Economic Development According to Chandler*

Niklas Engbom — NYU – Stern
Hannes Malmberg — Minnesota
Tommaso Porzio — Columbia
Federico Rossi — Warwick
Todd Schoellman — Minneapolis Fed

April 2025
Click here for latest version.

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.

*We thank participants at numerous conferences and seminars for helpful comments and feedback. We are particularly grateful to Jan Grobovšek, Bryan Seegmiller, and Michael Peters for insightful discussions. The views expressed herein are those of the authors and not necessarily those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.

1 Introduction

In a seminal contribution, Chandler (1977) documents how American businesses transformed during the Second Industrial Revolution. Innovation in this era yielded new technologies that leveraged economies of scale and scope to raise productivity in select industries.[1] Chandler shows that the firms that adopted these technologies became large and encountered logistical challenges in terms of sourcing a constant supply of inputs, coordinating high-velocity production, and marketing and selling outputs. The firms that successfully met these challenges did so by adopting *managerial capitalism*: they recruited and trained a hierarchy of white-collar workers such as managers, accountants, purchasing agents, and clerks. Firms and countries that failed to make these investments did not fully benefit from new technologies and lost ground to their competitors (Chandler, 1977, 1990).

The main contribution of this paper is to show that the core insight of Chandler about the complementarity between managerial capitalism and technologies that leverage economies of scale or scope is relevant for understanding development today.. We start by using representative data sets drawing on nearly one hundred countries around the world to show that larger firms use white-collar labor more intensively everywhere, consistent with complementarity. Development is associated with a shift towards white-collar-intensive production, particularly in the manufacturing and low-skill service sectors emphasized by Chandler's historical work.

We then document new facts about the relationship between human capital and the adoption 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 educational attainment. 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 employment in large firms as a country develops.

These facts motivate us to develop a model of the adoption of managerial capitalism and its role for development. The model features the complementarity between managerial capitalism and technologies that leverage economies of scale or scope that

[1] See Kuznets (1973) for a broad overview of this economic transition.

is central to Chandler. However, our perspective differs in one important dimension. Chandler's study of U.S. history takes the view that innovation of new technologies and growth in markets led to the adoption of managerial capitalism and the accumulation of skills.[2]

We seek instead to understand why these technologies and production in large firms have not been adopted in developing countries more than a century after they were developed. Our empirical evidence motivates us to model (lack of) human capital as one potential explanatory factor. We also allow for firm-size distortions, which stand in for other barriers to setting up and operating large firms.

The model features a continuum of workers with heterogeneous skills. Workers make an occupational and a sectoral choice. 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.[3] 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

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

[3] Tamkoç (2024) formulates a model where upper managers can hire middle managers to increase their span of control that has some similar properties, but he does not provide an underlying foundation for the production function.

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 reorganization 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. To keep the exposition brief we describe the data briefly and focus on one main result for each fact, but additional discussion and results are available in Appendix A.

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.[4] 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.[5]

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-

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

[5] 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).

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: WHITE-COLLAR SHARE AND FIRM SIZE

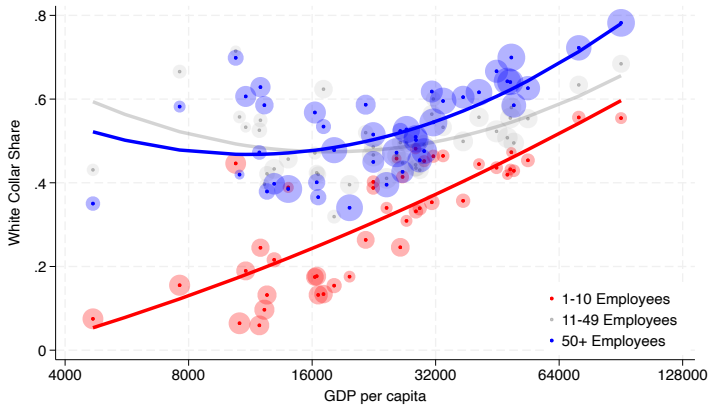


Figure 1 plots the share of white-collar workers by firm size category in each country against the country's PPP GDP per capita, taken from Penn World Tables 10.01 (Feenstra, Inklaar and Timmer, 2015). Each marker in this figure captures a country × firm size category, with the three firm size categories 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 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. Similar results apply for the handful of countries where we can construct alternative proxies of modern firms; see Appendix A.1 for details.

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 218 cross-sections from 74 different countries span-

ning 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.

FIGURE 2: SECTORS AND WHITE-COLLAR LABOR

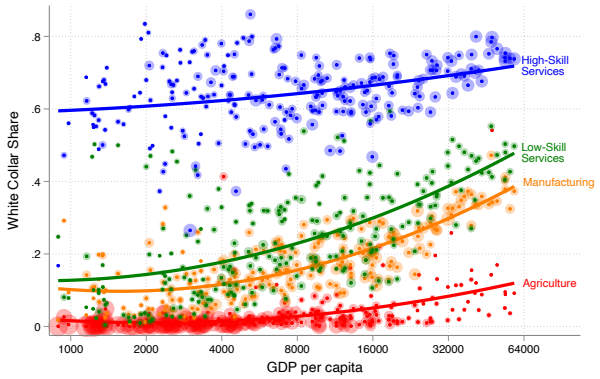


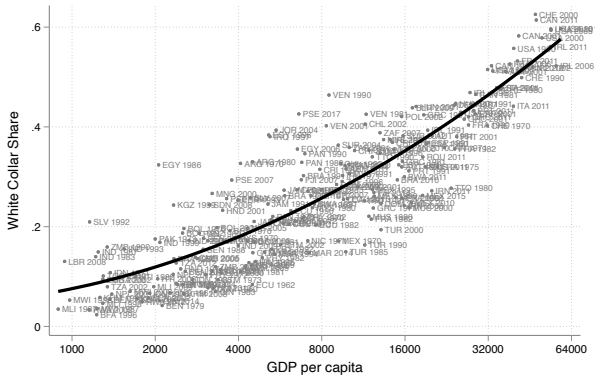
Figure 2 plots the share of white-collar workers by sector in each country against the country's PPP GDP per capita. Each marker in this figure captures a country $\times$ year $\times$ sector, with the four sectors plotted using different colors. There are two main findings in this figure. First, there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

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 $\times$ 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.

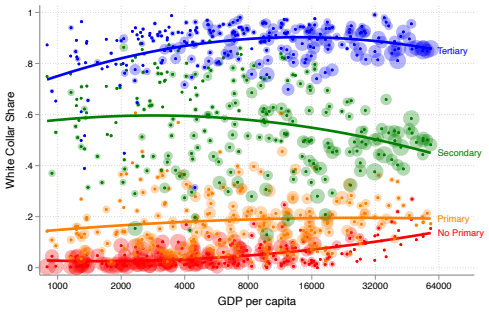
FIGURE 3: WHITE-COLLAR WORK AND DEVELOPMENT



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 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

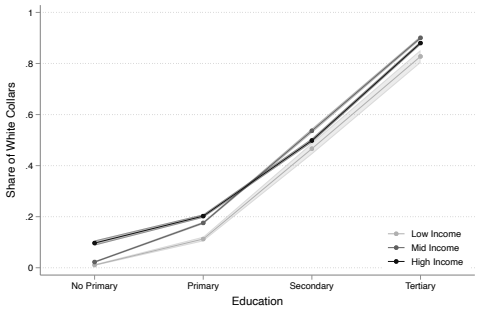


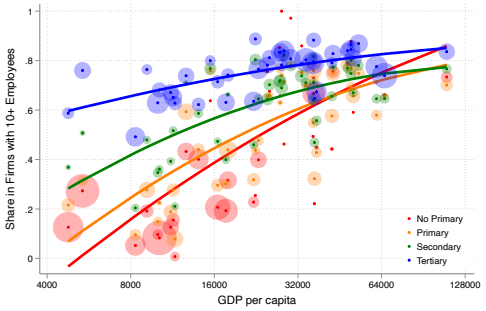
Figure 4b provides an alternative way to visualize this fact. It plots the average share of white-collar workers by education level for countries in three income groups: low-income, middle-income, and high-income countries. These income groups are based on official World Bank classifications and are 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.

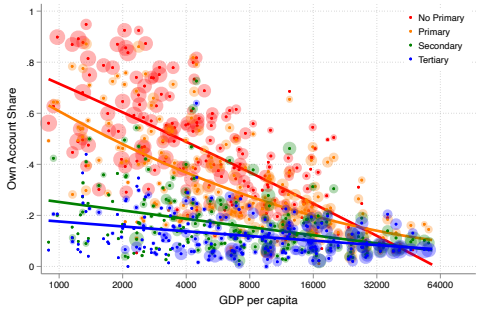
This fact turns out to be extremely robust. Appendix A.3 shows that similar facts hold in both the time series and the cross section, as well as if we use alternative measures of skills. A direct implication of these findings is that differences in aggregate human capital account for almost all of the cross-country variation in the share of white-collar workers. We formalize this idea using shift-share accounting and show that the exact figure is that education accounts for 90 percent of the variation in our baseline exercise and 84–105 percent across a number of alternative specifications.[6] Overall, the strength and consistency 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 $\times$ 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 $\times$ year $\times$ 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

[6] 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).

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. Again, Appendix A.4 provides additional results.

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 individuals with heterogeneous skills who make occupational choices. Individuals 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 presents a simplified, one-sector version of the model. In Section 4 we characterize optimal choices for this

model and provide analytical results that build intuition for key mechanisms. We enrich the model, including by adding multiple sectors, when we take it to the data in Section 5. Proofs for this section and the next are in Appendix B.

3.1 Environment

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

The core element of our model is the entrepreneur's problem, which integrates a task assignment model in the spirit of Acemoglu and Restrepo (2018) or Akcigit, Alp and Peters (2021) into the Lucas (1978) model of span of control. The production process uses two task inputs. First, there is a single production task that can only be accomplished by hiring laborers, for example machine operators on an assembly line.

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

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

Formally, an entrepreneur with skill z solves

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

s.t.

$$\tilde{n}(i) = \max\{1, a(i) n_p(i)\}$$

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

The choice of optimal technology

Without loss of generality, we order tasks in descending order by their relative productivity $a(i)$. We assume that the size-dependent wedge depends only on the share of tasks that are professionalized: $\tilde{\tau}(\{n_p(i)\}) = \tilde{\tau}(q)$, where $q \equiv \int_0^1 \mathbb{I}_{n_p(i)>0} di$. Under these assumptions, Lemma 1 shows that the multi-dimensional problem (1) can be simplified to the choice of the share q of tasks to professionalize and how many professionals and laborers to hire.

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

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

where

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

The main implication is that the entrepreneur's problem can be reduced to a standard maximization of profits given a Cobb-Douglas production function over two types of labor, with one additional twist. The entrepreneur also chooses the share of tasks to professionalize, 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 $y(z)$ to be the optimally chosen output by an entrepreneur with productivity z, which solves problem 2.

Occupational Choice

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

Each worker chooses the occupation that maximizes income:

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

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

3.2 Equilibrium

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

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

1. *entrepreneurs maximize firm profits solving (1);*
2. *$\omega_{\pi,j}(z)$, $\omega_{p,j}(z)$, $\omega_{\ell,j}(z)$ satisfy the occupational choice (3), that is,*

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

3. the markets for professionals and laborers clear:

$$\int q(z)n_p(z)\omega_\pi(z)dG(z) = \int z^\rho \omega_p(z)dG(z)$$
$$\int n_\ell(z)\omega_\pi(z)dG(z) = \int z^\chi \omega_\ell(z)dG(z);$$

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 $a(i)$ that makes it straightforward to impose concavity and that also yields convenient analytical solutions.

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

Intuitively, β controls the overall level of productivity of professionalizing tasks, while θ controls the dispersion of productivity of professionalizing tasks. This function implies that log productivity is a decreasing, concave function of i with $\lim_{i\to 1}\log(a(i)) = -\infty$, which makes it straightforward 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

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

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

We also 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* is defined as $\mathbb{W} \equiv \log \frac{w_p \gamma_\ell}{w_\ell \gamma_p}$.

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

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

Entrepreneurial 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. 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:

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

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

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

Equations (4) and (5) show that the expressions for labor utilization and profits are similar to their counterparts in standard span of control models (Lucas, 1978).[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

[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.

scale $\eta(q)$, the distortion the entrepreneur faces $\tilde{\tau}(q)$, and the return to entrepreneurial skills z.

We use equation (4) to characterize the optimal organization of production, which encompasses both the share of tasks that are professionalized q and the scale of production. Lemma 2 establishes that when there is sufficient heterogeneity in the cost of professionalizing different tasks (θ is sufficiently large), then the optimal organization of production is a smooth and well-behaved function of the entrepreneur's skill.[8]

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

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

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

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

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

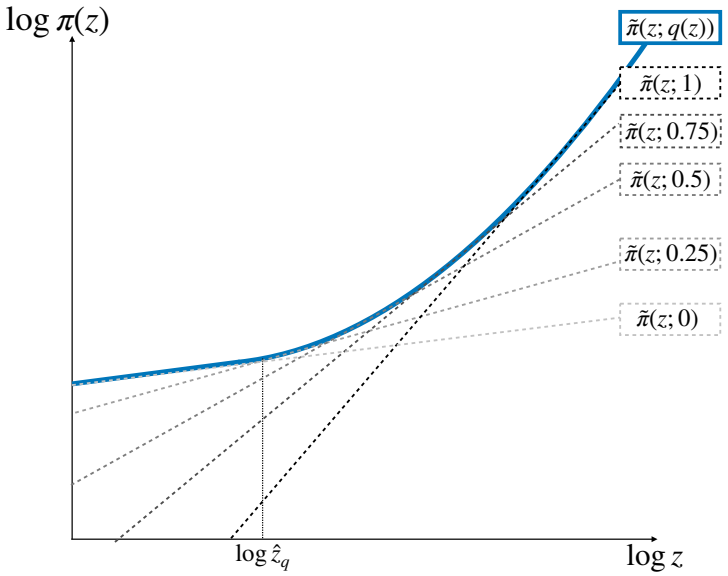
$$\frac{\partial \log y(z)}{\partial \log z} = \begin{cases} \frac{1}{1-\gamma_\ell} & \text{if } z \leqslant \hat{z}_q \\ \frac{1+\gamma_p \frac{dq(z)}{d\log z}}{1-\eta(q(z))} & \text{if } z > \hat{z}_q. \end{cases}$$

Figure 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 more convex in z. This reflects that a higher q reduces the degree of diminishing returns, disproportionately benefiting more skilled entrepreneurs. The blue line is the upper envelope of the gray curves. It represents the resulting profits of entrepreneurs for each level of z, taking into account the optimal choice of the organization of production.

Lemma 2 and Figure 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 $\eta(0)=\gamma_\ell$) and so operate small

[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.

FIGURE 6: TECHNOLOGY CHOICE AND FIRM PROFITS



firms in equilibrium. The elasticity of output with respect to skill is $\frac{1}{1-\gamma_\ell}$, which is the familiar expression from Lucas (1978). We think of this set of entrepreneurs as capturing the traditional organization of production, including own account work or work in small firms with little labor specialization as described in Bassi et al. (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 $\frac{\mu}{1-\gamma_\ell}$ and is increasing in q, which is consistent with recent evidence from Quieró (2022) that the thickness of the firm size distribution tail is increasing in the entrepreneur's education level. We think of these firms that professionalize some tasks as modern 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 for optimal occupational choice, which informs us about which workers actually choose entrepreneurship.

[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.

Occupational Choice, Equilibrium, and Duality

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 χ and ρ satisfy

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

Note that the elasticity for modern entrepreneurs applies for 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)**.** Given Assumption 3, the equilibrium satisfies the following properties

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

2. the equilibrium incomes satisfy

   - $w_\ell z^\chi \geqslant \tilde{\pi}(z, 0)$ with equality if and only if $\omega_\pi(z)\mathbb{I}_{z \leqslant \hat{z}_q} > 0$
   - if $\hat{z}_0 = \hat{z}_1 : w_\ell z^\chi = w_p \hat{z}_1^\rho$, $w_p \hat{z}_2^\rho = \pi(\hat{z}_2)$;
   - if $\hat{z}_0 < \hat{z}_1 : w_\ell z^\chi = \pi(\hat{z}_0)$, $\pi(\hat{z}_1) = w_p \hat{z}_1^\rho$, $w_p \hat{z}_2^\rho = \pi(\hat{z}_2)$;

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

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

Lemma 3 describes shows that the equilibrium can take one of two possible equilibrium structures, 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.10 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 ρ. Finally, the blue line shows the profit of entrepreneurs (both traditional and modern), which take into account the optimal choice of technology q.

FIGURE 7: OCCUPATIONAL CHOICE AND ENDOGENOUS DUALITY

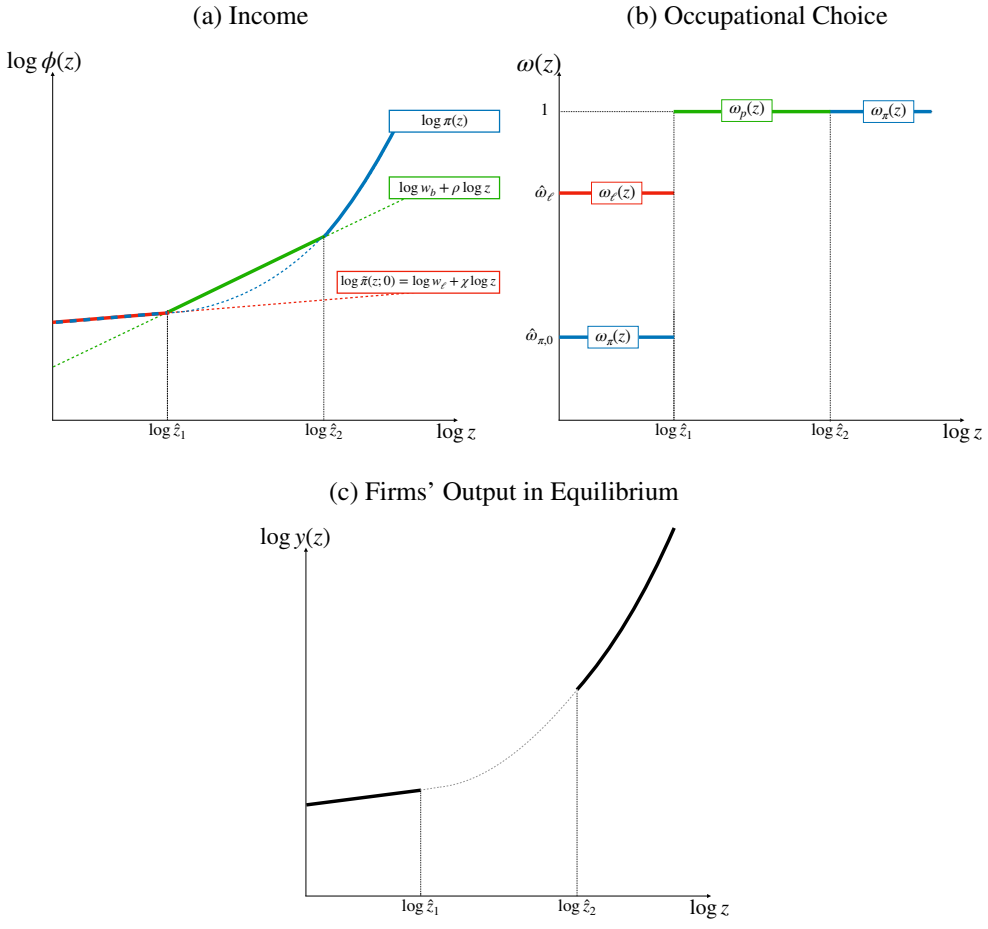


Figure 7b shows the resulting occupational choice. Workers with low skill levels are indifferent between becoming traditional entrepreneurs or laborers. Workers with intermediate levels of skills earn the most as professionals and consequently choose that occupation. Workers with the highest levels of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

Blue and White Collar Workers

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: $\omega_B(z) \equiv \omega_\ell(z) + \omega_\pi(z)[1-q(z)]$.

DEFINITION 4. *White-collar workers* are professionals and share q of entrepreneurs who professionalize share q of tasks: $\omega_W(z) \equiv \omega_p(z) + \omega_\pi(z)q(z)$.

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 productivity of hired professionals does not vary across tasks within sector: $\theta = 0$.

ASSUMPTION 5. The income of laborers and traditional entrepreneurs is equally skill-sensitive, $\chi = \frac{\mu}{1-\gamma_\ell}$; the income of professionals is as skill-sensitive as the profits of modern entrepreneur, $\rho = \frac{\mu}{1-\gamma_p-\gamma_\ell}$.

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.

The properties established in Lemma **??** 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)**.** Start from an equilibrium.. an increase in the supply of skills from a distribution $G(z)$ to a distribution $G'(z)$, such that $G'(\kappa z) = G(z)$ for a $\kappa > 1$. There exist a value $\hat{\kappa}$ such that until $\kappa < \hat{\kappa}$

Then the increase in supply, as long as .. yields.

that which first order stochastically dominates $G(z)$. This change yields the following:

1. an increase in the share of white-collar workers and a decline in the share of traditional entrepreneurs;
2. an increase in average firm size;
3. no change in the skill premium;
4. no change in the occupational choices for workers conditional on skill level z.

While the increase in supply past $\hat{\kappa}$ yields the following:

1. a constant share of white-collar workers and a decline in the share of traditional entrepreneurs;

2. constant firm size;

3. a decline in the skill premium;

4. the probability to work in a white collar occupation declines conditional on skill level z.

Split it in two.

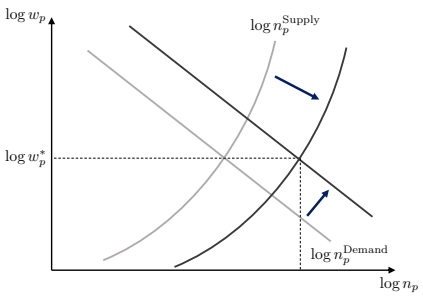
Proposition 1 builds on the fact that the skill premium is invariant to shifts in the supply of skills (Property 3 of Lemma **??**). For this reason, it is useful to explain further why this is the case in the model. To do so, we explain why both the wages of professionals and of laborers are constant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

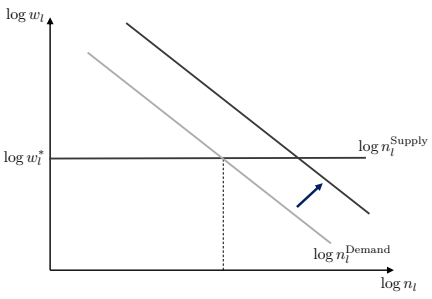
An increase in skills decreases the supply of laborers. It also increases the share of modern entrepreneurs and hence the demand for laborers. However, low-skilled workers are indifferent between being laborers or traditional entrepreneurs and Assumption **??** guarantees that there are at least some 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

(a) Professionals



(b) Laborers



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 the skill premium is invariant to the supply of skills, the rest of the results can be naturally understood as arising through composition effects. The increase in the aggregate supply of skills leads to more modern entrepreneurs and an increase in the size of modern firms. 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, 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 share of white-collar workers and a decline in the share of traditional entrepreneurs;
2. an increase in average firm size;
3. an increase in the wage premium;
4. 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 shifts as the increase in the supply of skills. However, along other dimensions

it works differently. It generates an increase in the wage premium, which implies that 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 Quantitative Model

We now turn to a quantitative version of the model. We enrich the model in several dimensions, including by adding multiple sectors so that it can speak to structural transformation. We calibrate the model so that it matches 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. Finally, we validate the model using quasi-experimental evidence on the role of expansions of schooling and improvements in management from the literature. In Section 6, we use the model to study a number of counterfactuals of interest.

5.1 Multi-Sector Model

We start by expanding the model to include multiple sectors. The model of Section 3 and the analysis of Section 4.2 can be thought of as applying to a single sector. The quantitative model includes four sectors, corresponding to those shown in Section 2: agriculture, manufacturing, low-skill services, and high-skill services, each with different prices p_j, with j denoting sectors. We need to specify three model elements: how the production process differs by sector; how workers choose among sectors; and how we close the multi-sector model.

We allow all of the key production parameters to vary by sector. This includes the total factor productivity A_j; the returns to scale in each type of labor, $\gamma_{p,j}$ and $\gamma_{\ell,j}$; the scalability of production, which is controlled by β_j; and the the returns to skills when working as an entrepreneur or a professional, μ_j and ρ_j.

The production parameters and prices determine the income schedule offered to workers of each skill level in each sector $\phi_j(z)$. We amend workers' utility functions to allow them to have direct preferences over the sector in which they work. These preferences consist of both a level of utility $\nu_{\mu,j} \equiv \tilde{\nu}_{\mu,j} p_j A_j$ and an idiosyncratic relative preference drawn from a type-I extreme value distribution with shape parameter

ν_σ. These assumptions imply that the share of workers with skill level z that choose sector j is given by

$$\sigma_j(z) \quad = \quad \frac{\tilde{\nu}_{\mu,j} p_j A_j \phi_j(z)^{\nu_\sigma}}{\sum_{k \in J} \tilde{\nu}_{\mu,k} p_k A_k \phi_k(z)^{\nu_\sigma}}. \tag{6}$$

Finally, we close the model by assuming a fictitious representative consumer with the average income of all workers who chooses sectoral consumption to maximize a non-homothetic CES utility function as in Comin, Lashkari and Mestieri (2021). This approach allows us to capture consumption responses to changing prices and rising (average) incomes, without requiring us to solve for and aggregate the expenditures of the entire distribution of workers. A useful way to understand our approach is to reference the associated Hicksian demand function with

$$\log\left(\frac{p_j c_j}{p_k c_k}\right) = (1-\sigma)\log\left(\frac{p_j}{p_k}\right) + (1-\sigma)(\varepsilon_j - \varepsilon_k)\log(U) + \log\left(\frac{D_j}{D_k}\right) \tag{7}$$

where D_j shifts the level of demand for goods produced by sector j and U is total utility.

In our calibration, we set $c_j = y_j$ and p_j as given and choose the level of preferences D_j so that the observed expenditures are optimal at observed prices. Our counterfactual experiments imply changes in relative prices of the output of different sectors and changes in the level of average income and utility. We use (7) to model the shift in demand induced by changes in relative prices, which is controlled by the parameter σ, and the shift in demand associated with changes in average income, which are controlled by the parameters ε_j. Equation (7) acts as a relative labor demand curve for different sectors, while (6) acts as a relative labor supply curve; we solve for the shift in relative prices and quantities that are consistent with these expressions.

In Section 4.2 we derived some results that help build intuition for how the model functions. We now provide one final result that is useful for understanding how labor reallocates across sectors in our experiments.

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.

This lemma follows directly from equation (6) and the observation that workers' wages and entrepreneurs' profits are also homogeneous of degree 1 in revenue productivity. Standard forces that generate structural transformation do so by altering sectoral productivities and prices. This lemma implies that these forces generate a proportional expansion of a sector's labor at all skill levels, but not a shift in the sector's skill composition. In order to understand changes in a sector's skill composition, we need to look

to other factors in the model, such as a change in the re-organization of production.

5.2 Extensions and functional forms

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 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 $z_{\mu,1} = 0$.

5.3 Externally calibrated parameters

We break the calibration procedure into two parts. We start with a set of parameters that are set exogenously based on a direct correspondence with an empirical moment or existing estimates in the literature. Table 1 summarizes these parameters. Panel A shows the share of workers in each education group, υ_i, which corresponds directly with the share in middle-income countries from Minnesota Population Center (2020).

The extent to which task productivity falls as more tasks are professionalized, θ, and entrepreneur's ability to manage hired professionals, λ, both govern how productive it is for an entrepreneur to scale up by hiring white collar professionals. Consequently, we normalize one, $\theta \equiv 1$, and calibrate internally λ. [CAN WE JUST GET RID OF λ THROUGHOUT?]

We take the estimated price elasticity of demand in Panel B as well as the estimated income elasticity of demand by sector in Panel C from Comin, Lashkari and Mestieri (2021). We set the firm-size wedge to 0 in all sectors. We take sectoral prices from Inklaar, Marapin and Gräler (2023), and recover differences in the level of demand for each sector, $\mathbb{P}_j$, so that the model matches these differences.

We set the parameter $\nu_\sigma = 5$ to be consistent with the evidence that the long-run sectoral labor supply is highly responsive to sectoral labor prices. For example, the calibrated model of Lagakos and Waugh (2013) implies that the elasticity of relative sectoral labor supply with respect to relative labor prices varies but is in the range of 4–6.5. Several papers in the trade literature estimate the long-run effects of tariff reductions on wages and employment by sector, which implicitly provides an estimate of the sectoral labor supply elasticity. Revenga (1992) shows that the five-year empirical responses are

TABLE 1: EXOGENOUSLY SET PARAMETERS

Parameter	Description	Value				Source
Panel A. Education-specific		No primary	Primary	Secondary	Tertiary	
υ	Employment share	0.20	0.38	0.29	0.12	Minnesota Population Center (2020)
Panel B. Aggregate						
σ	Elasticity to aggregate output	0.50				Comin, Lashkari and Mestieri (2021)
Panel C. Sector-specific		Agri.	Manu.	HS	LS	
ϵ_j	Income-elasticity of demand	0.11	1.00	1.21	1.00	Comin, Lashkari and Mestieri (2021)
τ_j	Wedge	0.00	0.00	0.00	0.00	Factor share of white collar labor
α_j	Factor share of professionals	0.27	0.55	0.90	0.66	Exogenously set
p_j	Sectoral price	1.43	1.00	0.43	0.70	Inklaar, Marapin and Gräler (2023)

consistent with an elasticity of 4.35 across manufacturing industries, whereas the simulated models of Dix-Carneiro (2014) and Ashournia (2018) imply larger elasticities of at least 7.0.[10]

Finally, note that for a firm that has completely modernized, $q = 1$, the factor share of white-collar labor is $\alpha_j \equiv \frac{\gamma_{p,j}}{\gamma_{p,j}+\gamma_{\ell,j}}$. We externally calibrate the auxiliary parameter α_j to match the share of wage payments going to white-collar workers among large firms in sector j. Combined with an internally calibrated value for overall decreasing returns to scale, $\eta_j \equiv \gamma_{p.j} + \gamma_{\ell,j}$, we can recover the underlying structural parameters $\gamma_{p,j}$ and $\gamma_{\ell,j}$.

5.4 Internally calibrated parameters

We calibrate the remaining parameters internally to jointly match a set of moments in the data. To reduce the dimensionality of the problem, we start by imposing the following restrictions. First, we set $\chi_j = \frac{\mu}{1-\gamma_{\ell,j}}$ so that the estimated model is consistent with Assumption 2. Second, we introduce the auxiliary sector-specific parameter $\eta_j \equiv \gamma_{p,j} + \gamma_{\ell,j}$, which together with the externally calibrated factor share α_j determine the two structural parameters $\gamma_{p,j}$ and $\gamma_{\ell,j}$.

We are left with 22 parameters to calibrate internally. We pick them to minimize the

[10]The results of Ashournia (2018) are consistent with an elasticity of 7.0. Dix-Carneiro (2014) estimates that a 30 percent tariff reduction in Brazil lowers wages in the protected sectors by roughly half and leads to the exit of all workers from those sectors.

equally-weighted absolute deviation between XX moments in the model and data[11]

$$\mathbf{p}^* = \arg\min_{\mathbf{p}} \sum_{m \in \mathcal{M}} \left| m^{\text{model}} - m^{\text{data}} \right|$$

We use absolute deviations since our targeted moments are either in logs or employment shares.[12] While identification of the 22 parameters is joint, some moments particularly inform some parameters. We start by heuristically discussing our choice of targets, and then present our parameter estimates.

Targeted moments

Table 2 lists the moments that we target, sorted by the parameter that they particularly inform. The average difference in skills between education group i and $i-1$ is informed by the difference in average wages between the two groups. Because more educated workers on average are more skilled, they tend to be more likely to be a white collar worker. The extend to which they are so is modulated by the strength of the preference shocks for occupation, ξ. In particular if ξ is larger—meaning that workers base their occupational choice more on differences in pecuniary aspects of occupations—high skilled workers are more likely to be white collar. Hence, the white collar share by education informs ξ. Panel (a) of Figure 9 illustrates this logic by plotting the white collar share of an education group relative to the white collar share of college graduates as ξ varies around its estimated value (holding all other parameters fixed). The standard deviation of skills within education groups, z_σ, is informed by the standard deviation of residual wages, after taking out education fixed effects.

The mean preference shifter for a sector, $\nu_{\mu,j}$, is informed by the employment share of sector j. The mincer regression coefficient in sector j informs the sensitivity of white collar efficiency units of labor to skill in sector j, ρ_j. In particular, if ρ_j is higher in a sector, everything else the same white collar workers provide more efficiency units of labor in that sector, raising the skill premium in the sector. Panel (b) of Figure 9 shows how the mincer regression coefficient in sector j varies with ρ_j around the optimum, holding all other parameters fixed. Both these parameters and their corresponding moments are expressed relative to manufacturing, $\nu_{\mu,\text{mgf}} = 1$ and $\rho_{\text{mfg}} = 1$.

Preferences of sectors as summarized by ν_σ are informed by sorting of different

[11] Although we include the XX moments in Table 2 in our calibration, we note that the distribution of individuals over sectors conditional on education sums to one, so that in practice we have four fewer moments.

[12] The one exception is the Mincer regression coefficient by sector. We also target absolute deviations between model and data also in this dimension.

education groups across sectors. In our estimated model, some sectors—high-skilled services in particular—have a higher return to skill. Since highly educated workers on average have higher skills, they want to sort into such sectors, with an intensity that is modulated by how much they care about the pecuniary value of being in that sector, ν_σ. Panel (c) of Figure 9 illustrates this logic by plotting the share of workers by education group that work in high-skilled services as ν_σ varies around its estimated value, holding all other parameters fixed. When ν_σ is high, workers care mostly about the pecuniary value of being in a sector, leading college educated workers to be relatively more likely to sort into high-skilled services.

A higher overall curvature in production in sector j, $\eta_j = \gamma_{l,j} + \gamma_{p,j}$, implies a larger average firm size in the sector. *Ceteris paribus*, a higher sensitivity of entrepreneurial efficiency units to skills, μ, implies that the most skilled entrepreneurs are effectively even more productive. As a result, they grow even larger, raising the employment share of large firms. Panels (a)–(h) of Figure 10 illustrate that while η_j and μ move average firm size and the employment share of large firms in the same direction, the relative extent to which each parameter moves each of these moments differs. That is, the two moments contain independent variation that we use to separately inform η_j and μ.

Finally, we target for the intercept and slope in the productivity of professionalizing tasks, β_j and θ, the share of own account and white collar workers in each sector. If β_j is higher, it is more productive to employ professional workers in the sector. Since professional workers are best employed together with blue collar workers, a higher β_j also raises demand for blue collar workers. That is, it benefits modern firms on behalf of traditional firms. As a result, a higher β_j lowers the share of own account workers in sector j. A higher θ means that the productivity of white collar labor quickly declines in the number of tasks that are professionalized. Consequently, the white collar share is lower. Panels (i)–**??** of Figure **??** illustrates this.

Parameter estimates

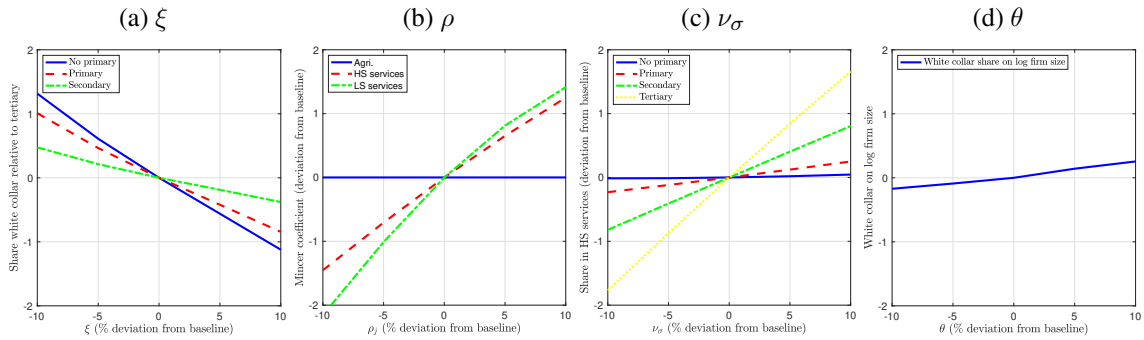
Table 3 summarizes our internally calibrated parameter values. Panel A shows the parameters that vary by education, namely the average skill by education. Not surprisingly, more educated workers are more productive. For instance, college educated workers are roughly twice as productive as their high-school educated peers, $z_{\mu,4} \approx XX$ (recall that $z_{\mu,i}$ reflects the incremental productivity of education group i over $i-1$).

Panel B summarizes our estimates of the economy-wide parameters. The overall standard deviation of (log) skills is XX. Although we did not impose it, efficiency units of traditional entrepreneurial labor are less sensitive to skill than efficiency units of pro-

TABLE 2: TARGETED MOMENTS IN MODEL AND DATA

Parameter	Moment	Value							
Panel A. Heterogeneity across education									
		No primary		Primary		Secondary		Tertiary	
		Data	Model	Data	Model	Data	Model	Data	Model
z_μ	Incremental res. wage			0.31	0.19	0.37	0.45	0.65	0.82
ξ	Occupation by education								
	Blue collar worker	0.59	0.62	0.61	0.51	0.39	0.31	0.09	0.10
	White collar worker	0.02	0.04	0.08	0.17	0.38	0.43	0.75	0.73
	Modern entrepreneur	0.01	0.01	0.03	0.04	0.05	0.10	0.11	0.12
	Traditional entrepreneur	0.37	0.33	0.28	0.27	0.18	0.16	0.05	0.05
Panel B. Aggregate moments									
		Data	Model						
z_σ	St.d. of residual log wage	0.64	0.65						
θ	WC share on log firm size	0.01	0.01						
Panel C. Heterogeneity across sectors									
		Agriculture		Manufacturing		HS services		LS services	
		Data	Model	Data	Model	Data	Model	Data	Model
$\nu_{\mu,j}$	Employment share (rel.)	-0.03	-0.03			0.05	0.05	0.06	0.08
ρ_j	Mincer coefficient (rel.)	-0.03	-0.05			0.02	0.06	-0.01	-0.02
ν_σ	Education by sector								
	No primary	0.39	0.26	0.20	0.22	0.09	0.12	0.18	0.22
	Primary	0.40	0.45	0.45	0.39	0.25	0.29	0.43	0.41
	Secondary	0.18	0.24	0.27	0.28	0.37	0.35	0.32	0.28
	Tertiary	0.02	0.04	0.07	0.11	0.29	0.24	0.08	0.08
η_j	Log average firm size	0.71	0.71	1.52	1.52	2.29	2.24	1.03	1.02
μ	Share at large firms	0.17	0.00	0.41	0.41	0.62	0.64	0.17	0.18
β_j	Occupation by sector								
	Blue collar worker	0.49	0.51	0.64	0.58	0.32	0.30	0.50	0.37
	White collar worker	0.02	0.00	0.14	0.20	0.58	0.60	0.14	0.27
	Modern entrepreneur	0.01	0.00	0.03	0.08	0.05	0.08	0.06	0.07
	Traditional entrepreneur	0.48	0.49	0.19	0.14	0.05	0.02	0.29	0.29

FIGURE 9: INDUCED VARIATION IN THE TARGETED MOMENT, AGGREGATE OUTCOMES



fessional labor in all sectors, $\mu < \min_{j \in \mathcal{J}} \rho_j$. Non-pecuniary factors are more important for the sectoral choice than the occupational choice, $\nu_\sigma < \xi$.

Panel C shows the parameters that vary by sector. High-skilled services are closest to constant returns to scale η_j, followed by low-skilled services, manufacturing and agriculture. Hired professional labor is most productive in high-skilled services, followed by manufacturing, low-skilled services and agriculture: $\beta_{\text{hs}} > \beta_{\text{mfg}} > \beta_{\text{ls}} > \beta_{\text{ag}}$. Efficiency units of white collar labor is most sensitive to skill in high-skilled services, manufacturing, low-skilled services and agriculture.

Finally, panel D shows the parameters that are implied by our other estimates. There are large differences across sectors in the curvature in white collar workers, $\gamma_{p,j}$. The same amount of income in agriculture versus high-skilled services provides roughly three times as high utility, $\tilde{\nu}_{\mu,\text{ag}} \approx 3\tilde{\nu}_{\mu,\text{hs}}$.

TABLE 3: INTERNALLY CALIBRATED PARAMETERS

Parameter	Interpretation	Value			
Panel A. Education-specific					
		No primary	Primary	Secondary	Tertiary
z_μ	Average skills relative to previous level		0.82	0.80	0.91
Panel B. Aggregate					
z_σ	St.d. of skills conditional on education (log)	0.81			
μ	Skill-sensitivity of entrepreneur	0.06			
θ	Productivity of hired professional, slope	0.40			
ν_σ	Sectoral preference shock	3.35			
ξ	Occupational preference shock	5.38			
Panel C. Sector-specific					
		Agriculture	Manufacturing	HS services	LS services
η_j	Sum of DRTS, $\eta_j \equiv \gamma_{p,j} + \gamma_{l,j}$	0.70	0.93	0.93	0.91
β_j	Productivity of hired professional, intercept	0.73	0.96	1.22	1.26
ρ_j	Skill-sensitivity of professionals	0.43	1.00	1.03	0.67
$\nu_{\mu,j}$	Auxiliary preference shifter, $\nu_{\mu,j} \equiv \tilde{\nu}_{\mu,j} p_j A_j$	1.09	1.00	0.47	1.07
Panel D. Implied parameters					
		Agriculture	Manufacturing	HS services	LS services
χ_j	Skill-sensitivity of laborer	0.13	0.11	0.07	0.09
$\gamma_{p,j}$	Curvature in professionals	0.19	0.51	0.84	0.60
$\gamma_{l,j}$	Curvature in laborers	0.51	0.42	0.09	0.31
$\tilde{\nu}_{\mu,j}$	True preference shifter	2.21	1.00	0.81	0.87
A_j	Sectoral TFPQ	0.35	1.00	1.35	1.76
$\mathbb{P}_j$	Sectoral demand shifter	-5.99	0.00	3.77	0.94

FIGURE 10: INDUCED VARIATION IN THE TARGETED MOMENT, OUTCOMES BY SECTOR

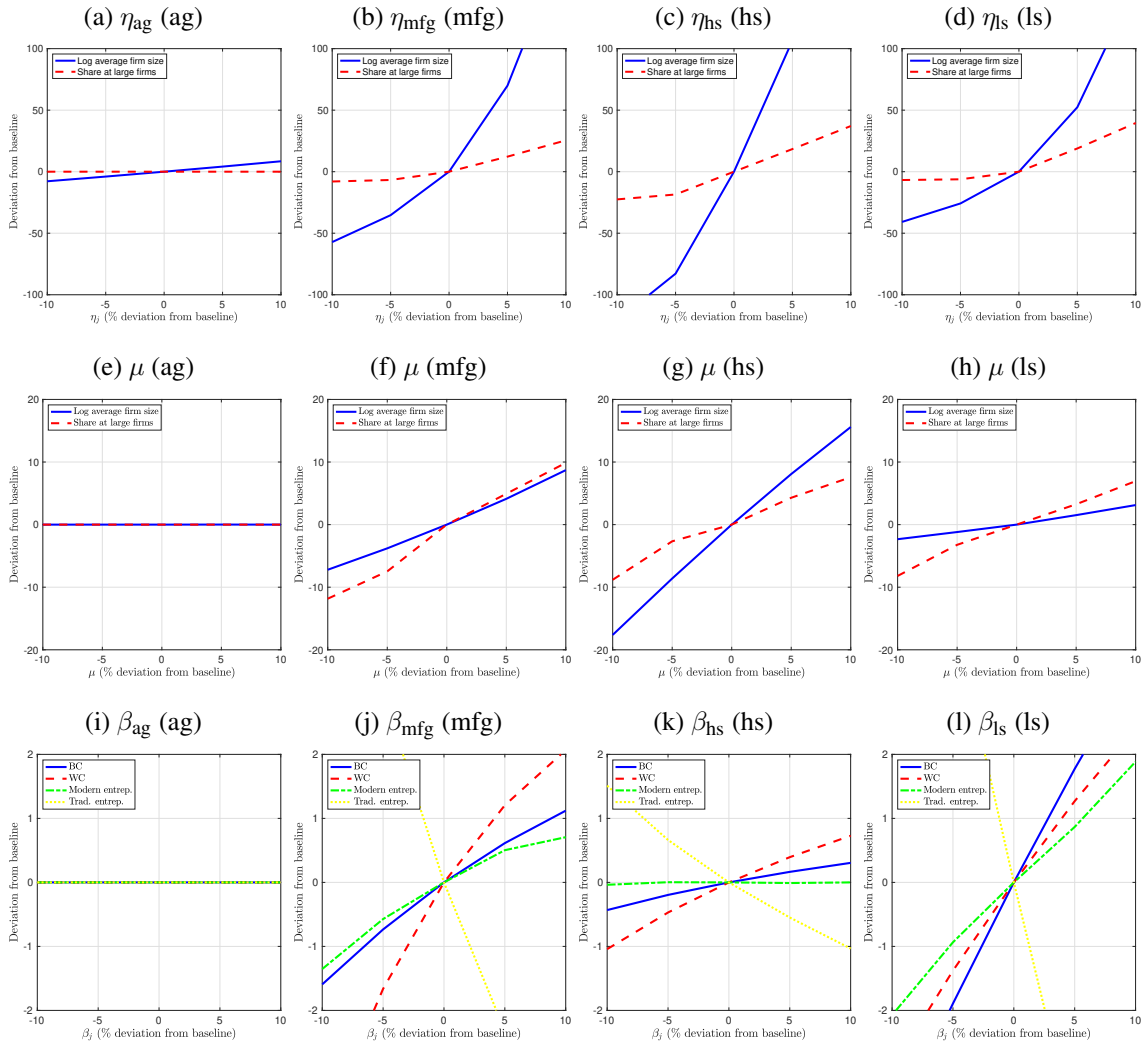


TABLE 4: DERIVATIVE OF EACH MOMENT WITH RESPECT TO EACH PARAMETER

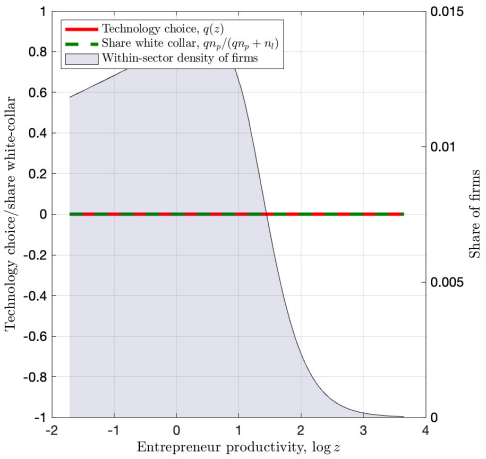
	$z_{\mu,2}$	$z_{\mu,3}$	$z_{\mu,4}$	z_σ	μ	θ	ν_σ	ξ	η_j				β_j				ρ_j			$\nu_{\mu,j}$		
									ag	mfg	hs	ls	ag	mfg	hs	ls	ag	hs	ls	ag	hs	ls
(1)	**2.5**	-0.7	-0.3	0.5	4.3	-1.1	-0.0	-0.0	-0.9	-0.6	4.6	-0.1	0.0	-0.2	0.6	-0.1	-0.0	0.4	-0.1	0.0	2.1	-0.6
(2)	0.6	**4.5**	-0.3	-1.5	0.8	-0.2	0.0	0.0	-0.0	-2.0	4.3	-1.5	-0.0	-0.4	0.7	-0.3	-0.0	1.2	0.0	0.5	2.5	-0.9
(3)	0.1	0.1	**5.6**	-3.9	-5.8	0.9	0.0	-0.0	1.0	-3.5	-0.2	-3.3	-0.0	-0.3	0.4	-0.4	-0.0	3.4	-0.1	1.1	1.6	-1.1
(4)	-0.4	-0.8	-0.8	**2.0**	-0.3	0.9	-0.0	-0.0	1.2	-3.2	1.0	-3.1	0.0	-0.6	0.4	-0.7	-0.0	0.5	-0.5	1.6	1.5	-1.3
(5)	0.0	0.0	0.0	0.0	**0.0**	0.0	-0.0	-0.0	0.0	0.0	0.0	0.0	0.0	-0.0	-0.0	-0.0	0.0	-0.0	0.0	-0.0	0.0	-0.0
(6)	1.5	2.2	1.9	1.6	**29.8**	-9.5	-0.2	0.1	0.3	32.8	-5.9	0.1	0.0	3.1	-0.8	0.1	-0.0	-3.4	-0.1	0.6	-2.6	0.7
(7)	1.5	0.4	2.5	2.6	**26.0**	-2.5	0.0	0.2	0.1	-0.7	32.3	-0.6	-0.0	0.1	0.5	0.2	0.0	-1.9	0.1	0.2	0.5	0.4
(8)	1.8	1.7	1.7	1.7	**21.7**	-7.9	-0.2	0.0	0.2	-0.1	-5.0	30.2	-0.0	0.1	-0.6	3.3	-0.0	-2.5	2.1	0.6	-2.0	0.6
(9)	-0.0	0.0	0.0	0.0	-0.0	**0.0**	0.0	-0.0	0.0	-0.0	-0.0	-0.0	-0.0	0.0	0.0	0.0	0.0	-0.0	-0.0	-0.0	0.0	0.0
(10)	0.4	-0.1	-0.1	-0.8	-1.6	**-0.8**	0.0	-0.0	-0.2	-0.2	-0.4	-0.3	0.0	1.1	-0.1	-0.1	-0.0	0.2	-0.1	0.1	-0.2	0.1
(11)	0.1	-0.3	-0.5	-1.1	-1.0	**-0.3**	0.0	0.0	-0.2	-0.1	-0.8	-0.3	0.0	-0.1	0.3	-0.1	-0.0	-0.5	-0.1	0.0	0.1	0.0
(12)	1.5	0.6	-0.1	-1.1	-0.5	**-1.4**	-0.0	-0.0	-0.4	-0.2	-3.2	6.0	0.0	-0.1	-0.5	3.2	-0.0	-0.8	2.1	0.3	-1.5	0.3
(13)	-0.7	-0.5	-0.2	-0.5	-1.9	1.2	**-0.0**	0.0	-0.3	-2.4	-2.2	-1.7	-0.0	-0.5	-0.2	-0.3	-0.0	-0.2	-0.1	3.5	-0.9	-2.0
(14)	-0.9	-0.3	-0.2	-0.5	-0.8	1.6	**-0.0**	0.0	1.0	-2.6	-2.9	-2.1	-0.0	-0.5	-0.3	-0.5	-0.0	-0.3	-0.2	3.5	-1.3	-1.7
(15)	-1.0	-1.0	-0.1	0.1	0.1	1.6	**-0.0**	0.0	1.5	-2.0	-3.1	-1.8	-0.0	-0.4	-0.4	-0.4	0.0	-0.5	-0.3	2.7	-1.6	-1.2
(16)	-0.5	-0.5	-0.6	0.7	0.5	0.8	**-0.1**	0.0	0.8	-0.6	-1.6	-0.6	0.0	-0.1	-0.3	-0.2	0.0	-0.5	-0.2	0.9	-0.9	-0.3
(17)	0.0	-0.0	-0.1	-0.1	0.5	-0.5	**-0.1**	-0.0	0.1	8.0	-4.0	-1.8	0.0	1.6	-0.5	-0.4	0.0	-1.1	-0.3	-1.1	-2.0	-1.7
(18)	0.0	-0.0	-0.1	-0.2	0.3	-0.3	**-0.0**	-0.0	-0.3	8.7	-4.7	-2.4	-0.0	1.9	-0.6	-0.6	0.0	-1.0	-0.4	-1.1	-2.4	-1.6
(19)	-0.3	-0.3	-0.1	-0.2	0.2	-0.0	**-0.0**	-0.0	-0.4	9.1	-5.8	-2.6	0.0	2.0	-0.9	-0.7	-0.0	-1.4	-0.5	-0.9	-3.2	-1.4
(20)	-0.7	-0.6	-0.5	0.1	1.6	0.0	**-0.1**	-0.0	-0.2	9.5	-7.5	-2.0	-0.0	2.0	-1.2	-0.5	-0.0	-2.9	-0.6	-0.3	-4.3	-0.8
(21)	1.3	1.0	0.5	0.7	1.9	-1.3	**0.0**	0.0	0.1	-2.0	10.6	-1.7	0.0	-0.4	1.2	-0.4	0.0	2.1	-0.4	-0.5	5.0	-1.1
(22)	1.6	0.6	0.4	0.8	1.3	-1.7	**0.0**	0.0	-0.3	-2.6	12.6	-2.4	-0.0	-0.6	1.7	-0.6	-0.0	2.3	-0.6	-0.7	6.2	-1.2
(23)	2.0	1.9	0.2	0.1	0.5	-2.1	**0.1**	0.0	-0.5	-3.9	15.1	-3.8	-0.0	-0.9	2.3	-1.0	-0.0	3.4	-1.1	-0.7	8.1	-1.6
(24)	1.9	1.8	1.7	-1.2	-2.9	-0.9	**0.2**	0.0	-0.4	-6.8	16.6	-6.5	-0.0	-1.4	2.7	-1.6	-0.0	6.1	-2.2	-0.3	9.4	-2.0
(25)	-0.6	-0.5	-0.3	-0.1	-0.6	0.6	**0.1**	-0.0	0.2	-3.6	-4.4	5.1	0.0	-0.7	-0.5	1.1	0.0	-0.8	0.9	-1.9	-2.1	4.8
(26)	-0.7	-0.3	-0.1	-0.0	-0.8	0.4	**0.0**	-0.0	-0.4	-3.5	-5.0	6.9	-0.0	-0.8	-0.7	1.6	0.0	-0.9	1.2	-1.6	-2.5	4.6
(27)	-0.7	-0.7	-0.1	0.0	-0.8	0.4	**0.0**	-0.0	-0.5	-3.2	-6.2	8.2	-0.0	-0.7	-0.9	2.1	-0.0	-1.5	1.9	-1.1	-3.4	4.2
(28)	-0.7	-0.7	-0.6	0.4	0.8	0.1	**-0.1**	-0.0	-0.2	-2.0	-7.4	9.1	-0.0	-0.5	-1.2	2.2	-0.0	-2.8	3.0	-0.3	-4.2	3.1
(29)	-1.3	-1.3	-1.3	2.4	1.1	0.9	-0.1	**-0.1**	0.6	-0.4	-1.4	0.3	0.0	0.1	-0.3	0.2	-0.0	-0.8	-0.3	0.3	-1.0	0.0
(30)	0.9	-1.5	-1.3	1.6	0.6	-0.4	-0.0	**-0.1**	0.1	-0.3	2.1	1.2	0.0	0.2	0.2	0.6	-0.0	-0.2	0.1	-0.5	0.7	0.0
(31)	1.2	1.4	-1.3	0.0	0.1	-1.1	-0.0	**-0.0**	-0.3	-0.2	3.2	1.2	0.0	0.1	0.4	0.6	-0.0	0.3	0.3	-0.9	1.5	0.1
(32)	-0.0	0.0	0.0	0.0	-0.0	0.0	0.0	-0.0	**6.1**	-0.0	-0.0	-0.0	-0.0	0.0	0.0	0.0	0.0	-0.0	-0.0	-0.0	0.0	0.0
(33)	4.0	3.2	2.0	1.8	33.3	-15.1	-0.2	0.3	0.1	**88.4**	-12.5	-0.5	-0.0	8.6	-1.8	-0.1	0.0	-5.3	-0.6	1.2	-6.0	1.1
(34)	4.6	3.9	3.7	4.0	48.2	-8.4	0.1	0.8	-0.2	-1.0	**95.0**	-1.3	0.0	0.0	2.8	-0.1	-0.0	-1.0	-0.2	0.5	-3.1	0.6
(35)	4.2	2.6	0.9	-0.6	15.9	-9.6	-0.2	0.0	-0.4	-0.3	-10.9	**65.0**	-0.0	-0.1	-1.6	9.0	-0.0	-4.2	6.9	1.1	-5.4	1.0
(36)	0.0	-0.0	-0.0	-0.0	0.0	-0.0	-0.0	0.0	-3.1	0.0	0.0	0.0	**-0.0**	-0.0	-0.0	-0.0	-0.0	0.0	0.0	0.0	-0.0	-0.0
(37)	-0.8	-0.4	-0.2	0.1	-1.3	1.8	0.0	-0.0	0.1	-5.7	2.3	0.2	-0.0	**-1.8**	0.3	0.1	0.0	0.7	0.1	-0.2	1.1	-0.2
(38)	-0.3	-0.2	-0.1	0.1	-0.1	0.3	-0.0	-0.0	0.0	0.0	-1.1	0.1	-0.0	0.0	**-0.2**	0.0	0.0	-0.4	0.1	-0.1	0.5	-0.1
(39)	-1.9	-1.0	-0.1	0.8	-1.3	2.2	0.1	-0.0	0.3	0.1	4.7	-11.2	-0.0	0.1	0.7	**-4.0**	0.0	1.5	-3.4	-0.5	2.3	-0.4
(40)	-0.0	-0.1	-0.1	0.0	0.4	0.1	0.0	-0.0	0.2	-0.3	0.2	-0.1	0.0	-0.1	0.0	-0.0	**-0.0**	0.2	-0.0	-0.0	0.1	-0.0
(41)	-0.0	0.1	0.2	0.0	-0.5	0.1	0.0	-0.0	0.0	-0.3	-0.0	0.0	-0.0	-0.1	0.0	0.0	0.0	**0.6**	0.0	-0.0	-0.0	0.0
(42)	0.1	0.0	-0.0	0.0	0.1	-0.0	0.0	-0.0	-0.0	-0.3	-0.1	0.5	0.0	-0.1	-0.0	0.2	0.0	-0.0	**0.5**	0.0	-0.0	0.0
(43)	-0.7	-0.4	-0.1	-0.0	-1.1	1.6	0.0	0.0	1.1	-10.9	2.5	0.5	0.0	-2.3	0.4	0.2	0.0	1.0	0.2	**3.9**	1.5	0.1
(44)	1.8	1.4	0.6	0.5	0.2	-1.5	0.1	0.0	-0.1	-12.1	18.7	-0.9	-0.0	-2.6	2.6	-0.2	-0.0	4.4	-0.4	0.4	**9.7**	0.1
(45)	-0.5	-0.3	-0.1	0.2	-1.0	0.6	0.1	-0.0	-0.0	-12.0	-0.3	9.5	-0.0	-2.6	-0.0	2.3	0.0	0.1	2.0	-0.4	-0.1	**5.8**

(1) wagegap.edu2.All; (2) wagegap.edu3.All; (3) wagegap.edu4.All; (4) wagestdres.All; (5) medlargecondsector.agriculture; (6) medlargecondsector.manufacturing; (7) medlargecondsector.serviceshigh; (8) medlargecondsector.serviceslow; (9) wccondsector.agriculture; (10) wccondsector.manufacturing; (11) wccondsector.serviceshigh; (12) wccondsector.serviceslow; (13) empsharecondedu.edu1.agriculture; (14) empsharecondedu.edu2.agriculture; (15) empsharecondedu.edu3.agriculture; (16) empsharecondedu.edu4.agriculture; (17) empsharecondedu.edu1.manufacturing; (18) empsharecondedu.edu2.manufacturing; (19) empsharecondedu.edu3.manufacturing; (20) empsharecondedu.edu4.manufacturing; (21) empsharecondedu.edu1.serviceshigh; (22) empsharecondedu.edu2.serviceshigh; (23) empsharecondedu.edu3.serviceshigh; (24) empsharecondedu.edu4.serviceshigh; (25) empsharecondedu.edu1.serviceslow; (26) empsharecondedu.edu2.serviceslow; (27) empsharecondedu.edu3.serviceslow; (28) empsharecondedu.edu4.serviceslow; (29) wccondedureledu4.edu1.All; (30) wccondedureledu4.edu2.All; (31) wccondedureledu4.edu3.All; (32) fsize.agriculture; (33) fsize.manufacturing; (34) fsize.serviceshigh; (35) fsize.serviceslow; (36) owncondsector.agriculture; (37) owncondsector.manufacturing; (38) owncondsector.serviceshigh; (39) owncondsector.serviceslow; (40) mincerrelmanu.agriculture; (41) mincerrelmanu.serviceshigh; (42) mincerrelmanu.serviceslow; (43) empsharerelmanu.agriculture; (44) empsharerelmanu.serviceshigh; (45) empsharerelmanu.serviceslow;

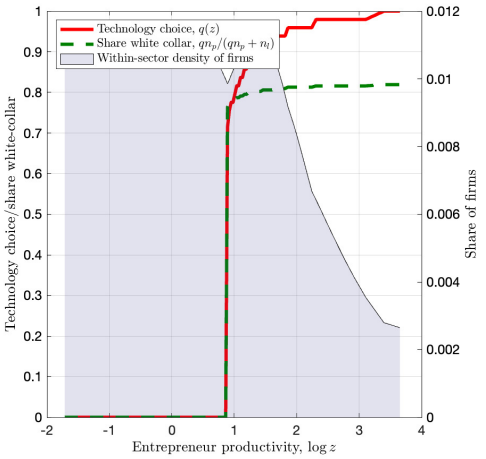
5.5 Understanding the model

FIGURE 11: MODEL MECHANISMS: TECHNOLOGY CHOICE

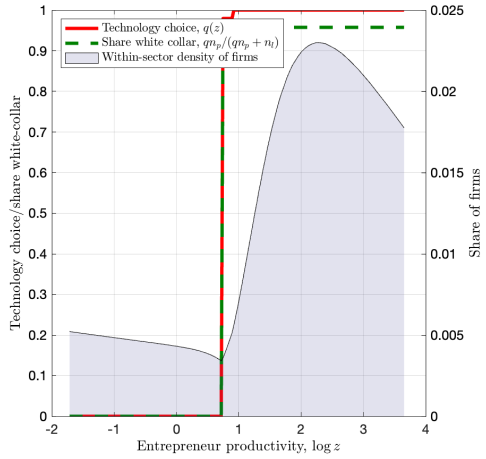
(a) Agriculture



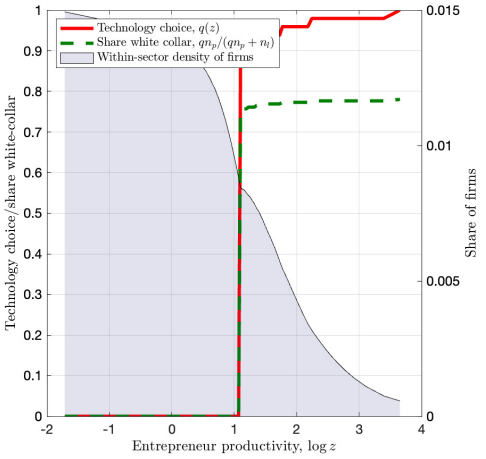
(b) Manufacturing



(c) High-Skill Services



(d) Low-Skill Services



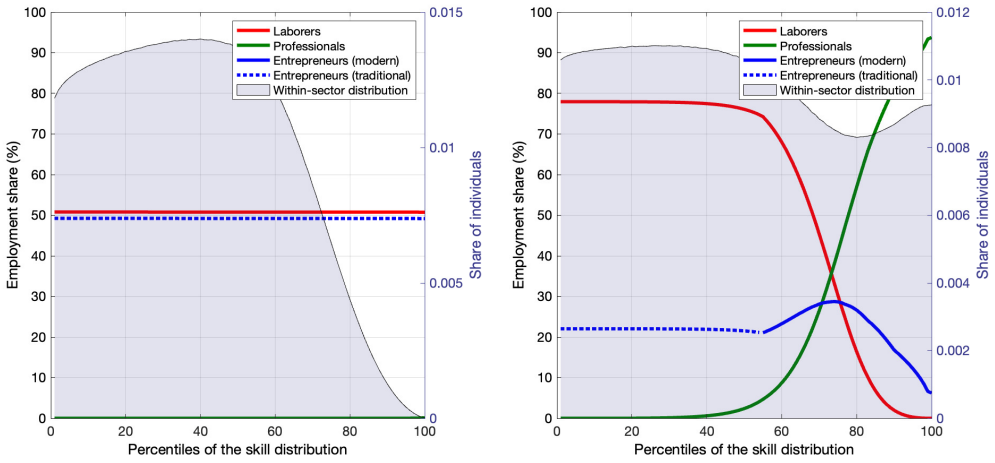
The last section focused on how the model fit the data. In this section we illustrate the underlying choices that drive these results. Figure 12 shows how workers of different skill levels are allocated across sectors and occupations. Each of the four panels shows one sector, with percentiles of the 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 en-

trepreneurship (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.

FIGURE 12: MODEL MECHANISMS: OCCUPATIONAL AND SECTORAL CHOICE

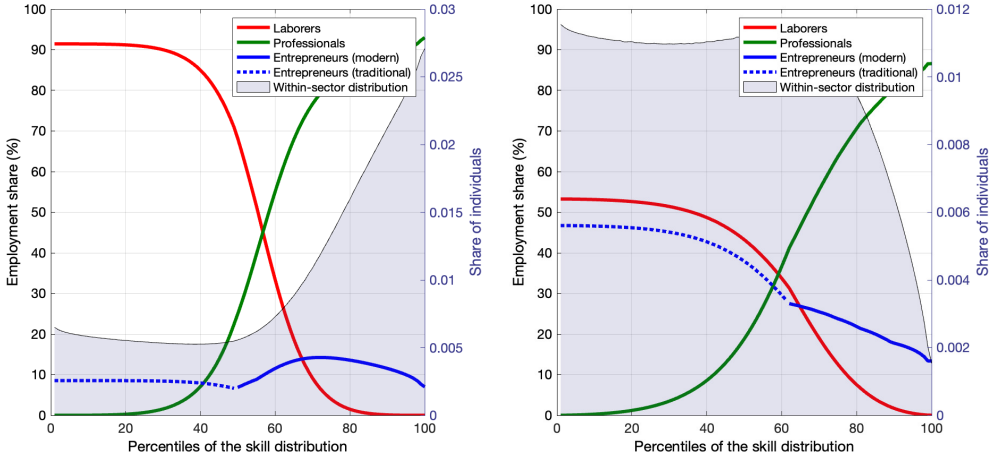
(a) Agriculture

(b) Manufacturing



(c) High-Skill Services

(d) Low-Skill Services



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 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.

5.6 Validation with Quasi-Experimental Evidence

Our model emphasizes the importance of human capital for the adoption and expansion of managerial capitalism. We showed analytically in Section 4.2 that an increase in the aggregate supply of skills generates changes in occupational choices, wages, firm size, and firm structure that are qualitatively consistent with the cross-country patterns we documented in Section 2. Now that we turn to a quantitative evaluation of the model, a natural question is whether the implied quantitative role for skills is in line with the data. Our approach is to validate our calibrated model by comparing its predictions to the results from quasi-experimental studies that provide well-identified evidence on the magnitude of the relevant mechanisms.

We draw on evidence from two different literatures that provide complementary information. The first is a growing literature that provides evidence on the causal effects of expanding access to education, typically by building more schools. This literature shows that not only does expanding access lead to higher educational attainment, but that it also induces a shift towards white-collar occupations and work in more skill-intensive sectors. This information is useful for pinning down the first part of our model's causal chain.

Our approach is to simulate a model economy that matches key attribute of those studied in each paper in the literature. Specifically, we match each economy's broad

TABLE 5: 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

income level (low, middle, or high), initial sectoral composition, and initial educational attainment. We then feed in an exogenous increase in educational attainment consistent with the paper's reported causal effect of expanding access on educational attainment and re-solve the model. We validate the model by comparing its predictions for changes in the other outcomes, such as occupational choices, to those reported in the relevant study.

We focus here on the results of Cox (2023), who provides the widest range of relevant results. Cox studies the results of a large quasi-exogenous expansion of colleges in Brazil that induced a 1.5 percentage point increase in tertiary attainment among affected cohorts. He also finds that young cohorts were more likely to engage in white-collar work and that firms in affected regions became larger. The first row of Panel A in Table 5 shows his estimated results.[13] We simulate the effect of a similar 1.5 percentage point increase in the share of college-educated workers in the model, with the corresponding effects reported in the second row of Panel A. 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

The remaining papers report the effect of expanding educational attainment on workers' sectoral and occupational choices, but do not report results on firm size or firm structure. Our results are also broadly consistent with their findings, as we show in Appendix C. In particular, the model consistently predicts that expanding educational attainment leads to more white collar-workers, a decline in agricultural employment,

[13] He reports the effects of an expansion of college among young cohorts on overall number of large firms. We rescale his estimates 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 5 reports the re-scaled point estimate and confidence interval in the last column.

and an increase in skilled services employment, with the magnitudes in line with the literature.[14] Cox (2023)

The main drawback of the literature on the causal effects of expanding access to education is that it has not evaluated the effects on any measure of its effects on firm structure. This fact motivates us to consider evidence from a second, complementary literature on the causal effect of improving firm management. Broadly, this literature shows that providing information similar to what is taught in a business school curriculum to a firm's owner or head manager improves firm productivity and also leads to changes in firm structure. This information is useful for pinning down the second part of the model's causal chain, from skill of firm entrepreneurs to optimal firm structure. We focus on two papers that provide different measures of firm re-structuring, Bloom et al. (2013) and Giorcelli (2019).

Bloom et al. (2013) studies a consultant/management training intervention in India. They show that treated firms and entrepreneurs raised their productivity by 17 percent. They also delegated 0.1 standard deviations more tasks to hired white-collar workers in their plants, which allowed them to expand overall size by 24 percent through operating more plants. Our approach again is to simulate a model economy that matches key attributes of India, including its broad income level, sectoral composition, and education level. We then model the experiment as a partial equilibrium experiment that raises the skill level z of a randomly chosen set of entrepreneurs by an amount sufficient to raise their firm's measured productivity by 17 percent. We measure the growth in firm size through growth in employment. We measure the change in tasks allocated by standard normalizing the pre-treatment optimally chosen level of q among all entrepreneurs and then simulating the effect of the treatment in terms of an increase in q measured using this standard normalized variable.

Giorcelli (2019) studies the effects of a program that offered Italian firm managers exposure to and training in U.S. managerial methods as part of the Marshall Plan. She shows that firms that were quasi-randomly given places in the program had 49 percent higher productivity fifteen years after the program, as compared to firms that applied to and were deemed eligible for the program, but who were denied training by unexpected budget cuts. Treated firms had 33 percent more employees and a 10 percent higher ratio of managers per worker. She also reports other outcomes that are consistent with our mechanism but harder to compare to our model; for example, treated firms were 24 percentage points less likely to be managed by a family member of the owner. We simulate a middle income model economy with sectoral composition and education level

[14] See Porzio, Rossi and Santangelo (2022), Russell, Yu and Andrews (forthcoming), Nimier-David (2023), Coelli et al. (2023), and Vu (2024).

consistent with post-War Italy. We again model the experiment as a partial equilibrium experiment that raises the skill level z of a randomly chosen set of entrepreneurs by an amount sufficient to raise their firm's measured productivity by 45 percent. We measure the growth in employment and the change in the ratio of managers per worker, measured in efficiency units.

Table 5 shows that (hopefully) the model fits the data.

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

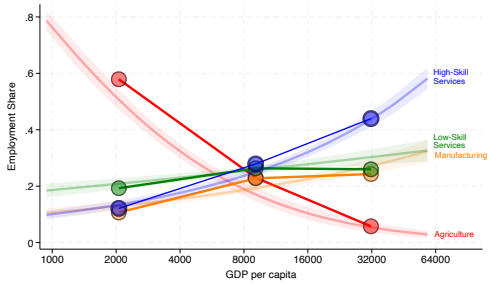
We start by using the quantitative model to studying the effect of structural transformation on the organization of production. It is well-known that growth in aggregate and sectoral productivities can generate structural transformation across sectors through non-homothetic preferences and price effects (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 13 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.

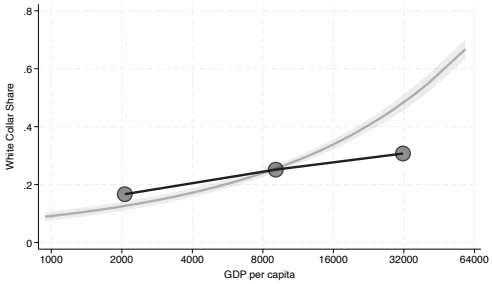
As shown in Figure 13a, the model successfully matches patterns of structural transformation across sectors. It also produces changes in the aggregate share of white-collar workers and the aggregate share of workers employed in large firms (Figures 13b and 13c) that are qualitatively consistent with the data.

FIGURE 13: STRUCTURAL TRANSFORMATION WITH FIXED SKILLS

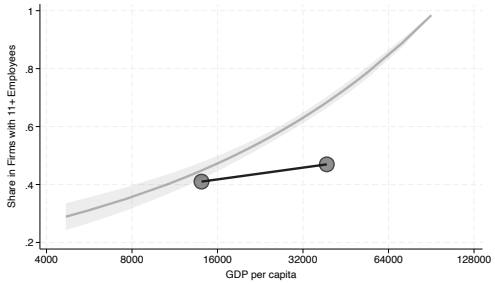
(a) Sectoral Employment



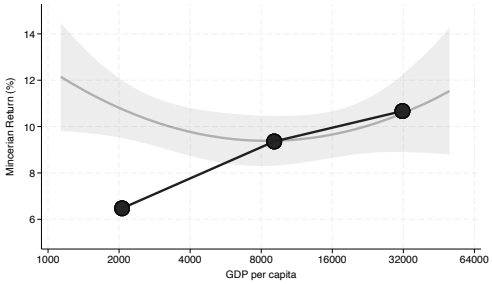
(b) Aggregate White-Collar Share



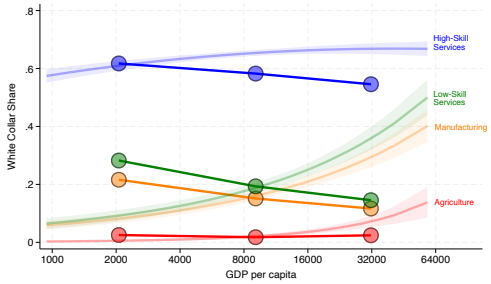
(c) Employment in Large Firms



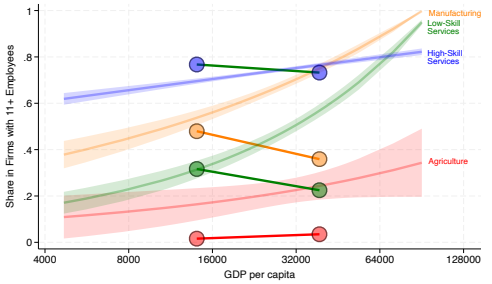
(d) Mincerian Return



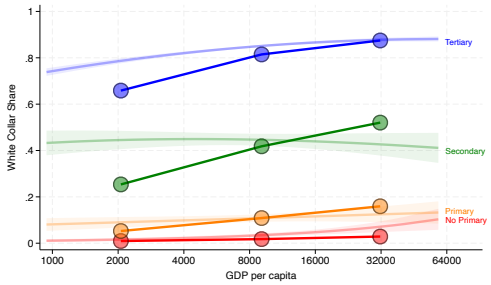
(e) White-Collar Share by Sector



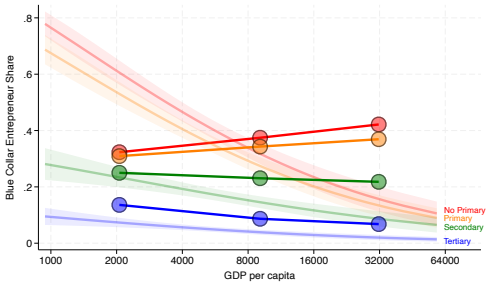
(f) Employment in Large Firms by Sector



(g) White-Collar Share By Education



(h) Blue-Collar Entrepreneurs By Education



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 14c and 14f).

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 13e and 13f. 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 13d) leads workers of a given education level to substitute towards white-collar work, again contrary to the data (Figure 13g). 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

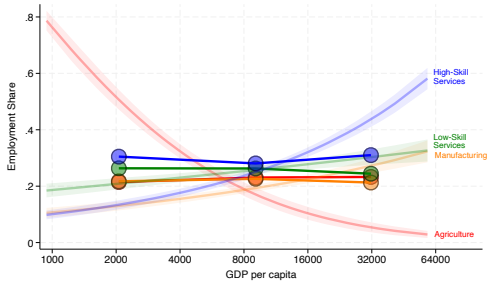
We conduct a second counterfactual exercise to show that the supply of skills is a potential candidate explanatory factor for the re-organization of production. For this exercise, we again take the economy calibrated to the average middle-income country. We feed into the model instead the distribution 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 14 using the same format as in Figure 13 above.

Figure 14a 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.

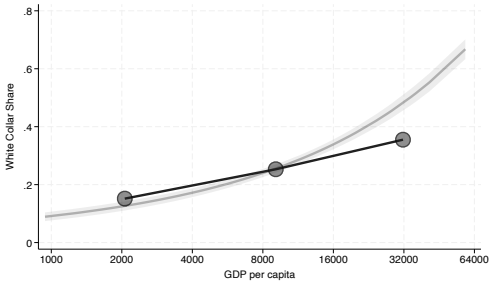
The remaining figures show that the effects of skill supply on the organization of

FIGURE 14: EXPANSION OF SKILL SUPPLY

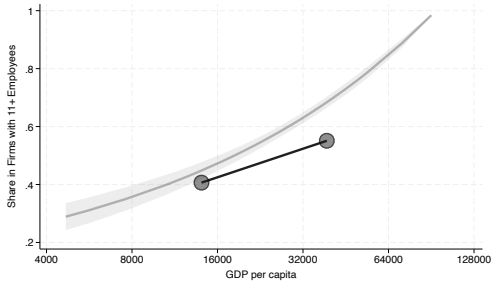
(a) Sectoral Employment



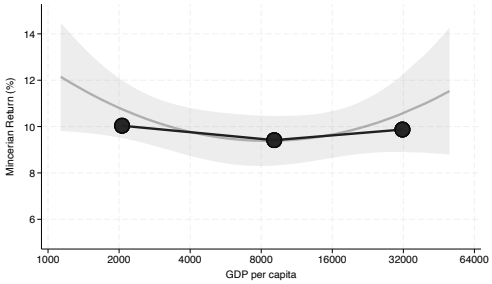
(b) Aggregate White-Collar Share



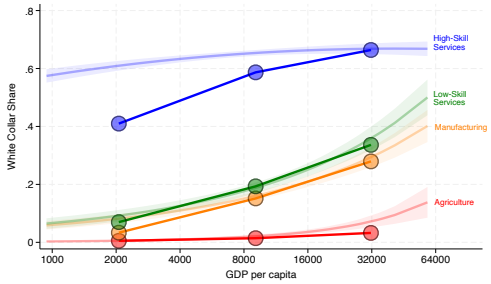
(c) Employment in Large Firms



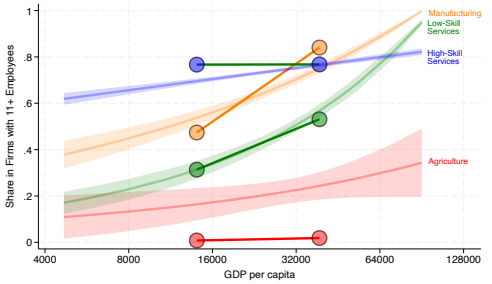
(d) Mincerian Return



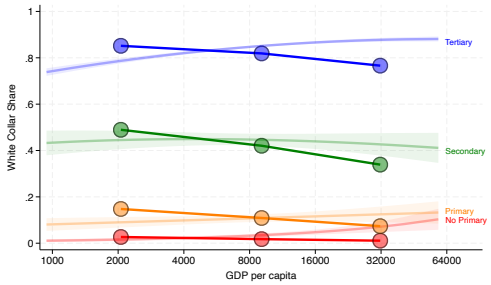
(e) White-Collar Share by Sector



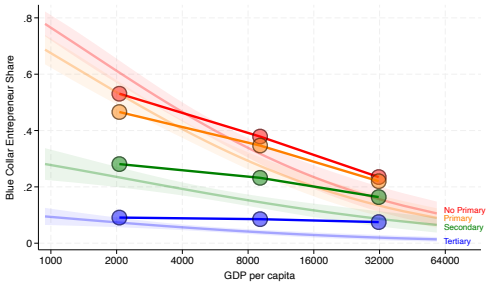
(f) Employment in Large Firms by Sector



(g) White-Collar Share By Education



(h) Blue-Collar Entrepreneurs by Education



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 14c and 14f).

production are qualitatively in line with the data. Figures 14b and 14c 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 14d 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 14g), 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 14e and 14f. 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): it is largest in manufacturing and low-skill services and essentially does not happen in agriculture. Finally, Figure 14h 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.

References

Acemoglu, Daron, and Pascual Restrepo. 2018. "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment." *American Economic Review*, 108(6): 1488–1542.

Akcigit, Ufuk, Harun Alp, and Michael Peters. 2021. "Lack of Selection and Limits to Delegation: Firm Dynamics in Developing Countries." *American Economic Review*, 111(1): 231–275.

Amaral, Pedro S., and Alberto Rivera-Padilla. 2024. "Cross-Country Income Dispersion, Human Capital, and Technology Adoption." mimeo, Cal State University – Fullerton.

Ashournia, Damoun. 2018. "Labour Market Effects of International Trade When Mobility is Costly." *Economic Journal*, 128(616): 3008–3038.

Banerjee, Abhijit V., and Andrew F. Newman. 1993. "Occupational Choice and the Process of Development." *Journal of Political Economy*, 101(2): 274–298.

Banerjee, Abhijit V., and Esther Duflo. 2005. "Growth Theory through the Lens of Development Economics." In *Handbook of Economic Growth*. Vol. 1A, , ed. Philippe Aghion and Steven N. Durlauf, Chapter 7, 473–554. Amsterdam:Elsevier.

Bassi, Vittorio, Jung Hyuk Lee, Alessandra Peter, Tommaso Porzio, Ritwika Sen, and Esau Tugume. 2023. "Self-Employment Within the Firm." NBER Working Paper 31740.

Bloom, Nicholas, and John Van Reenen. 2010. "Why do Management Practices Differ Across Firms and Countries?" *Journal of Economic Perspectives*, 24(1): 203–224.

Bloom, Nicholas, Benn Eifert, Aprajit Mahajan, David McKenzie, and John Roberts. 2013. "Does Management Matter? Evidence from India." *Quarterly Journal of Economics*, 128(1): 1–51.

Buera, Francisco J, Joseph Kaboski, and Yongseok Shin. 2011. "Finance and Development: A Tale of Two Sectors." *American Economic Review*, 101(5): 1964–2002.

Buera, Francisco J., Joseph P. Kaboski, Richard Rogerson, and Juan I. Vizcaino. 2022. "Skill-Biased Structural Change." *Review of Economic Studies*, 89(2): 592–625.

Caunedo, Julieta, Elisa Keller, and Yongs Shin. 2023. "Technology and the Task Content of Jobs Across the Development Spectrum." *World Bank Economic Review*, 37(3): 479–493.

Chandler, Jr., Alfred D. 1977. *The Visible Hand: The Managerial Revolution in American Business.* Cambridge, Massachusetts:The Belknap Press of Harvard University Press.

Chandler, Jr., Alfred D. 1990. *Scale and Scope: The Dynamics of Industrial Capitalism.* Cambridge, Massachusetts:The Belknap Press of Harvard University Press.

Coelli, Federica, Difei Oouyang, Weidi Yuan, and Yuan Zi. 2023. "Educating Like China." mimeo, University of Zurich.

Comin, Diego, Danial Lashkari, and Martí Mestieri. 2021. "Structural Change with Long-Run Income and Price Effects." *Econometrica*, 89(1): 311–374.

Cox, Alvaro. 2023. "From Classroom to Prosperity: Fostering Development Through Higher Education." mimeo, Yale University.

Dix-Carneiro, Rafael. 2014. "Trade Liberalization and Labor Market Dynamics." *Econometrica*, 82(3): 825–855.

Donovan, Kevin, Will Jianyu Lu, and Todd Schoellman. 2023. "Labor Market Dynamics and Development." *Quarterly Journal of Economics*, 138(4): 2287–2325.

Feenstra, Robert C., Robert Inklaar, and Marcel P. Timmer. 2015. "The Next Generation of the Penn World Table." *American Economic Review*, 105(10): 3150–3182.

Ferraro, Domenico, Maurizio Iacopetta, and Pietro Peretto. 2024. "The Rise and Evolution of the Innovative Firm: A Tale of Technology, Market Structure, and Managerial Incentives." mimeo, Arizona State University.

Fried, Stephie, and David Lagakos. 2023. "Electricity and Firm Productivity: A General-Equilibrium Approach." *American Economic Journal: Macroeconomics*, 15(4): 67–103. https://doi.org/10.1257/mac.20210248.

Giorcelli, Michela. 2019. "The Long-Term Effects of Management and Technology Transfers." *American Economic Review*, 109(1): 121–152.

Gottlieb, Charles, Jan Grobovšek, and Alexander Monge-Naranjo. 2023. "Occupation Choices, Human Capital and Cross-Country Income Differences." mimeo, St. Gallen.

Gottlieb, Charles, Markus Poschke, and Michael Tueting. 2024. "Skill Supply, Firm Size, and Economic Development." mimeo, St. Gallen.

Herrendorf, Berthold, and Todd Schoellman. 2018. "Wages, Human Capital, and Barriers to Structural Transformation." *American Economic Journal: Macroeconomics*, 10(2): 1–23.

Hjort, Jonas, Hannes Malmberg, and Todd Schoellman. 2023. "The Missing Middle Managers: Labor Costs, Firm Structure, and Development." mimeo, University of Minnesota.

Inklaar, Robert, Ryan Marapin, and Kaira Gräler. 2023. "Tradability and Sectoral Productivity Differences Across Countries." GGDC Research Memorandum 195.

Kongsamut, Piyabha, Sergio Rebelo, and Danyang Xie. 2001. "Beyond Balanced Growth." *Review of Economic Studies*, 68(4): 869–882.

Kuznets, Simon. 1973. "Modern Economic Growth: Findings and Reflections." *American Economic Review*, 63(3): 247–258.

Lagakos, David, and Mike Waugh. 2013. "Specialization, Agriculture, and Cross-Country Productivity Differences." *American Economic Review*, 103(2): 948–980.

Le Nestour, Alexis, Laura Moscoviz, and Justin Sandefur. 2023. "The Long-Run Decline of Education Quality in the Developing World." Center for Global Development Working Papers 608. https://EconPapers.repec.org/RePEc:cgd:wpaper:608.

Lucas, Jr., Robert E. 1978. "On the Size Distribution of Business Firms." *Bell Journal of Economics*, 9(2): 508–523.

Minnesota Population Center. 2020. "Integrated Public Use Microdata Series, International: Version 7.3 [dataset]." *https://doi.org/10.18128/D020.V7.3*.

Ngai, L. Rachel, and Christopher A. Pissarides. 2007. "Structural Change in a Multisector Model of Growth." *American Economic Review*, 97(1): 429–443.

Nimier-David, Elio. 2023. "Local Human Capital and Firm Creation: Evidence from the Massification of Higher Education in France." mimeo, University of Chicago, Booth.

Porzio, Tommaso, Federico Rossi, and Gabriella Santangelo. 2022. "The Human Side of Structural Transformation." *American Economic Review*, 112(8): 2774–2814.

Quieró, Francisco. 2022. "Entrepreneurial Human Capital and Firm Dynamics." *Review of Economic Studies*, 89(4): 2061–2100.

Revenga, Ana L. 1992. "Exporting Jobs?: The Impact of Import Competition on Employment and Wages in U.S. Manufacturing." *Quarterly Journal of Economics*, 107(1): 255–284.

Rossi, Federico. 2022. "The Relative Efficiency of Skilled Labor across Countries: Measurement and Interpretation." *American Economic Review*, 112(1): 235–266.

Russell, Lauren C., Lei Yu, and Michael J. Andrews. forthcoming. "Higher Education and Local Educational Attainment: Evidence from the Establishment of U.S. Colleges." *Review of Economics and Statistics*.

Tamkoç, Nazım. 2024. "Managers, Talent Misallocation and Productivity." mimeo, World Bank.

Vu, Khoa. 2024. "Higher Education Expansion and the Rise of the Skill-Intensive Service Sector." Working Paper.

Contents

A Data Appendix **52**
A.1 Further Results: White-Collar Intensity of Modern Production 52
A.2 Further Results: White-Collar Intensity and Development 53
A.3 Further Results: Skills and White-Collar Employment 54
A.4 Further Results: Organization of Production and Skills 60

B Model Appendix **61**
B.1 Characterization of Optimal Interior Technology Choice 61
B.2 Visualizations of Alternative Occupational Choice Rules 61
B.3 Proofs of Select Results 63

C Additional Validation Results **67**

D Details on Quantitative Results **67**
D.1 Computing moments (subroutine `computemoments.m`) 71

A Data Appendix

This appendix provides details on the data and further results related to the four motivating facts established in Section 2. Each subsection contains additional results for one fact.

A.1 Further Results: White-Collar Intensity of Modern Production

Our first motivating fact is that larger firms use white-collar labor more intensively than smaller firms. We view this as evidence of a broader point raised by Chandler, which is that modern production and managerial capitalism are complements. We proxy modern production based on firm size because this variable is widely available in labor force surveys. In this appendix we consider alternative proxies that draw on less widely available matched employer-employee data.

Our data come from Brazil (RAIS) and Sweden (JOBB). We use the Swedish data spanning 1990–2018, while the Brazilian data span **some years**. The data cover the universe of individuals aged 16 to 70 who legally reside in their respective countries and all formally registered firms, whether incorporated or unincorporated. One limitation of matched employer-employee data (as compared to household survey data) is that it does not cover informal firms or informal workers at formal firms. Our results for traditional firms thus capture only those that are formally registered and so may understate the differences between modern and traditional firms, particularly in Brazil.

The information on Brazilian & Swedish data needs to be filled in a bit

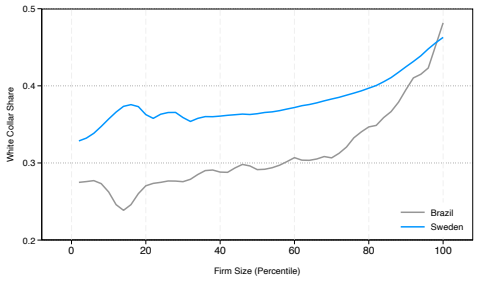
We start by measuring size as average employment at the establishment level during the year. This is the same concept used in the text, but matched employer-employee data allow us to measure firm size in a more continuous manner with more detail among large firms. Figure A.1a shows that the white-collar share of employment grows in firm size. The share is particularly large among the top 20–30 percent of firms in each country.

For Sweden, we also have access to firm financial data, which we use to construct real value added per worker as an alternative measure of whether a firm is modern. Figure A.1b shows that more productive firms also have much higher shares of white-collar workers.

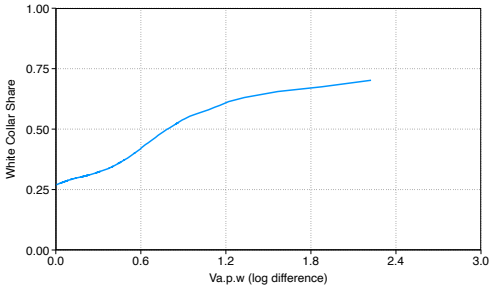
It would be great to have 1-2 more measures of "modern" here. Probably we should revive the figures with firm pay; can we residualize out occupation fixed effects so that it's less circular? And then in Sweden we have a bunch of other attempts, but something like "number of establishments" or "layers in the firm

FIGURE A.1: WHITE-COLLAR INTENSITY OF MODERN PRODUCTION

(a) Firm Size



(b) Value added per worker



hierarchy" would be ideal.

A.2 Further Results: White-Collar Intensity and Development

Our second motivating fact is that the share of white-collar workers varies systematically by sector and level of development. In the main text, we aggregate industries up to four broad sectors to be consistent with the literature on structural transformation. Here we show the same results for the most disaggregated sectors that are consistently harmonized in the IPUMS-International data, which correspond roughly to the 1-digit level.

High-skill services consist of industries whose workers have at least 13 years of schooling in the United States, which includes education; financial services and insurance; health; public administration; other services; and real estate and business services. Low-skill services consist of hotels and restaurants; private household services; communication and transportation; and wholesale and retail trade. Manufacturing includes also construction, mining, and utilities.

Figure A.2 plots the white-collar share of employment at the country $\times$ year $\times$ detailed industry level against GDP per capita.[15] The figure reveals again that there are significant differences across industries both in the level of the white-collar employment share and how it varies with development. Some industries, such as agriculture, household services, or public administration experience essentially no transformation. Others, such as hotels and restaurants or business services, experience only a muted transformation, while education and health services see a decline in the white collar share. The rise of managerial capitalism affects most manufacturing, wholesale and re-

[15] We focus focus on a subsample of 54 countries (153 cross-sections) where we observe separately all the 14 industries listed in Figure A.2. We do not use the "Other Services" category that might include different industries across countries.

tail trade, and transportation, which experience increases of approximately 30 percentage points, 35 percentage points, and 40 percentage points in the employment share of white-collar workers when comparing the poorest to the richest economies. These are precisely the industries emphasized most by Chandler (1977).

FIGURE A.2: DETAILED SECTORS AND WHITE COLLAR LABOR

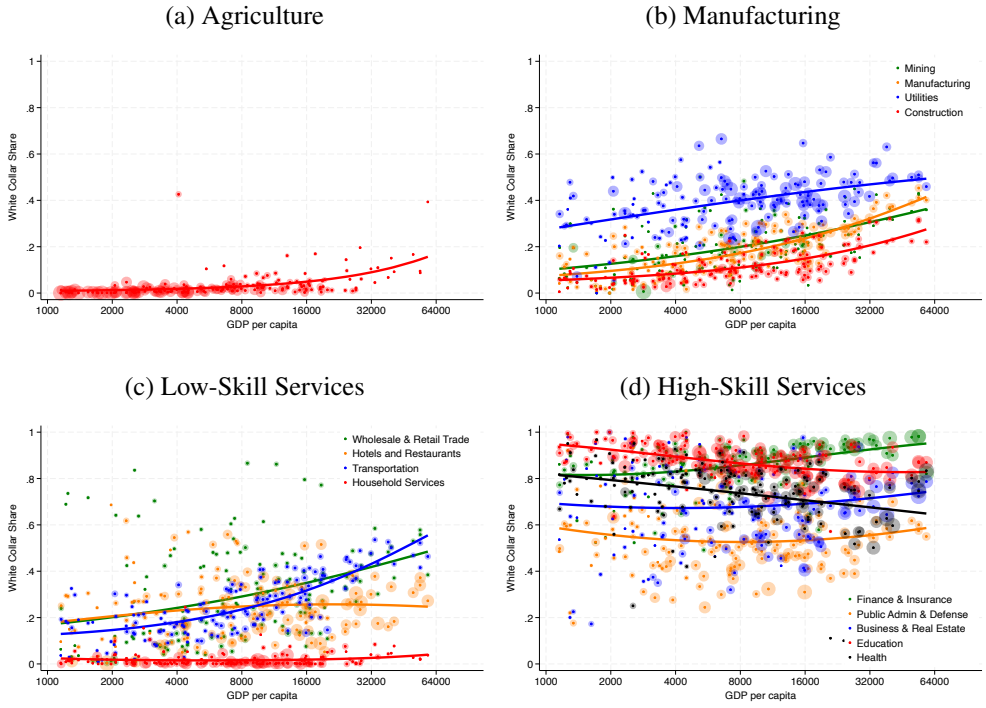


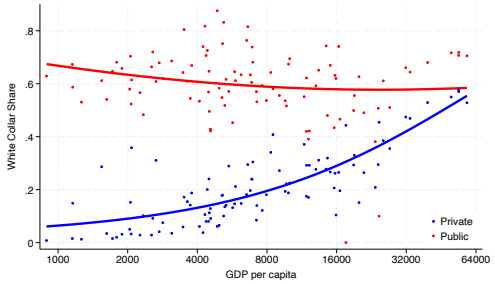
Figure A.3 further separates workers employed in privately and publicly owned enterprises (focusing on 41 countries and 97 cross sections where the two can be identified separately). Virtually all the rise in white collar employment associated with development is driven by the private sector. While the white collar share is everywhere higher in the public sector, this does not increase (and if anything) declines with economic development. This is again consistent with the narrative in Chandler (1977), which focuses primarily on the rise of managerial capitalism within private enterprises. **CHECK - IS THIS FAIR?**

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

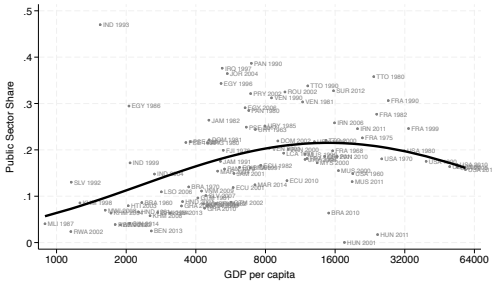
Our third motivating fact is that human capital accounts for almost all of cross-country differences in the share of white-collar workers. In the main text we use educational attainment as our proxy for human capital and show the results using cross-country data. We consider a number of alternative choices here.

FIGURE A.3: PUBLIC SECTOR AND WHITE COLLAR LABOR

(a) White Collar Share



(b) Public Sector Share

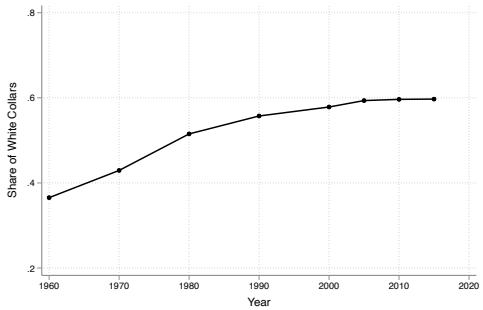


A.3.1 Time-Series Results

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.4 starts by focusing on the United States, the country with the longest available time series. Figure A.4a shows that the white-collar share of employment increased by more than 20 percentage points between 1960 and 2015. Figure A.4b 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.4a can be accounted for by changes in the educational composition over time.

FIGURE A.4: WHITE-COLLAR OCCUPATIONS OVER TIME – UNITED STATES

(a) White-Collar Share Over Time



(b) Propensities by Decade

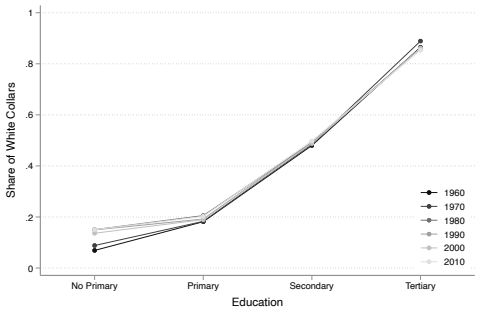
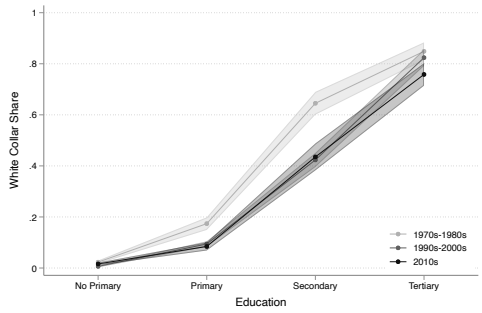


Figure A.5 shows the share of workers choosing a white-collar occupation conditional on education for all countries in the sample. Figures A.5a, A.5b, and A.5c show results for low-income, middle-income, and high-income countries, while the lines within each figure capture the estimated share for different time periods.

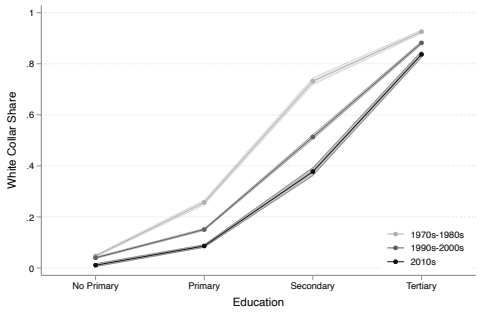
The share of workers choosing white-collar occupations is very stable in high-

FIGURE A.5: WHITE-COLLAR OCCUPATIONS OVER TIME – ALL COUNTRIES

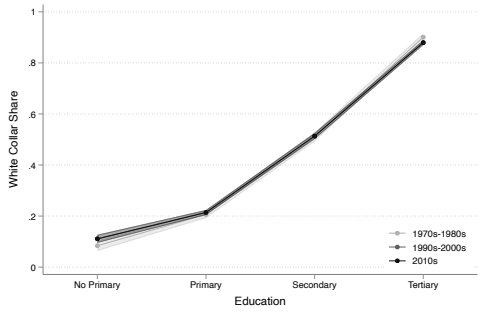
(a) Low Income



(b) Middle Income



(c) High Income



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

A.3.2 Sub-samples of Workers

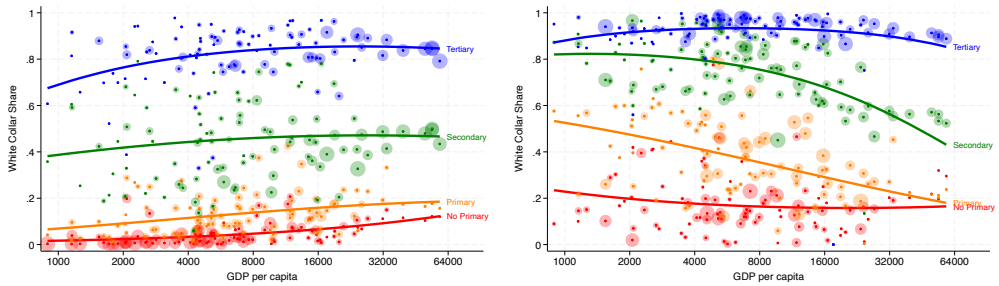
We can add: doctors & teachers, health, education

A.3.3 Alternative Measures of Skills: Adult Test Scores

In addition to educational attainment, we can study trends in white-collar employment shares as a function of adult test scores for a large number of countries around the world. For this analysis we use data from the Organisation for Economic Co-operation

FIGURE A.6: PRIVATE AND PUBLIC SECTOR

(a) Private Sector (b) Public Sector



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.7 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.7b 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.

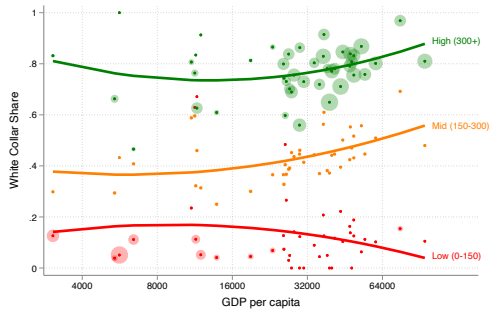
A.3.4 Alternative Measures of Skills: Childhood Test Scores

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

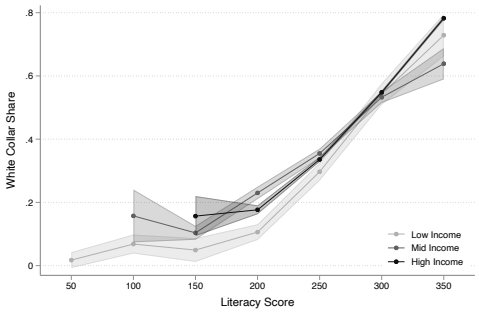
We source this data from two sources. First, we combine Programme for Inter-

FIGURE A.7: LITERACY AND WHITE-COLLAR OCCUPATIONS

(a) White-Collar Share by Literacy Score



(b) Estimated Propensities



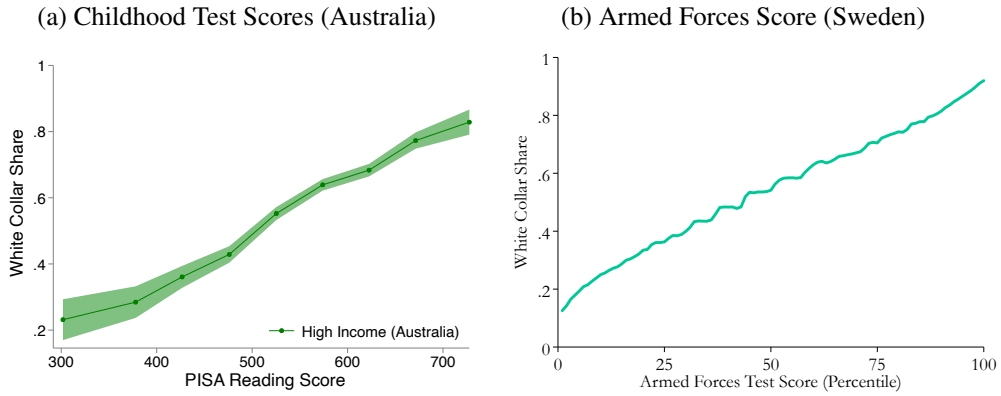
national Student Assessment (PISA) and Longitudinal Survey of Australian Youths (LSAY) data. The former measures literacy and mathematics proficiency of 15-year olds in countries around the world. The latter builds on the PISA in Australia. It tracks test-takers into early adulthood, as late as age 25, 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.8a 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.8b 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.

A.3.5 Literacy Conditional on Education

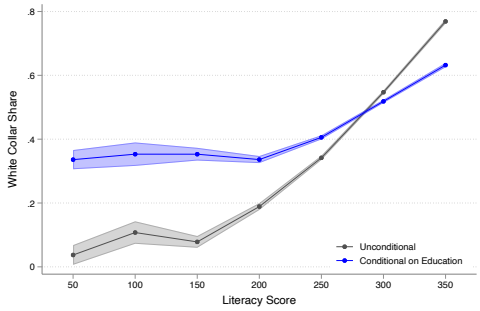
Using the PIAAC-STEP data this Appendix examines the relationship between occupational choices and literacy conditional on education. Figure A.9 plots the estimated white-collar employment share by literacy score (pooling all countries), with and without education dummies. While a marginal increase in 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

FIGURE A.8: WHITE COLLAR OCCUPATIONS AND ADULT SKILLS



30 percentage points. This corroborates the point that the sorting into white-collar jobs reflects skills and not just educational credentials.

FIGURE A.9: LITERACY CONDITIONAL ON EDUCATION



A.3.6 Summary Accounting Results

In Section 2.2 we document that human capital accounts for a substantial share of cross-country differences in the share of white collar workers. This appendix formalizes this 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.3.3).

A.4 Further Results: Organization of Production and Skills

Our fourth motivating fact is that the adoption of managerial capitalism affects the organization of production for workers of all education levels.

I'm a bit stumped here in terms of what additional results to show. Fede and Tommaso, you probably know better?

We can probably show: (i) time series results for own account from IPUMS, (ii) self-employment by literacy from PIAAC

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

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

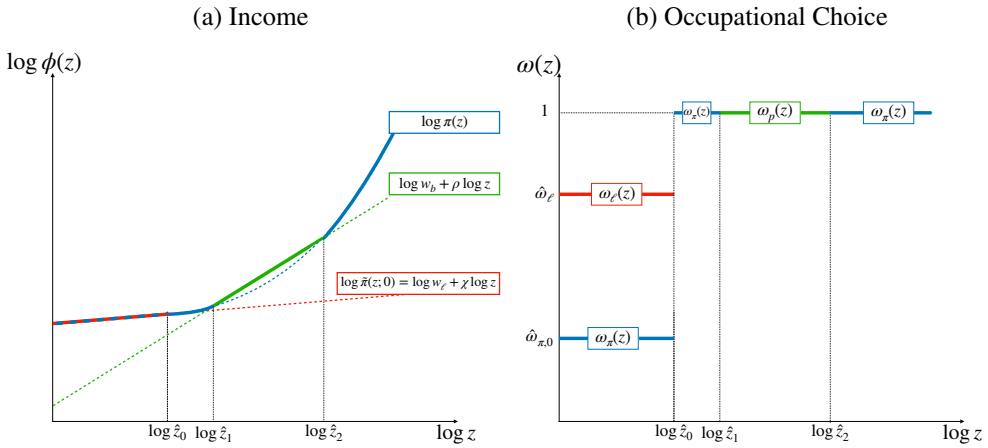
Note that we suppress the arguments of the functions q in equation (B.1) to simplify notation. This equation highlights the trade-offs entrepreneurs face when professionalizing the marginal task. Each term has an intuitive interpretation given by the term in brackets. The left-hand side captures the 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.10 shows the income schedule and occupational choices for this case.

FIGURE B.10: ALTERNATIVE OCCUPATIONAL CHOICE RULES



B.3 Proofs of Select Results

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

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

subject to

$$A \exp\left[\int_0^1 \log\left(\frac{\tilde{n}(i)}{\bar{\eta} - \gamma_l}\right) di\right]^{\bar{\eta}-\gamma_l} \left[\frac{z n_l}{A\gamma_1}\right]^{\gamma_l} \geqslant y$$
$$\tilde{n}(i) \leqslant \max\{\tilde{a}(i)(\bar{\eta} - \gamma_l)^{1/(\bar{\eta}-\gamma_l)}, \frac{z}{A} n_p(i)\}$$
$$n_p(i) \geqslant 0$$

First order conditions

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

We can further simplify to

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

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

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

However, this means that we have

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

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

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

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 qw_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 Additional Validation Results

D 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 $\{\sigma_j(z)\}_{j\in\mathcal{J}}$, loop over all sectors $j \in \mathcal{J}$ 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, $\{\phi_j(z)\}_{j\in\mathcal{J}}$, update the number of individuals with productivity z who opt to be in sector j, $\widehat{\sigma}_j(z)$, based on

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

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

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

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 $q(z)$

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

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

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

`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

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

`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

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

D.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

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

Consequently, the overall number of white collar individuals is

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

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

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

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

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

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

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

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

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

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

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

There is a mistake here, must be updated

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

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

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

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

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

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

The standard deviation of log firm size is

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

The standard deviation of log firm size in sector j is

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

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

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

Hence, economy-wide value added per worker is

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

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

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

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

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

meanwhile, average log pay of schooling group s is

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

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.