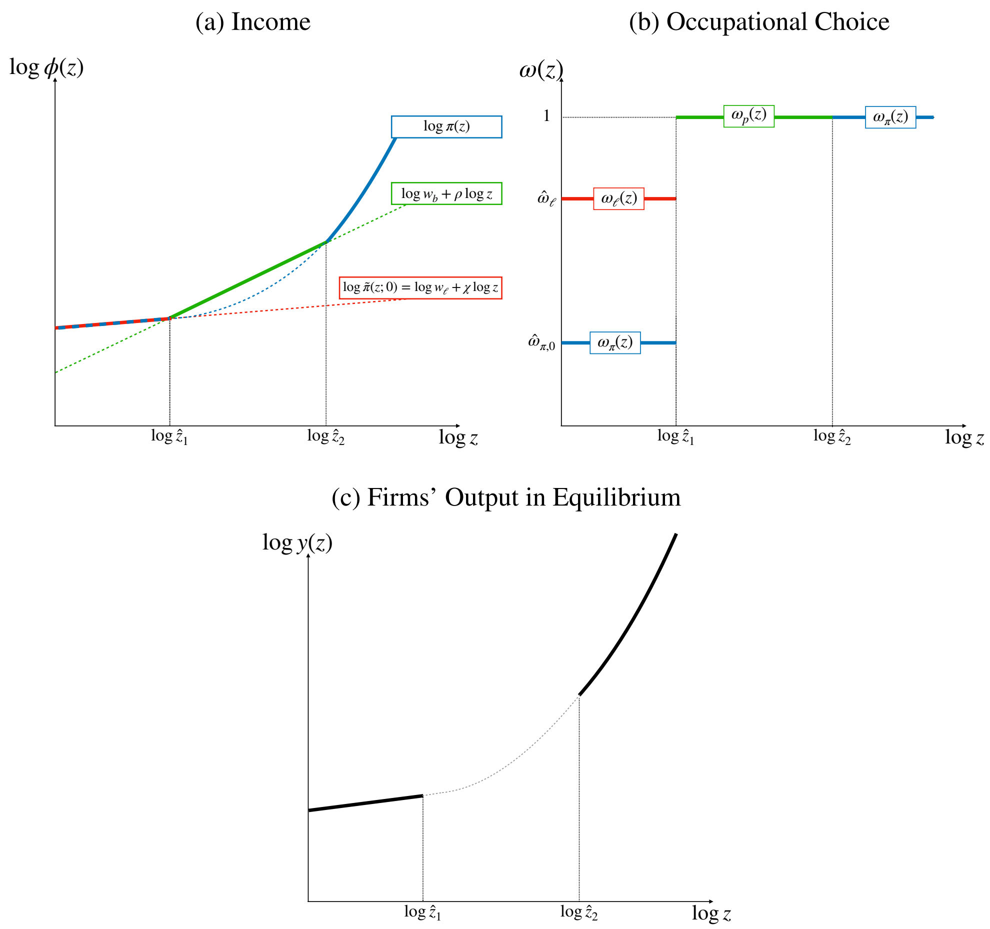


Figure 7b shows the resulting occupational choice. Workers with low skill levels are indifferent between becoming traditional entrepreneurs or laborers. Workers with intermediate levels of skills earn the most as professionals and consequently choose that occupation. Workers with the highest levels of skills choose the most skill-intensive occupation, which is modern entrepreneurship.

Finally, Figure 7c shows an interesting implication of Lemma 3: the occupational choice leads to an equilibrium with duality. If there are sufficiently many modern entrepreneurs in a sector, then they employ all of the low-skilled workers as production labor. However, if there are not, then the remaining low-skilled workers engage in own account work. In such an equilibrium, both the most and least skilled workers enter entrepreneurship, albeit of vastly different types.

Our empirical results in Section 2 focus on the share of workers engaging in blue-collar versus white-collar work. When taking the model to the data, we naturally map laborers to blue-collar workers and professionals to white-collar workers. The case of entrepreneurs is less clear. Entrepreneurs that start large, modern firms sit atop a management hierarchy and devote most of their time to setting the firm's strategic direction. Empirically, most entrepreneurs of large, modern firms probably report managerial occupation codes and so are likely to be classified as white-collar workers. On the other hand, Bassi et al. (2023) show that entrepreneurs that start small, traditional firms often have a time allocation similar to that of production workers in the same firm. Empirically, it is likely that many such entrepreneurs report production or sales occupations and so are classified as blue-collar workers. For example, the entrepreneur that founds a five-person carpentry firm or food stall may consider herself a carpenter or a chef rather than a manager or a chief executive officer. When taking the model to the data, we assume that the share of entrepreneurs who choose q that report white-collar occupations is q, which smoothly spans these two cases. Given this measurement assumption, the share of white-collar and blue-collar workers in the model are given by the following two definitions.

DEFINITION **3.** *Blue-collar workers* are laborers and a share $1-q$ of entrepreneurs who professionalize share q of tasks: $\omega_{B,j}(z) \equiv \omega_{\ell,j}(z) + \omega_{\pi,j}(z)[1-q_j(z)]$.

DEFINITION **4.** *White-collar workers* are professionals and share q of entrepreneurs who professionalize share q of tasks: $\omega_{W,j}(z) \equiv \omega_{p,j}(z) + \omega_{\pi,j}(z)q_j(z)$.

Sectoral Choice

Now that we have characterized the income level $\phi_j(z)$ and occupational choice $\omega_j(z)$ for all skill levels z and sectors j, we can characterize the optimal sectoral choice.

Recall from equation (2) that the share of workers with skill level z who choose sector j is proportional to the income they earn in that sector relative to all other sectors, $\sigma_j(z) = \phi_j(z)^\nu / \sum_{k \in J} \phi_k(z)^\nu$. Note that this expression takes into account the possibility that the income-maximizing occupation may differ across sectors even for a worker with fixed skills z. For example, a worker with an intermediate level of skills might find that working as a professional offers the highest income conditional on choosing the low-skill service sector but working as a laborer offers the highest income conditional on choosing the high-skill service sector.

The optimal sectoral choice thus depends on occupational choice, which in turn depends on parameters and equilibrium outcomes such as prices. The following Lemma provides a useful benchmark for understanding what patterns drive sectoral sorting.

LEMMA **4.** *An increase in $p_j A_j$ leads to a proportional increase in $\sigma_j(z)$ that is the same for all skill levels z.*

Intuitively, Lemma 4 reflects that workers' wages and entrepreneurs' profits are all homogeneous of degree 1 in revenue productivity. Increasing revenue productivity in sector j by a factor Λ thus increases the income of workers of all skill levels in sector j by Λ, which raises the proportion of workers who choose sector j at all skill levels by Λ^ν. This result is useful because standard forces that generate structural transformation do so by altering sectoral productivities and prices; the implication is that these forces cannot help us understand why workers sort across sectors based on skills or why such sorting might be different in developing versus developed countries.

The model generates sorting based on differential returns to skill by sector. Sectors with higher returns to skills for professionals (governed by ρ_j) and more skill sensitivity of operating a modern firm (governed by $(\mu + \lambda\gamma_{p,j})/(1 - \gamma_{p,j} - \gamma_{\ell,j})$) attract proportionally more skilled workers and hence have higher returns to skill. In the next section we focus on a simplified version of the model that allows us to provide analytical results to illustrate this case.

4.2 Analytical Results: the Growth of Managerial Capitalism

In this section we explore two forces that can generate the rise of managerial capitalism: 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 use four simplifying assumptions that we relax in our quantitative analysis in Section 5.

ASSUMPTION **4.** The cost of professionalization does not vary across tasks within sector: $\vartheta = 1$.

ASSUMPTION **5.** The income of laborers and traditional entrepreneurs is equally skill-sensitive in all sectors, $\chi_j = \chi = \frac{\mu_j}{1-\gamma_{\ell,j}} = \frac{\mu}{1-\gamma_\ell}$; the income of professionals is as skill-sensitive as the profits of modern entrepreneurs and these values are the same across sectors, $\rho_j = \rho = \frac{\mu_j+\lambda_j\gamma_{p,j}}{1-\gamma_{p,j}-\gamma_{\ell,j}} = \frac{\mu+\lambda\gamma_p}{1-\gamma_p-\gamma_\ell}$.

Assumption 4 implies that there are two types of entrepreneurs: traditional entrepreneurs who choose $q = 0$ and modern entrepreneurs who choose $q = 1$. Assumption 5 implies that not only are low-skilled workers indifferent between traditional entrepreneurship and working as a laborer, but also high-skilled workers are indifferent between modern entrepreneurship and working as a professional.

ASSUMPTION **6.** There is a positive mass of traditional entrepreneurs in each sector j: $\omega_{\pi,j}(z)\mathbb{I}_{z\leqslant\hat{z}_{q,j}} > 0$.

ASSUMPTION **7.** The model is a small open economy with fixed sectoral prices.

These last two assumptions imply that wages and prices do not vary in our counterfactuals. The following Lemma summarizes the behavior of the economy under these simplifying assumptions.

LEMMA **5** (Limit Case)**.** *Under assumptions 4, 5, 6, and 7 the equilibrium satisfies the following properties:*

1. *there is a sector-specific cutoff type $\hat{z}_j$, with*

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

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

2. *wages and profits satisfy*

$$\begin{aligned}
\log \pi_j(z \leqslant \hat{z}_j) &= \log w_{\ell,j} + \chi \log z \\
\log \pi_j(z > \hat{z}_j) &= \log w_{p,j} + \rho \log z \\
\log w_{\ell,j} &= \log (p_j A_j) + \gamma_\ell \log \gamma_\ell + (1-\gamma_\ell) \log (1-\gamma_\ell) \\
\log w_{p,j} &= \log w_{\ell,j} + \frac{\gamma_p}{1-\gamma_\ell} (\mathbb{A}_j + \log \gamma_p) - \tau \log \left(\frac{1-\gamma_\ell}{1-\eta} \right) \\
&\quad + \frac{1-\eta}{1-\gamma_\ell} \log (1-\eta) - \log (1-\gamma_\ell)
\end{aligned}$$

3. *the skill premium is purely a function of the distortion τ and parameters and does not depend on skill supply.*

The properties established in Lemma 5 make it feasible to analytically characterize the effects of the two exogenous forces that can contribute to the rise of managerial capitalism. We consider each in turn, starting with shifts in the supply of skills.

PROPOSITION **1** (Shift in the Supply of Skills)**.** *Consider an increase in the supply of skills from a distribution $G(z)$ to a distribution $G'(z)$ which first order stochastically dominates $G(z)$. This change yields the following:*

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

2. *an increase in average firm size;*

3. *take any two sectors j and k, the share of employment in sector j increases if and only if $\mathbb{A}_j > \mathbb{A}_k$;*

4. *the increase in white-collar share, the decline in traditional entrepreneurship, and the increase in firm size are due to both re-organization of production within each sector and a shift of employment towards more skill-intensive sectors;*

5. *the skill premium in each sector j is not affected;*

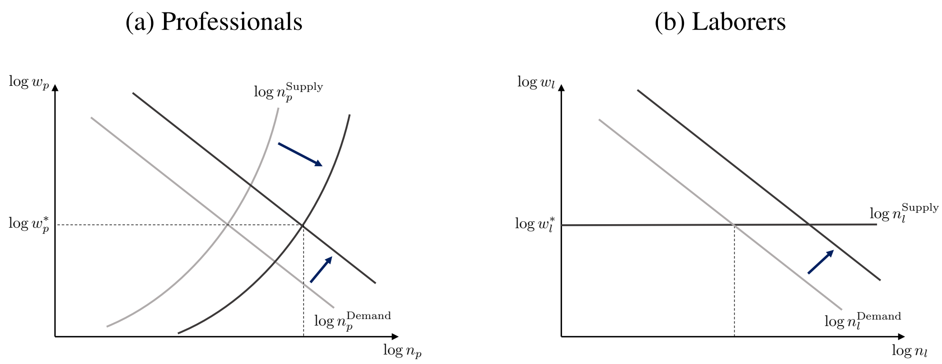
6. *the occupational and sectoral choice for each skill type z are not affected.*

Proposition 1 builds on the fact that the skill premium is invariant to shifts in the supply of skills (Property 3 of Lemma 5). For this reason, it is useful to explain further why this is the case in the model. To do so, we explain why both the wages of professionals and of laborers are constant in this counterfactual.

An increase in skills increases the supply of professionals because skilled workers have a comparative advantage in skill-intensive occupations. At the same time, an increase in skills also increases the share of modern entrepreneurs for the same reason, which in turn increases the labor demand for professionals. Generically, these two forces push the professional wage in opposite direction. In this analytical model, Assumptions 4 and 5 imply that all skilled workers are indifferent between working as professionals or modern entrepreneurs, which in turn implies that the supply and demand forces exactly offset and professional wages remain constant.

An increase in skills decreases the supply of laborers. It also increases the share of modern entrepreneurs and hence the demand for laborers. However, low-skilled workers are indifferent between being laborers or traditional entrepreneurs and Assumption 6 guarantees that there are at least some traditional entrepreneurs initially. These traditional entrepreneurs are effectively a reserve supply of potential laborers. They shift to working as laborers and wages remain fixed until there are no traditional entrepreneurs remaining. Figure 8 illustrates the shift in these labor markets.

FIGURE 8: AN INCREASE IN SKILL SUPPLY



The property that the skill premium is invariant to the supply of skills depends on the simplifying assumptions made for this analytical model. However, the property that skilled workers act as both labor supply and labor demand for professionals holds in the general model, as does the property that traditional entrepreneurs are a form of reserve supply of laborers. These properties are useful for building intuition about why the model generally produces muted movements in the skill premium. They are also important when taking the model to the data because the available evidence suggests that developing and developed countries have broadly similar relative wages despite vastly different supplies of skilled workers (Banerjee and Duflo, 2005; Rossi, 2022).

Given that sectoral prices are fixed and skill premia are invariant to the supply of skills, the rest of the results can be naturally understood as arising through composition effects. The increase in the aggregate supply of skills leads to more modern entrepreneurs and an increase in the size of modern firms within each sector. It also implies an expansion of more scalable sectors. The growth in the modern sector pulls workers from traditional entrepreneurship into working as laborers in large, modern firms.

It is worth emphasizing that these properties are broadly in line with the stylized facts outlined in Section 2. The aggregate rise in the share of large firms and the share of white-collar workers, as well as the relative expansion of more scalable sectors, is in line with the historical evidence of Chandler (Figures 1 and 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 4. Finally, the result that the expansion of education pulls blue-collar workers out of traditional entrepreneurship and into work in large firms is consistent with Figure 5.

Now 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. *an increase in the aggregate share of white-collar workers and a decline in the aggregate share of traditional entrepreneurs;*
2. *an increase in average firm size;*
3. *no change in sectoral employment;*
4. *an increase in the wage premium in each sector;*
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 able to replicate the same aggregate shifts as the increase in the supply of skills. However, along other dimensions it works differently. It does not generate a shift in sectoral employment. It generates an increase in the wage premium. And it alters the occupational choices of workers of a given skill level.

Propositions 1 and 2 illustrate the effects of these shifts in a simplified model that we can solve analytically. Our next goal is to study their quantitative importance in a calibrated model that relaxes the simplifying assumptions that permit these propositions.

5 Calibration

We calibrate the model to match important dimensions of the relationships among skills, occupational choices, sectoral choices, and the organization of production for middle-income countries. We focus on middle-income countries because they offer good data availability and also feature co-existence of modern and traditional firms.

5.1 Extensions and Functional Form Assumptions

Our quantitative model incorporates two extensions relative to the analytical model in Section 3. First, we allow sectors to offer workers different levels of utility $\nu_{\mu,j}$. These utility differences are necessary for the model to jointly fit sectoral employment shares and sectoral incomes. Without them, the model imposes a tight relationship between employment shares and incomes (equation (1)) that is falsified by the data. We assume that these preference shocks enter multiplicatively with the value of being in a sector.

Second, we assume that after workers make a sectoral choice, they 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. Workers are forward-looking and anticipate these draws when making sectoral choices. These taste shocks affect the elasticity of labor supply across occupations within a sector.

We next impose a series of functional form assumptions. We assume that the four discrete education groups that we observe consistently in the cross-country data (no primary, primary complete, secondary complete, tertiary complete) are proxies of unobserved skills. We assume that skills z of education group i are log normally distributed with mean $\sum_{k=1}^{i} z_{\mu,k} - z_{\sigma}^2/2$, where we normalize $z_{\mu,1} = 0$. The shares in each education group, υ_i, are taken directly from the data.

To reduce the number of parameters to be estimated, we then impose a few parametric restrictions. First, we restrict the parameters χ_j, μ_j, ρ_j, and λ_j that determine the skill sensitivity of income to vary by sector and occupation, but not by sector-occupation. This allows us to generate an ordering of skill sensitivity across occupations consistent with Assumption 2 and also to have differences in the skill sensitivity of sectors but reduces the number of parameters to estimate. In practice this means that we choose five parameters, which are $\tilde{\mu}$, $\tilde{\lambda}$, and $\{\rho_j\}$, with ρ_{mfg} normalized to one. The remaining parameters are set by $\mu_j = \tilde{\mu}\rho_j$, $\lambda_j = \tilde{\lambda}$, and $\chi_j = \frac{\mu_j}{1-\gamma_{\ell,j}}$. Note that the relative skill sensitivity of occupations will still vary across industries with these restrictions because the skill sensitivity of entrepreneurship also depends on the output elasticities $\gamma_{p,j}$ and $\gamma_{\ell,j}$. Sectors with less decreasing returns to scale offer higher returns to skilled

TABLE 1: EXOGENOUSLY SET PARAMETERS

Parameter	Description	Value				Source
		Agri.	Manu.	HS	LS	
		Panel A. Aggregate parameters				
υ_1	Share with no primary degree	0.258				Minnesota Population Center (2020)
υ_2	Share with primary degree	0.353				Minnesota Population Center (2020)
υ_3	Share with secondary degree	0.271				Minnesota Population Center (2020)
υ_4	Share with tertiary degree	0.117				Minnesota Population Center (2020)
σ	Elasticity to aggregate output	0.500				Comin, Lashkari and Mestieri (2021)
ν	Sectoral preferences shocks	2.000				Exogenously set
ξ	Occupational preferences shocks	4.000				Exogenously set
		Panel B. Sector-specific parameters				
ϵ_j	Income-elasticity of demand	0.110	1.000	1.210	1.000	Comin, Lashkari and Mestieri (2021)
τ_j	Wedge	0.000	0.000	0.000	0.000	Exogenously set
α_j	Factor share of white collar	0.271	0.550	0.663	0.902	Externally calibrated
$\log \mathbb{P}_j$	Demand shifter for sectoral output	1.790	0.000	-4.081	-1.676	Sectoral prices

entrepreneurs.

Second, we fix exogenously (calibrated from the data as we describe below), the factor shares of white-collar labor when $q = 1$: $\alpha_j \equiv \frac{\gamma_{p,j}}{\gamma_{p,j}+\gamma_{\ell,j}}$. Given this restriction, we estimate a sector-specific parameter $\eta_j \equiv \gamma_{p,j} + \gamma_{\ell,j}$, which captures the decreasing returns to scale for a firm where all administrative tasks have been professionalized.

Finally, without loss of generality we normalize mean productivity in manufacturing and the mean preference for working in manufacturing to be one, $A_{\text{mfg}} = \nu_{\mu,\text{mfg}} = 1$.

5.2 Estimation Approach, Targeted Moments and Identification

We break out calibration procedure into two parts. We start with a set of parameters that are set exogenously because they are taken directly from the data or are taken from estimates in the literature. Table 1 summarizes these parameters. Panel A shows the subset that relate to aggregate parameters. We take the share of workers in middle-income countries with each educational attainment level from Minnesota Population Center (2020). We take the estimated price elasticity of demand from Comin, Lashkari and Mestieri (2021). Absent reliable estimates, we currently fix the shape parameters of the sectoral and occupational preference shocks to $\nu = 2$ and $\xi = 4$.[10]

Panel B shows the exogenously set parameters that vary by sector. The estimated income elasticity of demand by sector also comes from Comin, Lashkari and Mestieri (2021). We currently set the firm-size wedge to 0 in all sectors, although we plan to explore this further in future work. We set the factor share of white-collar labor, α_j, so that a firm choosing $q = 0.9$ i the model would have the same factor share of payments

[10]While these values are broadly in line with the literature, we are currently devising a strategy to estimate them ourselves.

Table 2: Internally calibrated parameters

Parameter	Description	Value			
		Agri.	Manu.	HS	LS
		Panel A. Aggregate parameters			
$z_{\mu,2}$	Average skills of primary relative to no primary (log)	0.857			
$z_{\mu,3}$	Average skills of secondary relative to primary (log)	1.001			
$z_{\mu,4}$	Average skills of tertiary relative to secondary (log)	1.147			
z_{σ}	St.d. of skills conditional on education (log)	0.785			
$\tilde{\lambda}$	Skill-sensitivity of professionalizing	1.040			
ϑ	Productivity of professional tasks, curvature	4.538			
		Panel B. Sector-specific parameters			
μ_j	Skill-sensitivity of entrepreneurship	0.108	0.296	0.353	0.321
$\gamma_{p,j}$	Curvature in professionals	0.242	0.482	0.536	0.446
$\gamma_{l,j}$	Curvature in laborers	0.652	0.395	0.058	0.227
β_j	Productivity of professional tasks, intercept	0.504	0.093	0.614	0.350
$\nu_{\mu,j}$	Mean preference shifter	2.430	1.000	1.713	1.579
A_j	Sectoral TFP	0.335	1.000	0.562	0.842
ρ_j	Skill-sensitivity of professionals	0.366	1	1.193	1.085

to white-collar workers as the average we observe for large firms in sector j in high-income countries. Finally, we take sectoral prices from Inklaar, Marapin and Gräler (2023).

The remaining parameters are estimated endogenously to fit a rich set of moments. Table 2 shows the 34 parameters and their values, although it is worth noting that the parametric restrictions and normalizations that we imposed in the previous sections imply that there are only 24 independent underlying parameters.

Table 3 includes a list of the moments that we target. In total we target 87 moments and so our estimation is overidentified. The table is organized into five panels to help convey the five broad aspects of the data we are trying to match, which includes heterogeneity across sectors and education groups, how production is organized in each sector, occupational choices by educational attainment, and heterogeneity across firms. For each moment we give the corresponding figure below that shows how well the model fits the data. Finally, while we jointly select all the moments to fit a weighted loss function, the last column shows the parameter that each moment helps to identify. We verify this argument by computing the standard Jacobian matrix which studies how the moments vary in response to changes in the parameters. We now describe the intuition behind moment selection and identification.

Panel A shows that we target value added per worker, which we take from Inklaar, Marapin and Gräler (2023). Given that we also have data on sectoral prices, this moment pins down sectoral productivity A_j. We also target employment shares by sector, which we compute from Minnesota Population Center (2020). This moment is informative about the the preference for working in sectors $\{\nu_{\mu,j}\}$ (after conditioning on

TABLE 3: TARGETED MOMENTS

Moments	N	Model Fit	Parameters
A. Heterogeneity Across Sectors			
Value added per worker	4	Fig 9a	$\{A_j\}$
Employment shares	4	Fig 9b	$\{\nu_{\mu,j}\}$
B. Heterogeneity Across Education Groups			
Wage Gaps	4	Fig 10a	$z_{\mu,2}, z_{\mu,3}, z_{\mu,4}$
Mincer Returns (overall and within sector)	5	Fig 10b	$\{\rho_j\}$
C. Organization of Production within Sector			
Education groups shares	16	Fig 11	$\{\rho_j\}, z_\sigma$
Firm size	4	Fig 11	$\{\eta_{,j}\}$
Entrepreneurship (modern & traditional)	8	Fig 11	$\{\beta_j\}$
White collar share	4	Fig 11	$\{\eta_j, \beta_j\}$
D. Occupational Choice by Education Groups			
Relative sectoral shares	16	Fig 12	$\{\rho_j\}, z_\sigma$
Firm size	4	Fig 12	$\{\eta_{,j}\}$
Entrepreneurship (modern & traditional)	8	Fig 12	$\{\beta_j\}, \tilde{\mu}, \tilde{\lambda}$
White collar share	4	Fig 12	$\{\eta_j, \beta_j\}, \tilde{\mu}, \tilde{\lambda}$
E. Heterogeneity Across Firms			
Distribution of employment	3	Fig 13a	$\{\eta_j\}$
White collar share by firm size	3	Fig 13b	ϑ

sectoral incomes, which our other moments help identify).

Panel B shows that we target two moments related to wages, both taken from Minnesota Population Center (2020). The gaps in average wages across education levels helps to pin down differences in mean skill levels by education ($z_{\mu,2}, z_{\mu,3}, z_{\mu,4}$). The differences in the returns to education by sector are informative for the differences in how skill-intensive the sectors are, which we have tied to the parameter ρ_j.

Panel C shows that we target a rich set of moments on how production is organized by sector. This information helps the model match the extent of adoption of managerial capitalism and the co-existence of modern and traditional firms by sector. We match the share of workers in each sector by educational attainment, which we compute from Minnesota Population Center (2020). This moment also helps pin down the sectoral intensity parameter ρ_j, as well as the dispersion in skill z_σ. In the model, skilled workers sort to sectors that reward skills. In the data, we observe sorting by education, which is an imperfect proxy of skills. If z_σ is very large, even strong sorting based on skills would lead to weak sorting on education levels.

The remaining moments can best be understood jointly. We target the share of medium and large firms by sector, which we compute from Donovan, Lu and Schoellman (2023). We estimate the share of entrepreneurs who report blue-collar and white-collar occupations, which we compute from Minnesota Population Center (2020). And we estimate the share of white-collar workers by sector, which we compute from Minnesota Population Center (2020). Since we already target the share of white-collar entrepreneurs, this moment captures the extent of professionals in each sector. Jointly these moments speak to the returns to scale in production η_j and the scalability of the sector, which is controlled by β_j. For example, a sector with small firms, mostly blue-collar entrepreneurs, and few professionals would be inferred to have low returns to scale and low scalability. On the other hand, a sector with small firms, mostly white-collar entrepreneurs, and a high share of professionals would be inferred to still have low returns to scale but high scalability.

Panel D shows moments related to occupational choice by education groups. We target sectoral employment shares, which we compute from Minnesota Population Center (2020); employment shares by firm size, which we compute from Donovan, Lu and Schoellman (2023); share of white- and blue-collar entrepreneurs, which we compute from Minnesota Population Center (2020); and share of white-collar workers, which we compute from Minnesota Population Center (2020). To some extent, these moments help provide similar identification of the same parameters as those in Panel C. This is most true for relative sectoral employment shares.

In addition, matching these moments allows the model to pin down the relative skill-sensitivity of different occupations – i.e. the parameters $\tilde{\mu}$ and $\tilde{\lambda}$. If $\tilde{\mu}$ is low we should observe that low-ability individuals sort into traditional entrepreneurship and blue-collar work. Instead, a high $\tilde{\lambda}$ makes modern entrepreneurship more skill-sensitive than being a white-collar professional. As a result, $\tilde{\lambda}$ is identified by the differences between sorting to any white-collar occupation and to modern entrepreneurship specifically.

Finally, Panel E shows two sets of moments related to heterogeneity across firms. We target the distribution of employment and the white-collar employment share by firm size bin for small, medium, and large firms, all computed from Donovan, Lu and Schoellman (2023). These moments help pin down the curvature of the relative productivity of professionalizing tasks: ϑ. A high ϑ generates a large heterogeneity in relative productivity across tasks, thus implies that the white collar share would increase more gradually with firm size.

5.3 Model Fit and Estimation Results

We now describe how the model fits the data. Overall, the estimated model fits the data well. Given the large set of targets, we display the fit using a sequence of figures. Each figure has a common format: moments are listed across the x-axis, with the height of bars reflecting the values for the model (shown in blue) and the data (shown in red). We report exact figures above or below each bar. Table 3 summarizes what parameters each moment helps discipline.

FIGURE 9: MODEL FIT: HETEROGENEITY ACROSS SECTORS

(a) Value Added per worker (b) Employment shares

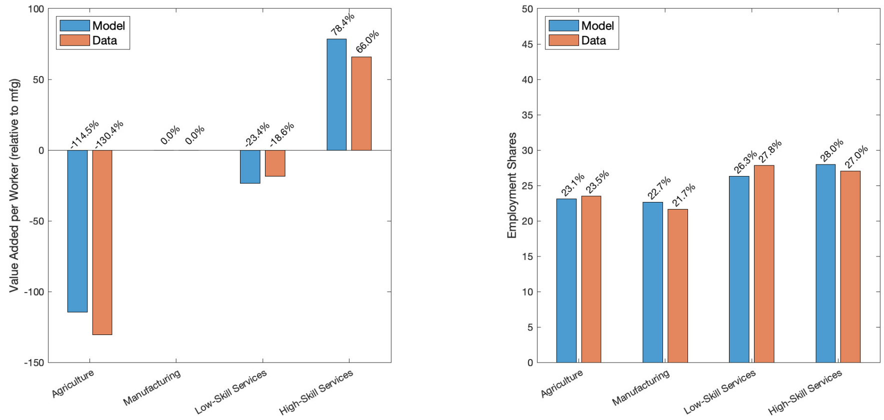


Figure 9 show that we match the differences across sectors in value added and employment shares. This finding is not surprising given that the model includes both sectoral productivities and sectoral preference shifters to help target these moments.

FIGURE 10: MODEL FIT: HETEROGENEITY ACROSS EDUCATION GROUPS

(a) Wage Gaps by Edu (b) Mincerian Returns

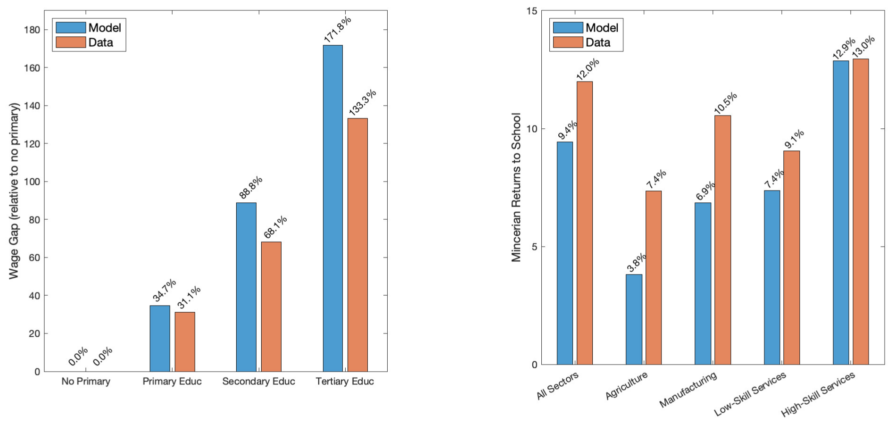


Figure 10 shows that our model is also able to match the wage gaps across education groups and variation in the returns to schooling across sectors. The model underestimates somewhat the Mincer returns in agriculture and low-skill services. This is probably due to the fact that the same parameters $\{\rho_j\}$ modulate both wages and workers sorting.

FIGURE 11: MODEL FIT: ORGANIZATION OF PRODUCTION WITHIN SECTOR

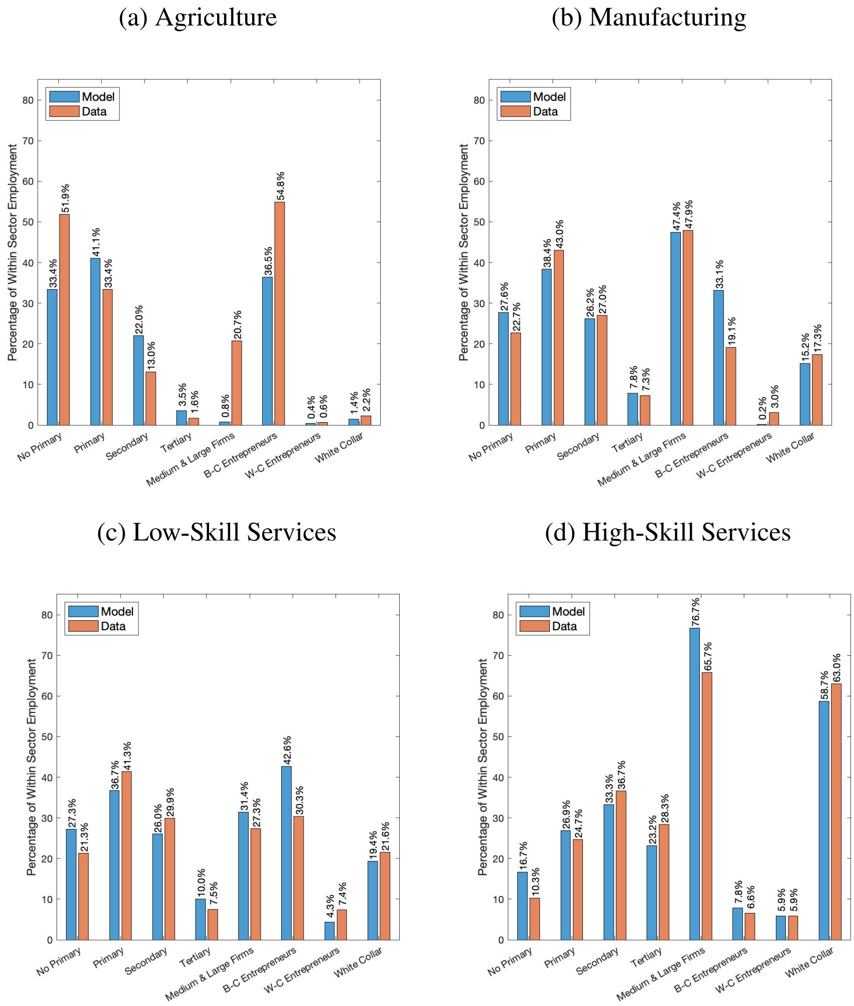
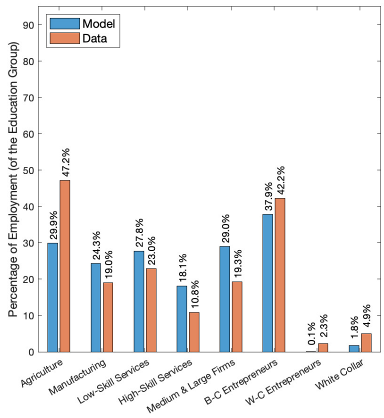


Figure 11 shows the fit by sector, with each subfigure showing one of the four sectors. The model does a very good job at matching the differences across sectors in the organization of production. It captures that agriculture draws heavily on less-skilled workers and is mostly organized through traditional entrepreneurship; that manufacturing has an intermediate organizational structure; and that high-skilled services particularly draws on more skilled, white-collar workers and is organized in large firms.

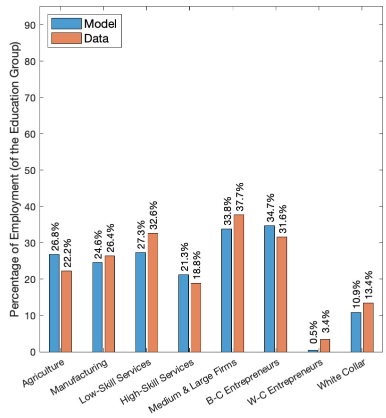
The main area where the model struggles when focusing on sectors is that empirically about twenty percent of agricultural workers are employed by large firms. The model cannot reconcile this with the fact that agriculture has almost no white-collar entrepreneurs and almost no professionals. In essence, the model is not designed to think about the fact that some agricultural firms are large but (evidently) not modern in the sense of having adopted managerial capitalism.

FIGURE 12: MODEL FIT: OCCUPATIONAL CHOICES BY EDUCATION GROUPS

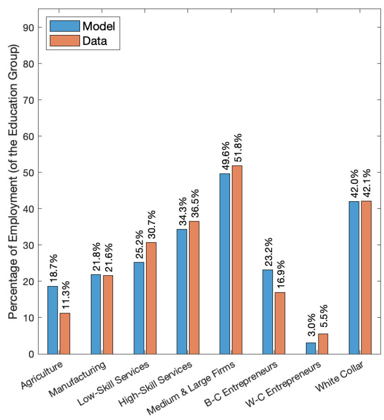
(a) No Primary



(b) Primary



(c) Secondary



(d) Tertiary

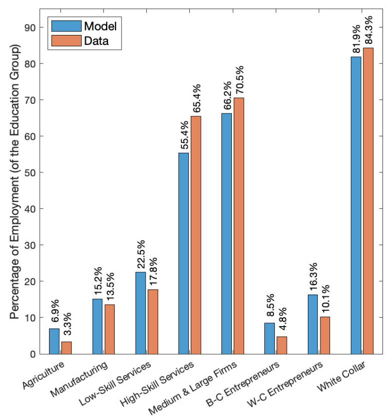
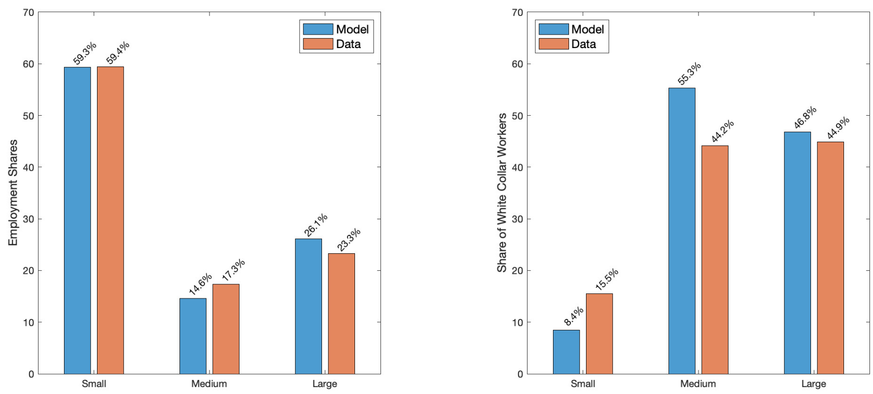


Figure 12 shows the fit by education level. The model does a good job of capturing the important gradients of occupational and sectoral choice by education level. This point is particularly clear if we compare Figure 12a to Figure 12d. The least-educated workers mostly work in agriculture or low-skill service sectors, work in small firms, and largely engage in traditional entrepreneurship. The most-skilled workers are heavily concentrated in high-skill service sectors, work in large firms, and engage entirely in white-collar occupations.

While the model broadly provides a good fit to the data, it has too high a share of tertiary-educated workers engaging in white-collar entrepreneurship. This happens because we calibrate modern entrepreneurship to be very skill-sensitive, which gives the most-educated workers in the model a very strong comparative advantage in modern entrepreneurship such that only such workers should start firms. Empirically, some less-educated workers also start firms.

FIGURE 13: MODEL FIT: HETEROGENEITY ACROSS FIRMS

(a) Distribution of Employment (b) White Collar Shares



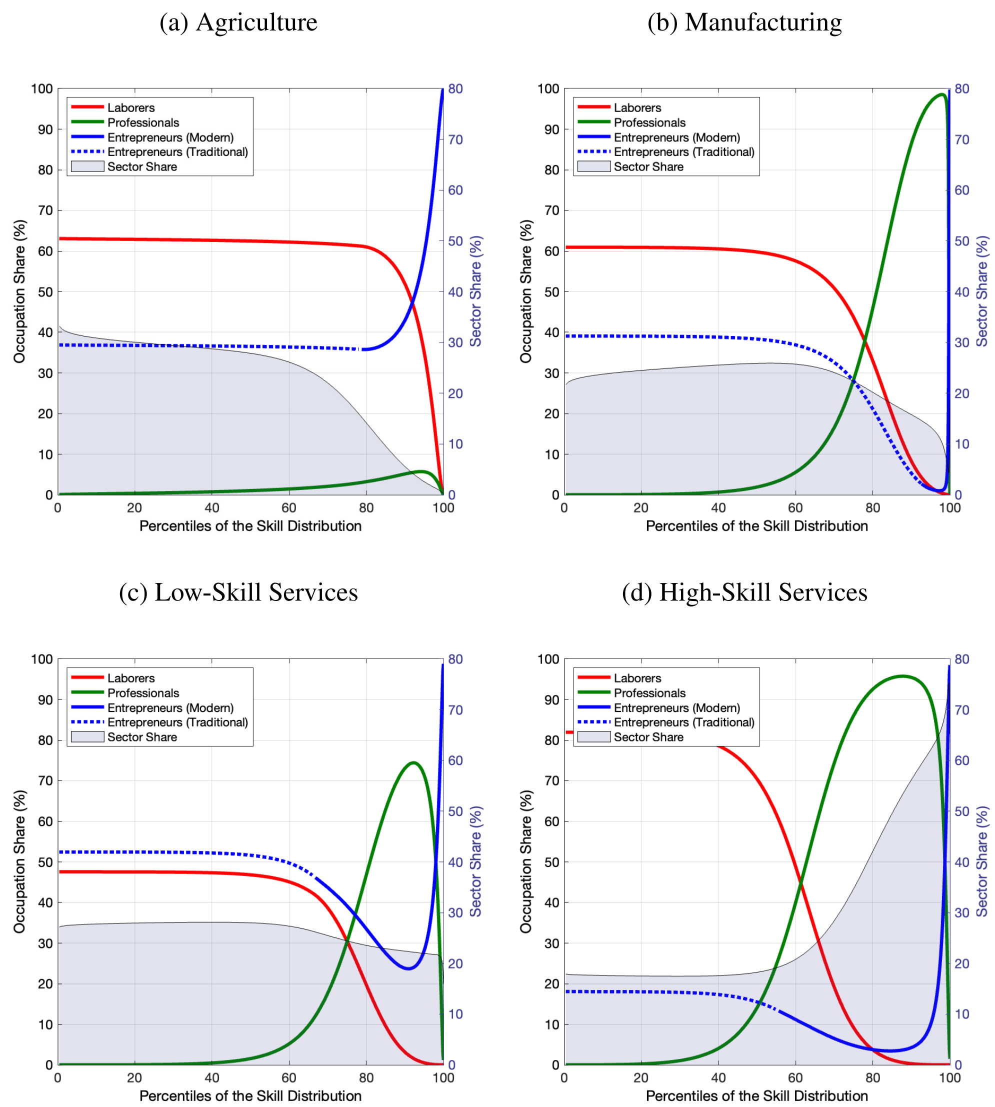
Finally, we discuss our estimated parameters, which are included in Table 2. In the interest of space, we focus our discussion on the estimated parameters that differ by sector. Our estimate of the degree of overall decreasing returns to scale, $\eta_j = \gamma_{p,j} + \gamma_{l,j}$ ranges from 0.51 in high-skilled services to 0.74 in manufacturing. High-skilled services is, however, much more scalable than the other sectors, as indicated by its high estimated β_j.

5.4 Model Mechanisms

The last section focused on how the model fit the data. In this section we illustrate the underlying choices that drive these results. Figure 14 shows how workers of different skill levels are allocated across sectors and occupations. Each of the four panels shows one sector, with percentiles of the skill distribution on the x-axes and choice probabilities on the y-axes. The shaded gray area (plotted using the right y-axis) shows the share of workers at each skill level that choose the given sector. The three lines show the share of workers at that skill level in the given sector who choose to work as a laborer, as a professional, and as an entrepreneur. For the share who choose entrepreneurship (shown in blue), we further distinguish whether they operate a traditional firm (shown in dashed blue) or a modern firm (shown in solid). These three lines are the quantitative analogues of Figure 7b in the theory.

Focusing first on the shaded areas, the figures show that there is a moderate degree of sorting. Workers with skills above roughly the 60th percentile of the skill distribution

FIGURE 14: MODEL MECHANISMS: OCCUPATIONAL AND SECTORAL CHOICE



are strongly sorted towards high-skill services. However, workers with skills below that level are roughly proportionally split among agriculture, manufacturing, and low-skill services, with the exception that the least-skilled workers are slightly more likely to enter agriculture.

Within each sector, the occupational choice rule is a smoothed version of Figure 7b, consistent with the addition of occupational preference shocks to the model. Broadly, it remains the case that less-skilled workers choose traditional entrepreneurship or work as laborers, workers with intermediate skill levels choose to become professionals, and the most skilled workers become modern entrepreneurs. However, we find some important sectoral differences in how these patterns play out that are explained by the estimated sector-level parameters.

Most workers in agriculture are entrepreneurs – largely traditional entrepreneurs – with some laborers and almost no professionals. Manufacturing and low-skill services display endogenous duality. This can be seen mostly clearly by studying the entrepreneurs, who are both the least skilled workers (who engage in traditional entrepreneurship) and the most skilled (who engage in modern entrepreneurship). Looking forward, these are the two sectors that can most easily be reshaped by the adoption of managerial capitalism, which expands the size and number of modern entrepreneurs and pulls the traditional entrepreneurs into the large firms as workers. Finally, high-skill services is dominated by large firms run by modern entrepreneurs and staffed by professionals, with a small share of traditional entrepreneurs.

5.5 Validation

The preceding section reveals that skills play an essential role in our theory. A natural question is whether the implied role for skills in the model is in line with the data. To test this and validate the model, we turn to evidence from the literature that studies the reallocation of labor in response to policy-induced, exogenous expansions of education (Porzio, Rossi and Santangelo, 2022; Coelli et al., 2023; Nimier-David, 2023; Russell, Yu and Andrews, forthcoming; Cox, 2023). We focus on the results of Cox (2023), who provides evidence from a middle-income country (Brazil) and documents both implications for occupational choice and firm size.

Cox studies the effects of a government reform in 1996 that allowed the operation of private, for-profit colleges in Brazil. He shows that colleges largely opened in regions that were previously underserved by public colleges and argues that this makes local pre-reform college capacity relative to the number of young adults an effective instrument for the subsequent expansion of college attainment. He shows that this instrument predicts the expansion of college among young cohorts.

Cox then uses this plausibly exogenous expansion of college attainment to estimate its causal importance for a number of dimensions of economic development. Two of these measures map directly to our model. First, he shows that an expansion of college attainment is associated with a large shift towards white-collar occupations among the affected cohorts. He reports two sets of estimates from weighted and unweighted specifications; Table 4 reports these point estimates as well as the 95 percent confidence intervals in brackets. Second, he shows that an expansion of college attainment is associated with a growth in the number of large firms. He reports the effects of an expansion of college among young cohorts on overall number of large firms. We rescale his esti-

TABLE 4: COMPARISON TO COX (2023)

	White-Collar Employment Share		Log(# Large Firms)
	Unweighted	Weighted	
Cox	0.86	0.88	1.95
	[0.35, 1.37]	[0.72, 1.04]	[0.73, 3.16]
Model	0.51		2.64

mates by the average size of the young cohort in the overall labor force so that we can interpret the coefficient as the effect of expanding aggregate college attainment. Table 4 reports the re-scaled point estimate and confidence interval in the last column.

We simulate the instrument in our model. Our baseline economy is calibrated to an average middle income country. We modify the model by fixing the educational attainment to be consistent with the data from the 2000 Brazilian census, the year closest to the policy reform studied by Cox. We hold the other parameters fixed. Cox shows that areas treated by the reform had about 1.5 percentage points higher growth in the share of tertiary educated workers over the subsequent decade. We exogenously move 1.5 percentage points of workers from secondary to tertiary education in the model, then compute the difference in the share of white-collar workers and the log of the number of large firms between the baseline and treated economy. Table 4 shows the model results in the last row.

Our estimate of the effect for the growth in white-collar employment shares is actually lower than Cox's estimates, at 0.51 versus 0.86–0.88. It falls within the confidence interval from the unweighted estimation but not for the weighted estimation. Our model estimate of the effect on the number of large firms is modestly larger than Cox's estimate, at 2.64 versus 1.95. This estimate does fall within the 95 percent confidence interval. We take from these results that broadly the quantitative importance of skills in the model is in line with the best available evidence from the literature; we find modestly lower importance for occupational choices and modestly higher importance for the growth in the number of large firms.

6 Counterfactual Experiments

The previous section showed that the calibrated quantitative model provides a good fit to the data along key dimensions. It is also broadly in line with external evidence on the causal role of schooling for occupational choice and the number of large firms from Cox (2023). In this section, we use the model as a laboratory to understand the implications of two counterfactual changes.

6.1 Counterfactual: Structural Transformation with Fixed Skills

We start by using the quantitative model to studying the effect of structural transformation on the organization of production. It is well-known that growth in aggregate and sectoral productivities can generate structural transformation across sectors through non-homothetic preferences and price effects (Kongsamut, Rebelo and Xie, 2001; Ngai and Pissarides, 2007; Comin, Lashkari and Mestieri, 2021). However, we show that these forces do not by themselves generate a re-organization of production that is consistent with the data.

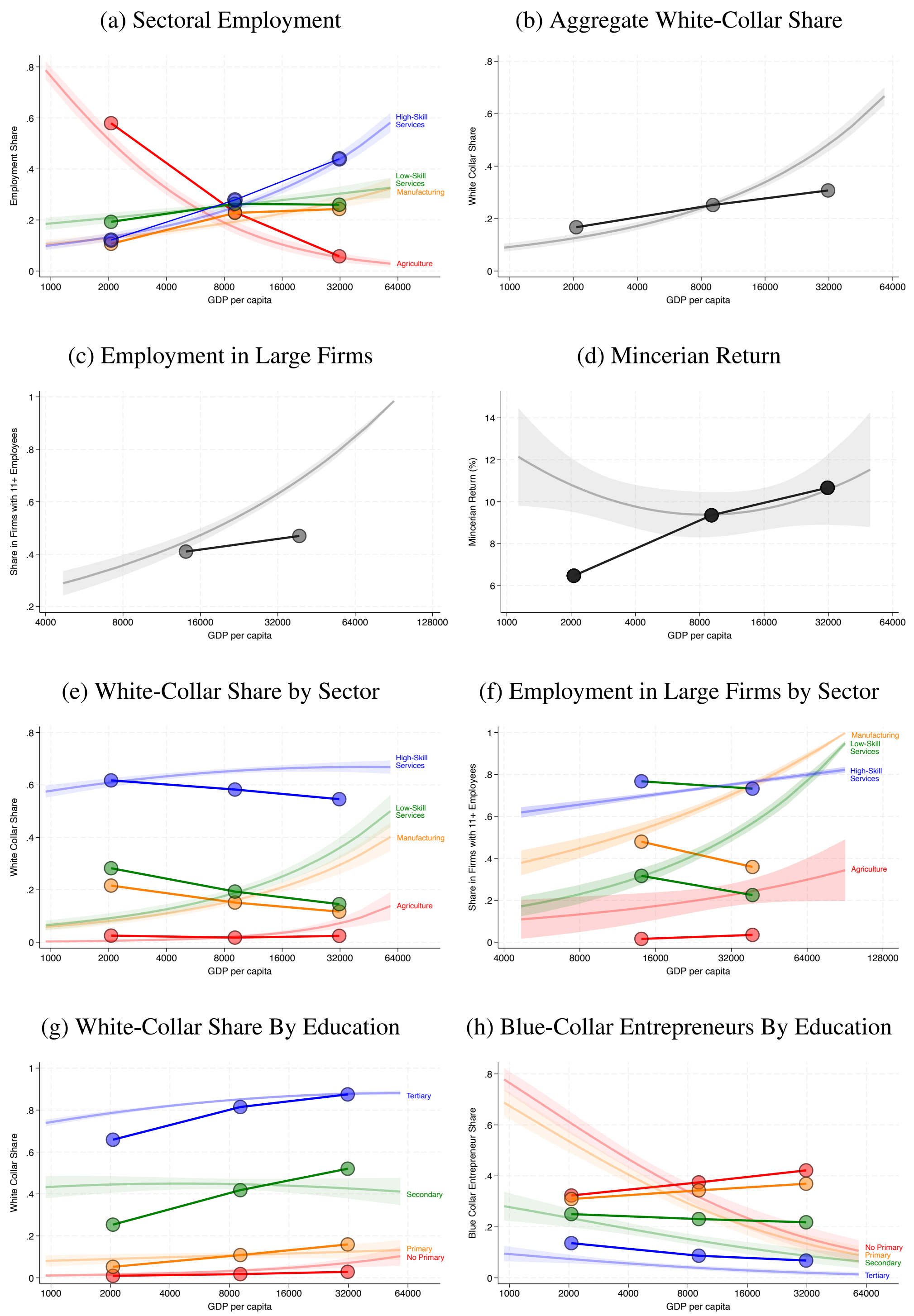
To illustrate this point, we start with the economy calibrated to the average middle-income country. We vary aggregate and sectoral productivities so that the model matches instead the sectoral employment shares in the low- or the high-income countries in the data. We hold all other parameters constant, including those governing the supply of skills. Figure 15 shows the results by comparing the model's predictions for low-, middle- and high-income countries to the data. In these counterfactual figures, we always summarize the data using the best fit line from a logistic regression and the 95 percent confidence interval, shown in light colors. The model results are shown in larger markers and connected with a darker line.

As shown in Figure 15a, the model successfully matches patterns of structural transformation across sectors. It also produces changes in the aggregate share of white-collar workers and the aggregate share of workers employed in large firms (Figures 15b and 15c) that are qualitatively consistent with the data.

However, the model produces a re-organization of production that goes in the wrong direction as compared to the data. This is clearest if we focus on the re-organization within sectors shown in Figures 15e and 15f. Within each sector, the white-collar share of employment declines and the share of workers employed in large firms declines, contrary to the data. Further, the model generates that the least-educated workers become more likely to engage in blue-collar entrepreneurship, again contrary to the data.

The underlying intuition for these figures is that structural transformation shrinks employment in agriculture, which is the least skill-intensive sector, and expands it in high-skill services, which is the most skill-intensive sector. The model generates an aggregate rise in white-collar employment and employment in large firms through between-sector composition effects. However, the total supply of skills is fixed. There are two margins for workers to adjust. First, the rising skill premium (Figure 15d) leads workers of a given education level to substitute towards white-collar work, again con-

Figure 15: Structural Transformation with Fixed Skills



Notes: In all figures, the light-colored lines display the best fits in the data from logistic regressions (with 95% confidence bands given by the shaded areas), while the dots connected by darker lines indicate the model's counterfactual results when varying the drivers of structural transformation, as described in the text. The x-axis coordinates of the dots correspond to the average GDP per capital for low-, middle- and high-income countries in the data (middle- and high-income only for Figures 16c and 16f).

trary to the data (Figure 15g). Second, within each sector there is a reduction in the use of skilled, white-collar workers, which leads to the re-organization of production towards smaller, traditional firms.

6.2 Counterfactual: Expansion of Skill Supply

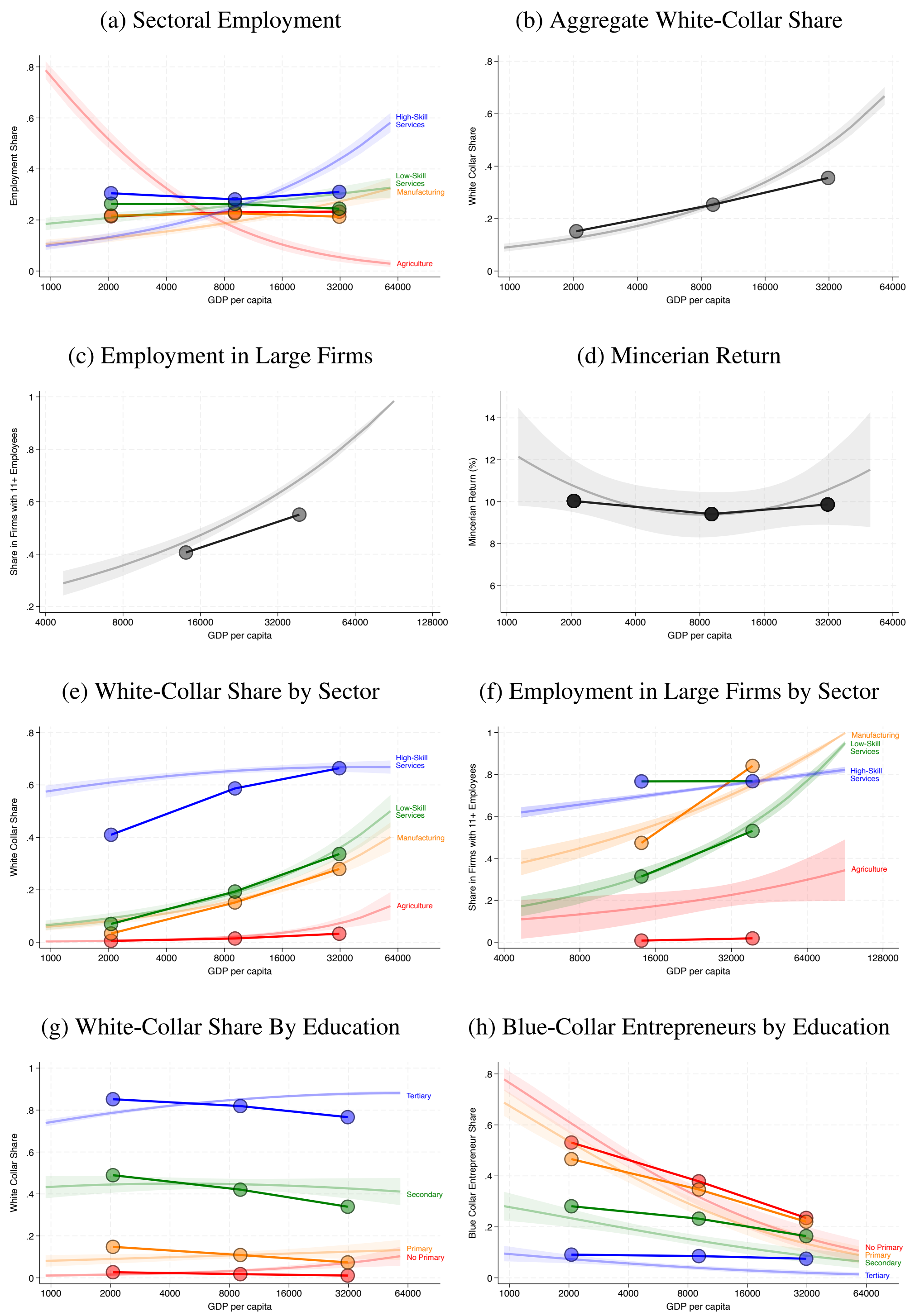
We conduct a second counterfactual exercise to show that the supply of skills is a potential candidate explanatory factor for the re-organization of production. For this exercise, we again take the economy calibrated to the average middle-income country. We feed into the model instead the distribution of educational attainment in the average low- or high-income countries in the data. We hold all other parameters constant. The results are displayed in Figure 16 using the same format as in Figure 15 above.

Figure 16a shows that varying skills produces a muted structural transformation across sectors, with smaller variations in sectoral employment shares compared to the data. Underlying these small shifts are two forces that push in opposite directions. First, an expansion of skills makes households richer, which generates the standard income effect: households demand a higher share of high-skill services and a lower share of agriculture. Second, an expansion of skills lowers the unit costs of high-skill services relative to agriculture, because high-skill services is more skill-intensive. This generates a substitution effect: given the standard elasticity of substitution less than one, households are not very willing to substitute towards high-skill services, which leads employment to shift away from high-skill services and towards agriculture. Quantitatively, these two forces roughly cancel.

The remaining figures show that the effects of skill supply on the organization of production are qualitatively in line with the data. Figures 16b and 16c show that the model generates a rise in the aggregate white-collar employment share and the aggregate employment share in large firms that are consistent with the data. Figure 16d shows that despite the large expansion of skills, the model does not generate a large rise in the skill premium. This is related to the fact that an increase in skills expands both the supply of and demand for professionals, as shown in Section 4.2. Because the skill premium does not move much, the share of white-collar workers by educational attainment is similar in low-income and high-income countries (Figure 16g), consistent with the data.

The model generates a re-organization of production within sectors that is also consistent with the data, as shown in Figures 16e and 16f. The white-collar employment share and share of workers in large firms rises in all sectors. Further, the extent of this rise varies across sectors in a manner consistent with the findings of Chandler (1977):

FIGURE 16: EXPANSION OF SKILL SUPPLY



Notes: In all figures, the light-colored lines display the best fits in the data from logistic regressions (with 95% confidence bands given by the shaded areas), while the dots connected by darker lines indicate the model's counterfactual results when varying educational attainment, as described in the text. The x-axis coordinates of the dots correspond to the average GDP per capital for low-, middle- and high-income countries in the data (middle- and high-income only for Figures 16c and 16f).

it is largest in manufacturing and low-skill services and essentially does not happen in agriculture. Finally, Figure 16h shows that the re-organization of production towards large firms that have adopted managerial capitalism pulls even the least educated workers from entrepreneurship to working in large firms, again consistent with the data.

6.3 Counterfactual: Structural Transformation and Skills

The preceding experiments suggest that generating simultaneous structural transformation and a re-organization of production requires a combination of forces. In future drafts, we plan to implement counterfactuals that illustrate this idea and help us understand the quantitative importance of the relevant driving forces.

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. Further, we show that there is a strong link between the rise of managerial capitalism and human capital. On one side, skills account for nearly all of cross-country differences in the share of white-collar workers; on the other, the adoption of managerial capitalism pulls even the least-educated workers out of own account work and into firms.

We develop a model of the endogenous adoption of managerial capitalism, calibrate it, and use it as a laboratory to understand the driving forces responsible for the re-organization of production. Our main result is that the re-organization of production is distinct from structural transformation. Rising incomes and shifting prices can explain why workers re-allocate across sectors, but they cannot explain the re-organization of production. Rising skills can explain the re-organization of production, but induces only a weak structural transformation of employment across sectors.

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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Contents

A Data Appendix

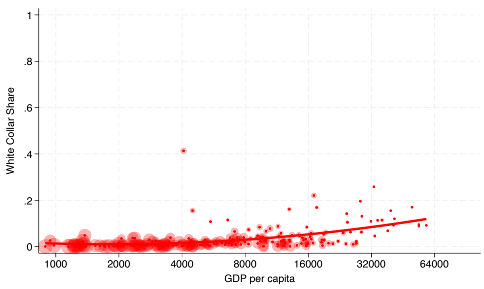
This appendix provides additional results related to the data and motivating facts documented in Section 2.

A.1 Detailed Industry Results

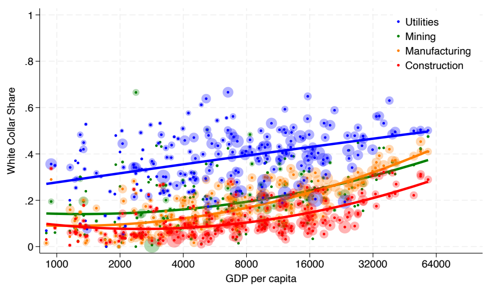
In the main text we aggregate industries to broad sectors in a fashion consistent with the structural transformation literature and then study the evolution of the white-collar share of employment for these broad sectors. Figure A.1 plots the white-collar share of employment at the country $\times$ year $\times$ detailed industry level against GDP per capita. Figure A.1a repeats the results for agriculture; Figure A.1b shows results for the four industries typically grouped into manufacturing; Figure A.1c shows results for the four industries grouped into low-skill services; and Figure A.1d shows results for the three industries grouped into high-skill services.

FIGURE A.1: DETAILED SECTORS AND WHITE COLLAR LABOR

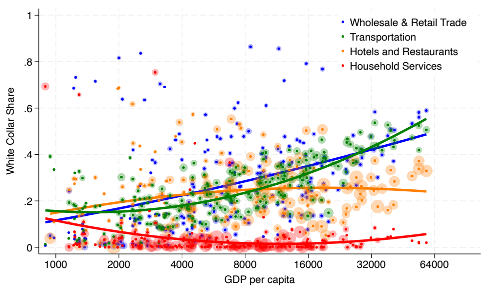
(a) Agriculture



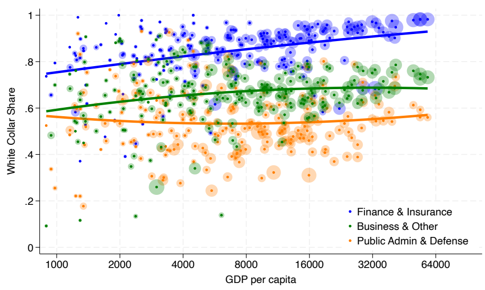
(b) Manufacturing



(c) Low-Skill Services



(d) High-Skill Services



Consistent with the historical evidence of Chandler (1977), there is significant heterogeneity in the evolution of the white-collar share of employment by industry. Some industries, such as agriculture, household services, or public administration experience essentially no transformation. Others, such as hotels and restaurants or business services, experience only a muted transformation. The rise of managerial capitalism 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.

A.2 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.2 starts by focusing on the United States, the country with the longest available time series. Figure A.2a shows that the white-collar share of employment increased by more than 20 percentage points between 1960 and 2015. Figure A.2b 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.2a can be accounted for by changes in the educational composition over time.

FIGURE A.2: WHITE-COLLAR OCCUPATIONS OVER TIME – UNITED STATES

(a) White-Collar Share Over Time   (b) Propensities by Decade

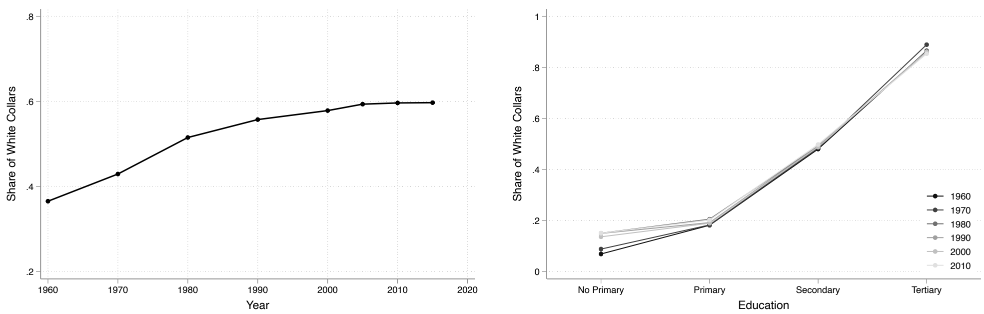
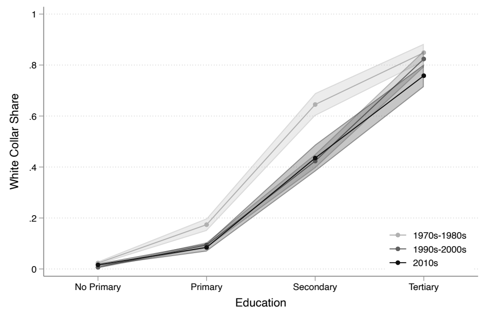


Figure A.3 shows the share of workers choosing a white-collar occupation conditional on education for all countries in the sample. Figures A.3a, A.3b, and A.3c show results for low-income, middle-income, and high-income countries, while the lines within each figure capture the estimated share for different type periods.

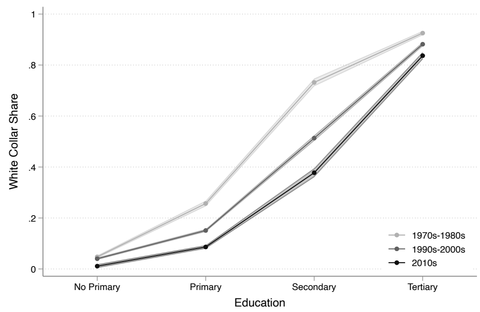
The share of workers choosing white-collar occupations is very stable in high-income countries. For low- and middle-income countries there is a decline in the white-collar share of primary- and secondary-educated workers. One possible explanation for this declining share is that the years 1970–2010 correspond to a period of massive educational expansion in these countries. Recent work suggests that this expansion may 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,

FIGURE A.3: WHITE-COLLAR OCCUPATIONS OVER TIME – ALL COUNTRIES

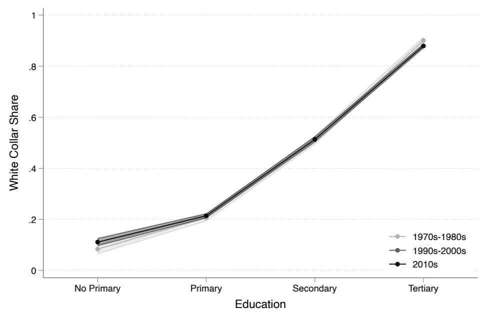
(a) Low Income



(b) Middle Income



(c) High Income



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.3 Alternative Measures of Skills

This section investigates the relationship between white-collar employment shares and skills for several alternative measures of skills.

A.3.1 Adult Test Scores

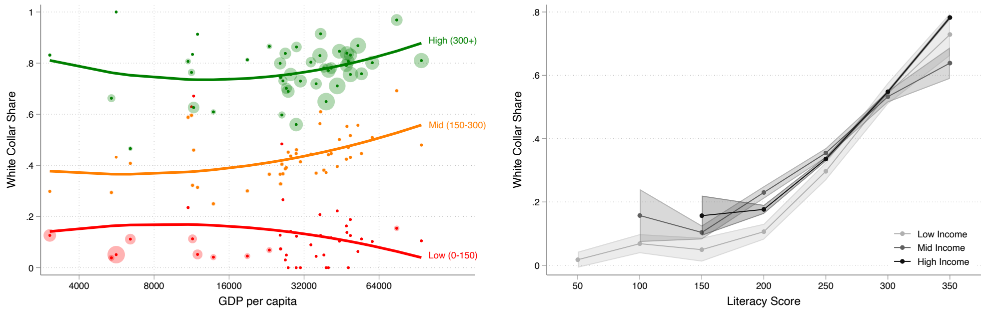
In addition to educational attainment, we can study trends in white-collar employment shares as a function of adult test scores for a large number of countries around the world. For this analysis we use data from the Organisation for Economic Co-operation and Development (OECD)'s PIAAC Survey of Adult 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 repeats Figure 4 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. Row (6) of Table A.1 shows that these results again imply that skills account for most of the correlation between white-collar employment shares and development.

FIGURE A.4: LITERACY AND WHITE-COLLAR OCCUPATIONS

(a) White-Collar Share by Literacy Score (b) Estimated Propensities



A.3.2 Childhood Test Scores

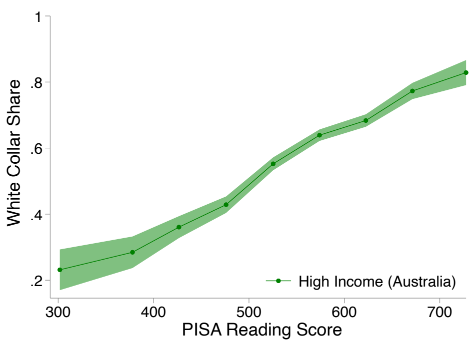
The advantage of adult test scores is that they measure the skills workers have (rather than how long they sat in a classroom). However, they are plausibly endogenous, in the sense that workers' skills may in part be caused by practicing and using those skills more in the course of performing their occupation. 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.

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)

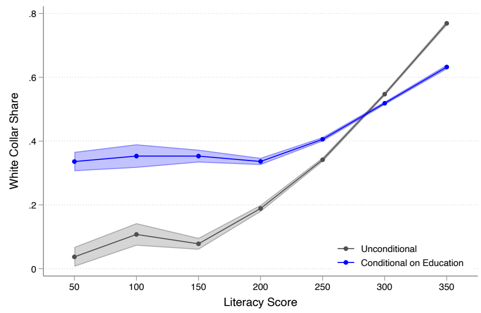


(b) Armed Forces Score (Sweden)

A.3.3 Literacy Conditional on Education

Using the PIAAC-STEP data this Appendix examines the relationship between occupational choices and literacy conditional on education. Figure A.6 plots the estimated white-collar employment share by literacy score (pooling all countries), with and without education dummies. While a marginal increase in literacy does not matter much at the bottom of a distribution, going from a score of 200 (around the 10th percentile of the global distribution) to a score of 350 (around the 99th percentile of the global distribution) keeping education constant increases the white-collar employment share by about 30 percentage points. This corroborates the point that the sorting into white-collar jobs reflects skills and not just educational credentials.

FIGURE A.6: LITERACY CONDITIONAL ON EDUCATION



A.4 Summary Accounting Results

In Section 2.2 we document that human capital accounts for a substantial share of cross-country differences in the share of white collar workers. This appendix formalizes this idea as a shift-share accounting result. We collapse the Minnesota Population Center (2020) 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	0.888
	(0.001)	(0.001)	
(2) Sector FE	0.048	-0.002	1.051
	(0.001)	(0.001)	
(3) Country and Decade FE	0.038	-0.001	1.019
	(0.007)	(0.004)	
(4) Men	0.084	0.000	0.997
	(0.002)	(0.001)	
(5) Women	0.169	0.028	0.836
	(0.002)	(0.001)	
(6) Literacy Score	0.133	0.008	0.939
	(0.002)	(0.002)	

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 3) 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)–(6) 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.3).

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

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

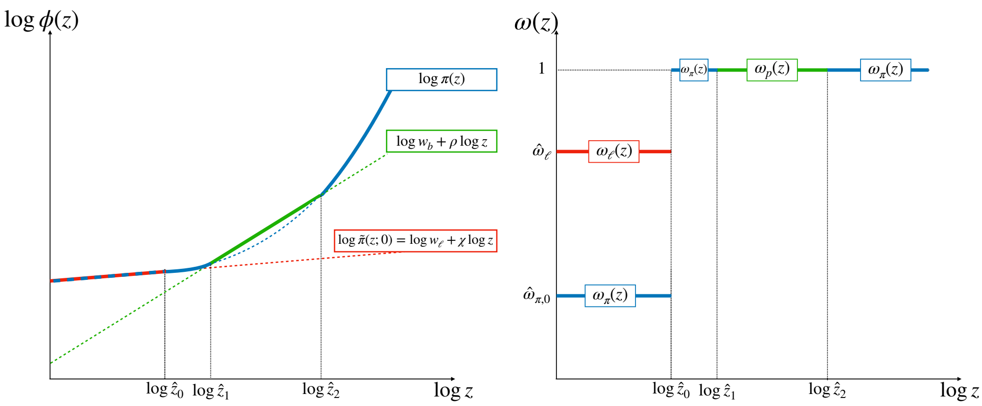
Note that we suppress the arguments of the functions q in equation (B.1) to simplify notation. This equation highlights the trade-offs entrepreneurs face when professionalizing the marginal task. Each term has an intuitive interpretation given by the term in brackets. The left-hand side captures the 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 7b 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.7 shows the income schedule and occupational choices for this case.

FIGURE B.7: ALTERNATIVE OCCUPATIONAL CHOICE RULES

(a) Income　　　　(b) Occupational Choice



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

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

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

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

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

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

$$n_p(i) > 0 \quad \forall i \leqslant \bar{\eta}$$

$$n_l > 0.$$

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

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

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

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

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 $q w_p$ and

w_l, we obtain

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

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

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

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

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

Which implies

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

C Details on Quantitative Results

We solve for the equilibrium using three nested loops: an **Outer Loop**, a **Middle Loop** and an **Inner Loop**. To that end, we first call `setup.m` to set up the problem calling the following subroutines:

1. `settings.m`: Define numerical settings;

2. `defineparameters.m`: Define parameters;

3. `constructgrids.m`: Construct an $N_z \times 1$ grid for productivity z such that, pooling all education groups, an equal share of individuals are in each skill bin;

It also assigns an initial guess for the share of individuals with skill z in sector j, $\sigma_j(z)$, as well as wages of laborers and professionals in each sector, $w_{l,j}$ and $w_{p,j}$, respectively.

We then proceed to solve the problem using the three nested loops.

Outer loop. Subroutine `betweensectors.m` proceeds accordingly:

1. Given $\{\sigma_j(z)\}_{j\in\mathcal{G}}$, loop over all sectors $j \in \mathcal{G}$ to solve for the within-sector equilibrium (calling `withinsectors.m`);

2. Based on the values of being in each sector at each productivity level z, $\{\phi_j(z)\}_{j\in\mathcal{G}}$, update the number of individuals with productivity z who opt to be in sector j, $\widehat{\sigma}_j(z)$, based on

$$\widehat{\sigma}_j(z) = \frac{1}{N_z} \frac{\phi_j(z)^\nu}{\sum_{k\in J} \phi_k(z)^\nu}$$

3. If $\sigma_j(z) = \widehat{\sigma}_j(z)$ for all j and z, stop. Otherwise update $\sigma_j(z) = \widehat{\sigma}_j(z)$ (potentially with some smoothing) and return above.

Middle loop. `withinsectors.m` with argument `market = 'laborers'`

1. Starts with a low wage of laborers, $w_{l,j}$, and calls `withinsectors.m` with argument `market = 'professionals'` to find the equilibrium wage for professionals, and the supply of and demand for laborers;

2. Next does a high wage of laborers, $w_{l,j}$, and calls `withinsectors.m` with argument `market = 'professionals'` to find the equilibrium wage for professionals, and the supply of and demand for laborers;

3. Finally uses bisection to find the equilibrium wage of laborers, at each step calling `withinsectors.m` with argument `market = 'professionals'` to find the associated equilibrium wage for professionals, such that supply of and demand for laborers equal.

Inner loop. `withinsectors.m` with argument `market = 'professionals'` takes a wage of laborers, $w_{l,j}$, as given and

1. Starts with a low wage of professionals, $w_{p,j}$, and solves for supply and demand of laborers and professionals using the following subroutines
   (a) `firmproblem.m` recovers optimized profits $\pi_j(z)$ as well as a choice of technology $q_j(z)$ and labor demand, $n_{l,j}(z)$ and $n_{p,j}(z)$;
   (b) `occupationalchoice.m` solves the within-sector occupational choice, $\omega_{l,j}(z)$, $\omega_{p,j}(z)$ and $\omega_{e,j}(z)$, and obtains maximized returns, $\phi_j(z)$;
   (c) `computesupply.m` computes the aggregate supply of laborers and professionals in sector j, $N^s_{l,j}$ and $N^s_{p,j}$;
   (d) `computedemand.m` computes aggregate demand for laborers and professionals, $N^d_{l,j}$ and $N^d_{p,j}$.
2. Next does a high wage of professionals, $w_{p,j}$, and solves for supply and demand of laborers and professionals using the subroutines described above;
3. Finally uses bisection to find the equilibrium wage of professionals such that supply of and demand for professionals equal, calling the subroutines described above.

We now elaborate further on the four subroutines called by the **Inner Loop**:

`firmproblem.m`. If parameter values are such that Lemma 2 holds (i.e. $\log\vartheta > \gamma_p^2/(1-\gamma_l)$), there is a sector-specific threshold $\hat{z}_j$ defined by

$$\hat{z}_j = \frac{1}{(1-\gamma_\ell)\,\lambda_j+\mu_j}\left[\left(1-\gamma_{\ell,j}\right)\left(1+\log\frac{w_{p,j}\gamma_{\ell,j}}{w_{\ell,j}\gamma_{p,j}}-\frac{1}{\gamma_{p,j}}\log\beta_j\right)-\log\left(p_jA_j\frac{\gamma_{\ell,j}}{w_{\ell,j}}\right)\right]$$

such that for $z<\hat{z}_j$, $q_j(z)=0$, while for $z>\hat{z}_j$, $q_j(z)$ solves equation

$$\left(\left(1-\gamma_{\ell,j}\right)\lambda_j+\mu_j\right)\left(\log z-\log\hat{z}_j\right) = q\left(\log\theta-\gamma_{p,j}\right)-\left(\frac{1-\gamma_{\ell,j}-\gamma_p}{\gamma_p}\right)\left(\log\theta\log\left(1-q\right)\right)$$

which can be differentiated to find a differential equation for $q(z)$

$$q_j'(z) = \frac{\frac{(1-\gamma_{\ell,j})\lambda_j+\mu_j}{z}}{\log\theta - \gamma_{p,j} + \frac{1-\gamma_{\ell,j}-\gamma_p}{\gamma_p}\frac{\log\theta}{1-q}}$$

the differential equation (obtained by differentiating (**??**))

$$q_j'(z) = \frac{\frac{1-\gamma_{l,j}}{z}}{\vartheta - \gamma_{p,j} + \vartheta\frac{1-\gamma_{p,j}-\gamma_{l,j}}{\gamma_{p,j}}\frac{1}{1-q_j(z)}}$$

subject to initial value $q_j(\hat{z}_j) = 0$. If the conditions required for Lemma 2 hold (and $\hat{z}_j < \overline{z}$, where $\overline{z}$ is the highest grid point for z), we numerically approximate this differential equation (if $\hat{z}_j < \underline{z}$, where $\underline{z}$ is the lowest grid point for z, we numerically find the optimal choice $q(\underline{z})$ and use this as initial value). If the condition required for Lemma 2 does not hold, we find the optimal q by choosing from a discretized set of possible q's.

Coefficients for the skill-sensitivity satisfy

$$\underbrace{\frac{\mu\rho_j}{1-\gamma_{\ell,j}}}_{\text{workers}} = \underbrace{\frac{\mu\rho_j}{1-\gamma_{\ell,j}}}_{\text{traditional entr.}} < \underbrace{\rho_j}_{\text{professionals}} < \underbrace{\frac{\mu+\lambda\gamma_{p,j}}{1-\gamma_{p,j}-\gamma_{p,j}}\rho_j}_{\text{Modern Entr with } q=1}$$

where we normalize $\rho_j = 1$ in high-skill services. Therefore, we need to pick: one level μ, one λ and three ρ_j in total.

Given a solution $q_j(z)$, optimal choices of laborers and professionals and profits are

$$\begin{aligned}
\eta_j(z) &= q_j(z)\gamma_{p,j} + \gamma_{l,j} \\
\alpha_j(z) &= q_j(z)\gamma_{p,j}/\eta_j(z) \\
\tilde{A}_j(z)^{-q} &= \exp\Big(-q_j(z)(\log\beta_j + \vartheta) + \vartheta(q_j(z)-1)\log(1-q_j(z))\Big) \\
\tilde{n}_j(z) &= \left(p_jA_j\tilde{A}_j(z)^{-q}\left(\frac{z}{w_{p,j}}\right)^{\alpha_j(z)}\left(\frac{1}{w_{l,j}}\right)^{1-\alpha_j(z)}\right)^{\frac{\eta_j(z)}{1-\eta_j(z)}} \\
n_{p,j}(z) &= \frac{\alpha_j(z)\eta_j(z)}{q_j(z)w_{p,j}}p_jA_j\tilde{A}_j(z)^{-q}\tilde{n}_j(z) \\
n_{l,j}(z) &= \frac{(1-\alpha_j(z))\eta_j(z)}{w_{l,j}}p_jA_j\tilde{A}_j(z)^{-q}\tilde{n}_j(z) \\
\pi_j(z) &= (1-\eta_j(z))p_jA_j\tilde{A}_j(z)^{-q}\tilde{n}_j(z)
\end{aligned}$$

`occupationalchoice.m`. The shares of individuals with productivity z working in sector j that picks occupation l, p and e respectively are given by

$$\begin{aligned}
\omega_{l,j}(z) &= \frac{\left(w_{l,j}\right)^{\xi}}{\left(w_{l,j}\right)^{\xi} + \left(z^{\lambda} w_{p,j}\right)^{\xi} + \left(\pi_j(z)\right)^{\xi}} \\
\omega_{p,j}(z) &= \frac{\left(z^{\lambda} w_{p,j}\right)^{\xi}}{\left(w_{l,j}\right)^{\xi} + \left(z^{\lambda} w_{p,j}\right)^{\xi} + \left(\pi_j(z)\right)^{\xi}} \\
\omega_{e,j}(z) &= \frac{\left(\pi_j\right)^{\xi}}{\left(w_{l,j}\right)^{\xi} + \left(z^{\lambda} w_{p,j}\right)^{\xi} + \left(\pi_j(z)\right)^{\xi}}
\end{aligned}$$

`computesupply.m`. Given the number of individuals in sector j with productivity z, $\sigma_j(z)$, and the occupational choice probabilities conditional on z, $\omega_{l,j}(z)$ and $\omega_{p,j}(z)$, compute the aggregate supply of laborers and professionals

$$\begin{aligned}
N_{l,j}^{s} &= \sum_{z \in \mathcal{Z}} \omega_{l,j}(z) * \sigma_j(z) \\
N_{p,j}^{s} &= \sum_{z \in \mathcal{Z}} z^{\lambda} * \omega_{p,j}(z) * \sigma_j(z)
\end{aligned}$$

`computedemand.m`. Given the number of individuals in sector j with productivity z, $\sigma_j(z)$, the occupational choice probability conditional on z, $\omega_{e,j}(z)$, optimal choice of technology $q_j(z)$, and optimal choice of labor $n_{l,j}(z)$ and $n_{p,j}(z)$, compute the aggregate demand for laborers and professionals

$$\begin{aligned}
N_{l,j}^{d} &= \sum_{z \in \mathcal{Z}} n_{l,j}(z) * \omega_{e,j}(z) * \sigma_j(z) \\
N_{p,j}^{d} &= \sum_{z \in \mathcal{Z}} q_j(z) * n_{p,j}(z) * \omega_{e,j}(z) * \sigma_j(z)
\end{aligned}$$

C.1 Computing moments (subroutine `computemoments.m`)

Having solved the model, we next compute a set of moments to match up with the data. Since $\sigma_j(z)$ is the number of individuals of productivity z in sector j and the grid for z is such that an equal share of individuals have each productivity, the distribution of individuals over sectors conditional on z is $\sigma_j(z)N_z$. Let $g(z|s)$ be the distribution of individuals over z conditional on schooling s and $\gamma(s)$ the employment share of individuals with schooling s. Then the fraction of employment with productivity z, that works in sector j and has schooling s is

$$gg(z,j,s) \;=\; gg(j|z)*g(z|s)*\gamma(s)$$

The number of entrepreneurs with productivity z in sector j with schooling s is

$$gg^e(z,j,s) \;=\; \omega_{e,j}(z)*gg(z,j,s)$$

Consequently, the number of firms with productivity z in sector j is

$$x(z,j) \;=\; \sum_{s\in\mathcal{S}} gg_e(z,j,s)$$

White collar workers. We define as white collar those individuals who work as professionals or modern entrepreneurs (i.e. those with $q>0$). We label everyone else as a blue collar worker. The number of white collar workers with productivity z that work in sector j and have schooling s is hence

$$wc(z,j,s) \;=\; \Big(\omega_{e,j}(z)*\mathbb{1}_{q_j(z)>0}+\omega_{p,j}(z)\Big)*gg(z,j,s)$$

Consequently, the overall number of white collar individuals is

$$wc \;=\; \sum_{s\in\mathcal{S}}\sum_{j\in\mathcal{J}}\sum_{z\in\mathcal{Z}} wc(z,j,s)$$

The number of white collar individuals in sector j is

$$wc_j \;=\; \sum_{s\in\mathcal{S}}\sum_{z\in\mathcal{Z}} wc(z,j,s)$$

The number of white collar individuals in education group s is

$$wc_s \;=\; \sum_{j\in\mathcal{J}}\sum_{z\in\mathcal{Z}} wc(z,j,s)$$

The number of white collar individuals in education group s and sector j is

$$wc_{j,s} \;=\; \sum_{z\in\mathcal{Z}} wc(z,j,s)$$

Own account workers. The number of laborers in sector j with schooling s is

$$laborers(j,s) = \sum_{z\in\mathcal{Z}} \omega_{l,j}(z) * gg(z,j,s)$$

We define own account workers as entrepreneurs with $q = 0$ as well as those working for such firms. Since we do not know the schooling level of a firm's laborers, we approximate traditional firms' share of laborers from each education group by the education group's share of all laborers in the sector

$$own_{j,s} = \sum_{z\in\mathcal{Z}} \left(1 + \frac{laborers(j,s)}{N_{l,j}^{s}} n_{l,j}(z)\right) \mathbb{1}_{q_j(z)=0} * gg^{e}(z,j,s)$$

The overall number of own account workers is hence

$$own = \sum_{s\in\mathcal{S}} \sum_{j\in\mathcal{J}} own_{j,s}$$

the number of own account workers in sector j is

$$own_j = \sum_{s\in\mathcal{S}} own_{j,s}$$

while the number of own account workers with schooling s is

$$own_s = \sum_{j\in\mathcal{J}} own_{j,s}$$

Average firm size. The overall number of firms is

$$M = \sum_{j\in\mathcal{J}} \sum_{z\in\mathcal{Z}} x(z,j)$$

The overall number of workers is

$$N = \sum_{s\in\mathcal{S}} \sum_{j\in\mathcal{J}} \sum_{z\in\mathcal{Z}} gg(z,j,s)$$

which by construction is one. Hence, average firm size is

$$fsize = \frac{N}{M}$$

The number of firms in sector j is

$$M_j = \sum_{z \in \mathcal{Z}} x(z,j)$$

The number of workers in sector j is

$$N_j = \sum_{s \in \mathcal{S}} \sum_{z \in \mathcal{Z}} gg(z,j,s)$$

Hence, average firm size in sector j is

$$fsize_j = \frac{N_j}{M_j}$$

Employment at large firms. The number of professional workers in sector j is

$$gg^p(j) = \sum_{s \in \mathcal{S}} \sum_{z \in \mathcal{Z}} \omega_{p,j}(z) * gg(z,j,s)$$

The number of professional units of labor in sector j is

$$gg^{pe}(j) = \sum_{s \in \mathcal{S}} \sum_{z \in \mathcal{Z}} z^{\lambda} \omega_{p,j}(z) * gg(z,j,s)$$

An entrepreneur with productivity z in sector j has firm size

$$fsize(z,j) = 1 + n_{l,j}(z) + \frac{gg^p(j)}{gg^{pe}(j)} n_{p,j}(z)$$

where we use the ratio of bodies to efficiency units of professional labor in the sector to convert a firm's demand for efficiency units of professional labor to bodies. The employment distribution over firms is

$$xe(z,j) = \frac{fsize(z,j) * x(z,j)}{\sum_{z \in \mathcal{Z}} \sum_{j \in \mathcal{G}} fsize(z,j) * x(z,j)}$$

The number of workers at firms with 10 or more employees is

$$large = \sum_{z \in \mathcal{Z}} \sum_{j \in \mathcal{G}} fsize(z,j) * (fsize(z,j) >= 10) * xe(z,j)$$

while the number of workers at firms with 10 or more employees in sector j is

$$large_j = \sum_{z \in \mathcal{Z}} fsize(z,j) * (fsize(z,j) >= 10) * xe(z,j)$$

The number of white collar workers at large firms. The number of white collar workers employed by firms with 10 or more employees is

There is a mistake here, must be updated

$$wclarge = \sum_{z \in \mathcal{Z}} \sum_{j \in \mathcal{G}} \left(1 + \frac{gg^p(j)}{gg^{pe}(j)} n_{p,j}(z)\right) * (fsize(z,j) >= 10) * xe(z,j)$$

where we again use the ratio of bodies to efficiency units of professional labor in the sector to convert a firm's demand for efficiency units of professional labor to bodies. The number of white collar workers employed by firms with 10 or more employees in sector j is

$$wclarge_j = \sum_{z \in \mathcal{Z}} \left(1 + \frac{gg^p(j)}{gg^{pe}(j)} n_{p,j}(z)\right) * (fsize(z,j) >= 10) * xeok(z,j)$$

Employment-unweighted average and st.d. of log firm size. The (employment-unweighted) mean of log firm size is

$$lnfsizemean = \frac{1}{M} \sum_{z \in \mathcal{Z}} \sum_{j \in \mathcal{G}} \ln fsize(z,j) * x(z,j)$$

The (employment-unweighted) mean of log firm size in sector j is

$$lnfsizemean_j = \frac{1}{M_j} \sum_{z \in \mathcal{Z}} \ln fsize(z,j) * x(z,j)$$

The standard deviation of log firm size is

$$lnfsizestd = \sqrt{\frac{1}{M} \sum_{z \in \mathcal{Z}} \sum_{j \in \mathcal{G}} \left(\ln fsize(z,j) - lnfsizemean)^2 * x(z,j)\right.}$$

The standard deviation of log firm size in sector j is

$$lnfsizestd_j = \sqrt{\frac{1}{M_j} \sum_{z \in \mathcal{Z}} \left(\ln fsize(z,j) - lnfsizemean_j)^2 * x(z,j)\right.}$$

Value added per worker. The value added of a firm with productivity z in sector j is the sum of profits and labor compensation

$$va(z,j) \quad = \quad \pi_j(z) + w_{l,j}n_{l,j}(z) + q_j(z)w_{p,j}n_{p,j}(z)$$

Hence, economy-wide value added per worker is

$$vapw \quad = \quad \frac{1}{N}\sum_{j\in\mathcal{J}}\sum_{z\in\mathcal{Z}} va(z,j)x(z,j)$$

where again by construction $N = 1$, while value added per worker in sector j is

$$vapw_j \quad = \quad \frac{1}{N_j}\sum_{z\in\mathcal{Z}} va(z,j)x(z,j)$$

Mincer regression. The number of workers with productivity z in sector j with schooling s working as laborers and professionals, respectively, is

$$\begin{aligned} ggg(z,j,s,l) &= \omega_{l,j}(z)gg(z,j,s) \\ ggg(z,j,s,p) &= \omega_{p,j}(z)gg(z,j,s) \end{aligned}$$

The corresponding log pay is

$$\begin{aligned} w(z,j,s,l) &= \ln w_{l,j}(z) \\ w(z,j,s,p) &= \lambda \ln z + \ln w_{p,j}(z) \end{aligned}$$

Consequently, the number of workers with schooling s in wage employment is

$$N_{l+p}(s) \quad = \quad \sum_{j\in\mathcal{J}}\sum_{o\in\{l,p\}}\sum_{z\in\mathcal{Z}} ggg(z,j,s,o)$$

meanwhile, average log pay of schooling group s is

$$wage_s \quad = \quad \frac{\sum_{j\in\mathcal{J}}\sum_{o\in\{l,p\}}\sum_{z\in\mathcal{Z}} w(z,j,s,o) * ggg(z,j,s,o)}{N_{l+p}(s)}$$

We project $wage_s$ on a constant and a linear in years of schooling (4, 8, 12 and 16), weighing by wage employment, $N_{l+p}(s)$, and record the resulting point estimate on the linear term.