NBER WORKING PAPER SERIES

SELF-EMPLOYMENT WITHIN THE FIRM

Vittorio Bassi
Jung Hyuk Lee
Alessandra Peter
Tommaso Porzio
Ritwika Sen
Esau Tugume

Working Paper 31740
http://www.nber.org/papers/w31740

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
September 2023, Revised March 2024

We would like to thank Johannes Boehm, David Lagakos, and Martina Kirchberger for insightful discussions of the paper. We also thank Oriana Bandiera, Natalie Bau, Lauren Bergquist, Nick Bloom, Bruno Crepon, Wouter Dessein, Kevin Donovan, Ben Faber, Luis Garicano, Doug Gollin, Chad Jones, Joe Kaboski, Pablo Kurlat, Rocco Macchiavello, Karen Macours, Virgiliu Midrigan, Lukas Nord, Andrea Prat, Simon Quinn, Imran Rasul, Roland Rathelot, Tristan Reed, Esteban Rossi-Hansberg, Todd Schoellman, John Van Reenen, Eric Verhoogen, Chris Woodruff, Guo Xu, and participants at many seminars and conferences from which we greatly benefited. Elena Spadini and Sai Zhang provided outstanding research assistance. All errors are our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Self-Employment Within the Firm
Vittorio Bassi, Jung Hyuk Lee, Alessandra Peter, Tommaso Porzio, Ritwika Sen, and Esau Tugume
NBER Working Paper No. 31740
September 2023, Revised March 2024
JEL No. L23,L25,O11,O14,O17

ABSTRACT

We collect time-use data for entrepreneurs and employees in a sample of 1,000 manufacturing firms in Uganda, representative of both small and large production units. We find that even the largest firms in this setting more closely resemble a collection of self-employed individuals sharing a production space than a modern firm in which labor is specialized. We interpret the evidence through an equilibrium model of occupational choice and task assignment within the firm. The estimated model shows that there are only small productivity gains from having talented entrepreneurs run large firms. As a result, given the currently used production technology, classic development interventions such as wage subsidies or capital grants would have muted effects on firm size and aggregate productivity.

Vittorio Bassi
University of Southern California
Department of Economics
3620 South Vermont Avenue, Kaprielian Hall
Los Angeles, CA 90089
and NBER
vbassi@usc.edu

Jung Hyuk Lee
University of Southern California
leejungh@usc.edu

Alessandra Peter
Department of Economics
New York University
19 W. 4th Street
New York, NY 10012
and NBER
alessandra.peter@nyu.edu

Tommaso Porzio
Columbia Business School
3022 Broadway
Uris Hall 824
New York, NY 10027
and NBER
tommaso.porzio@columbia.edu

Ritwika Sen
Northwestern University
ritwika.sen@kellogg.northwestern.edu

Esau Tugume
BRAC Uganda
tugume.esau@brac.net

1 Introduction

The modal firm in low-income countries is a self-employed individual (Hsieh and Olken, 2014). This fact has concerned academics and policy-makers alike, since economies organized as a multitude of small, independent production units tend to exhibit low aggregate productivity. Larger firms may achieve economies of scale and allow workers to specialize based on comparative advantage, ultimately improving the allocation of talent in the economy.

Helping firms in low-income countries grow has thus become a key policy priority. However, whether consolidating labor into larger firms can be a viable strategy for development hinges on the degree to which producing in a firm is different than producing alone. If firms are merely a collection of individuals sharing a physical space and other fixed production costs, the returns to scaling up could be minimal as firms do not foster labor specialization. Ultimately, the benefits from encouraging firms to expand depend on how labor is organized within firms—something for which we have very little empirical evidence in low-income countries.

This paper addresses this knowledge gap. We collect a unique dataset on time use within the firm in three large manufacturing sectors in Uganda, and interpret the evidence through an equilibrium model. We find that, in this context, the gains from organizing labor into firms are limited, since workers would mainly transition from self-employment to *self-employment within the firm*. Firms are not effective vehicles to leverage the skill of entrepreneurs and—irrespective of the firm size distribution—aggregate productivity closely tracks the distribution of talent in the population rather than the right tail of entrepreneurs.

We surveyed a sample of firms in carpentry, welding, and grain milling, representative of the both small and large production units. We chose these sectors because they consist of both small and relatively large firms (with about 10 employees), and because they are relevant for the Ugandan economy, as they account for 30% of total manufacturing employment.

The key innovation of our survey is to measure time use within the firm, tracking how entrepreneurs and their employees allocate each hour of their workday to 17 pre-specified tasks, including both "production" tasks (e.g., specific steps of the production process) and "non-production" tasks (e.g., interacting with customers, supervision, input procurement). To the best of our knowledge, this type of data is unique, at least in the context of a developing country.

Firms in our sample are well-established enterprises: they are profitable, have been operating for many years, and offer stable jobs. At the same time, firms primarily sell customized goods to local consumers, and this is true even among the largest ones.

Our core empirical contribution is to use our unique survey data to document new facts on labor specialization and how this varies with firm size. Initially, we pool the data for carpentry and welding as these two sectors are similar and comprise 85% of firms in our sample. We later contrast the results with grain milling.

We start by showing that the set of tasks performed by firms as well as the average share of time spent on each of them are remarkably similar across the size distribution. Larger firms operate as replicas of smaller ones, doing more of the same tasks.

We then argue that there is little evidence of horizontal, or "Smithian", specialization: on average, 85% of employees work on each production step, and this percentage varies little with firm size. The low specialization we measure is not a mechanical byproduct of firms being small or using simple production processes: the production process involves 7-10 core steps, and if employees were fully specialized, each step would be performed by only 25%–30% of the employees.

Next, we turn to vertical specialization, measured as the extent to which entrepreneurs spend more time on non-production tasks than employees.[1] Vertical specialization is more prevalent than horizontal specialization, especially in large firms, where entrepreneurs spend twice as much time as employees on non-production tasks. However, it is far from complete: even in firms with more than five employees, entrepreneurs spend only 50% of their time on non-production tasks, even though there would be enough non-production tasks to fill the entrepreneur's day.

Having established that labor specialization is limited, we explore several potential barriers to specialization that have been suggested by the literature. We correlate our measures of horizontal and vertical specialization with firm characteristics, exploiting our rich survey. We find that, for instance, there is more specialization in firms with skilled entrepreneurs and those with reliable employees, suggesting that low managerial ability and worker absenteeism could be obstacles to specialization. At the same time, the magnitude of these differences in specialization is small: limited specialization is pervasive across all firms in carpentry and welding.

[1]To validate our measure, we show that entrepreneurs are more skilled and non-production tasks are more skill-intensive.

We next focus on grain milling, and show that labor specialization is much stronger in this sector, especially among the largest firms. We show that one key difference between the three sectors is in the nature of demand, with customization being much less prevalent in grain milling. The fact that there is more specialization in the sector that produces more standardized goods suggests that lack of product standardization could explain why firms adopt a production technology that makes it difficult to specialize labor.[2] We further validate this hypothesis by showing that customization entails significant communication and coordination costs within the firm and makes it difficult to "unbundle" the production process into separate tasks.

We then develop a model to characterize and quantify the link between the within-firm organization of labor, and firm-level and aggregate productivity. The heart of the model is an assignment problem of heterogeneous workers to tasks, which we embed into a standard occupational choice framework. Production requires completing tasks of different complexity. When working together in a firm, individuals can unbundle the production process and assign the most complex tasks to the most skilled individuals. This specialization of labor increases firm productivity, but comes with an "unbundling cost", which encapsulates any technological barrier to labor specialization, such as, for example, communication costs linked to product customization.

The extent to which entrepreneurs can pass through their talent to their workers depends on the production technology in two ways: first, they can specialize on complex tasks, and second, everyone's productivity depends on entrepreneurial ability through a non-rival component. This captures that, for example, a good business idea will raise everyone's output irrespective of labor specialization. The pass-through of entrepreneurial ability then determines the firm size, returns to entrepreneurial skill and hence occupational choice, and ultimately aggregate productivity.

When either the unbundling cost is low or the non-rival component has an important role in production, entrepreneurs can fully pass through their ability to their workers, and firms are effective vehicles for leveraging and scaling their talent. On the other hand, when the unbundling cost is large and the non-rival component has a limited role, each worker is essentially *self-employed within the firm* and firm productivity is simply equal to the average ability of all individuals. In this case, firms

[2]The link between standardization, specialization, and scale of operations has been established in the literature both empirically and theoretically (Piore and Sabel, 1984; Holmes and Stevens, 2014; Vickery et al., 1999; Dessein and Santos, 2006).

are merely vehicles to share fixed costs and their optimal size is smaller.

The way in which firms are internally organized in turn has equilibrium effects that ripple through the economy. When the pass-through of entrepreneurial ability is high, talent is highly valued in the economy since it can be easily leveraged. As a result, only large, high-productivity firms operate while marginal entrepreneurs become workers, attracted by the higher equilibrium wage.

We estimate the model using data from carpentry and welding. We target a rich set of moments on the within-firm allocation of labor to tasks and across-firm heterogeneity in size, revenues, and worker earnings. To capture all other reasons why firms may be small (such as credit constraints), we allow for a convex "hiring cost" that we estimate to match the firm size distribution conditional on productivity and labor allocation within the firm. All parameters are jointly estimated, but we offer a heuristic identification argument verified through model simulations.

We use the model for three exercises. First, we show that our setting is close, in terms of firm size and productivity, to the polar case of self-employment within the firm, in which entrepreneurs do not pass through any of their talent to workers. We thus learn that firms in our context are not effective vehicles to leverage entrepreneurial talent and, as a result, organizing labor into larger firms would not have a large effect on the allocation of talent and aggregate productivity.

Second, we show that barriers to labor specialization are distinct from other constraints keeping firms small, such as lack of credit, captured in our model by the convex "hiring cost". A reduction in either the unbundling or the hiring cost leads to a reallocation of workers towards more skilled entrepreneurs. However, the latter has a smaller impact on specialization and firm productivity, as it does not affect the pass-through of entrepreneurial talent. In our model, there is a two-way relationship between labor specialization and size: it is easier to specialize in large firms, but also, lower barriers to labor specialization increase the returns to setting up larger firms. Our quantitative results are more consistent with firms being small because they are not specialized, rather than not being specialized because they are small.

Third, we show that the benefits of interventions aimed at spurring firm growth hinge on the internal organization of firms. Relative to our benchmark, re-calibrating the unbundling cost to match the (higher) specialization observed in grain milling would increase the aggregate productivity effect of a reduction in hiring cost by 60%.

Taken together, our findings offer a novel perspective on how firms operate in low-income countries, which could reshape strategies for economic development. We find that the organization of production pervasive among Ugandan firms is inherently difficult to scale up, and a key reason for this could be that firms mostly produce customized products which render labor specialization difficult. As a result, classic development interventions aimed at spurring firm growth, such as capital drops or business training programs, would have small effects unless these interventions also lead to the adoption of more scalable organizations.[3] We thus conclude the paper by discussing possible pathways for policy to foster product standardization and, in turn, labor specialization and firm scalability.

Related Literature and Contribution. We build on a classic literature in organizational economics, which has long emphasized the importance of labor specialization for productivity and growth (Chandler (1990); Becker and Murphy (1992); Bolton and Dewatripont (1994); Yang and Borland (1991); Garicano and Rossi-Hansberg (2006)). Our contribution is to offer a case study that shows how the internal organization of firms could help us understand why firms are small in developing countries.[4]

Our model follows the seminal work on the organization of knowledge into hierarchies (Garicano (2000); Garicano and Rossi-Hansberg (2006)). Like those papers, we focus on vertical specialization based on comparative advantage. Our model, to the best of our knowledge, is unique in allowing for an overlap in the tasks performed by individuals in different layers of the organization. In previous work, the size of layers and their number is endogenous, but the assignment of tasks to layers is fixed: higher layers fully specialize in more complex tasks. In our model, instead, an unbundling cost modulates the extent to which such specialization is possible.[5]

We contribute to the large literature studying firm size and productivity in developing countries (Bloom et al. (2010); Hsieh and Olken (2014)). Our paper is closest to the work that emphasizes the role of management (Bloom et al. (2013); Bruhn et al. (2018); Anderson and McKenzie (2022)) and limits to delegation (Akcigit et al.

[3]See De Mel et al. (2008), De Mel et al. (2019), Hardy and McCasland (2023), Bloom et al. (2013) and McKenzie and Woodruff (2021) for evidence on the returns to development interventions such as capital drops, wage subsidies and labor market matching programs, and entrepreneurial training.

[4]There is a relatively small, but growing literature studying the organization of firms in low-income countries (Hjort, 2014; Atkin et al., 2017; Macchiavello et al., 2020; Ghosh, 2022). This literature typically studies only a few large firms, and has not focused on labor specialization.

[5]Studies of organizational adaptation to changes in local conditions also highlight the difficulty of coordination across unbundled production tasks (Dessein and Santos, 2006; Caliendo and Rossi-Hansberg, 2012; Adhvaryu et al., 2023).

(2021)). These studies find that poor managerial practices and contractual as well as labor market frictions impede firm expansion and lower their productivity. We highlight how barriers to labor specialization *inside the firm* prevent entrepreneurs from leveraging the talent they already possess.[6]

Many before us have provided empirical evidence for and quantitative assessments of the role of labor specialization for productivity and growth.[7] In addition to our unique focus and setting, we make a methodological contribution. We show the importance of collecting time use data: in our developing country setting, relying on coarse occupational data, as the literature typically does, would not have allowed us to identify the key patterns of limited specialization.

Our study is also related to work on the role of frictions in output markets as a barrier to growth (Bold et al. (2022); Jensen and Miller (2018); Hjort et al. (2020); Startz (2019); Vitali (2022)). We argue that one specific feature of demand—the prevalence of customization—impacts firm productivity and size by affecting the internal allocation of labor.[8] More broadly, our findings reinforce the view that demand-side constraints play a primary role for development (Goldberg and Reed, 2022).

Finally, this study is part of our own broader agenda to study *how* firms in low-income countries operate. In particular, this paper is related to Bassi et al. (2022b). Both projects aim to redefine the notion of firm boundaries, and show that a rich modelling of the organization of production is necessary to properly design and evaluate policy interventions. The two papers, however, differ in their focus. Bassi et al. (2022b) studies the rental market for capital equipment and shows that firms operating next to each other manage to achieve scale collectively. This paper, instead, focuses on the within firm organization of labor, and shows that even large firms resemble a collection of self-employed individuals sharing a production premise.

[6] Our results also provide a plausible explanation for the low correlation between managerial skills and firm size in developing countries (Bloom et al., 2022).

[7] For example, Caliendo et al. (2015) use occupational data to study how French firms are organized, and Bandiera et al. (2022) to compare labor specialization across countries. A related literature exploits data on tasks within the firm to study horizontal specialization within production during the Industrial Revolution in the US (Atack et al., 2019, 2023) and in New York City hairdressers (Kohlhepp, 2023). Boehm and Oberfield (2023) use production data to study task specialization across firms in India, while Freund (2022) uses wage data to study how labor specialization and sorting affects inequality in Germany.

[8] Jensen and Miller (2018) is a study particularly related to ours in that they show that firms specialize labor as they grow larger. While we also show that small firm size reduces specialization, our key focus is to show that barriers to specialization hinder firm size in the first place, and to isolate and quantify each channel of the two-way relationship between specialization and firm size.

Structure of the Paper. In Section 2, we describe the survey and sample. Section 3 shows evidence on labor specialization. Section 4 develops the model, Section 5 describes the estimation, and Section 6 reports our quantitative results and counterfactuals. Section 7 concludes. Additional results are in the Online Appendix.[9]

2 Survey and Setting

We describe the survey and present key descriptives of our sample of firms to motivate the analysis in the rest of the paper.

2.1 Sampling

Our sample consists of manufacturing firms in the following three ISIC codes: (i) 3100 "manufacture of furniture", (ii) 2511 "manufacture of structural metal products", and (iii) 1061 "manufacture of grain mill products". For brevity, we refer to the three sectors as carpentry, welding, and grain milling. We chose these sectors because: (i) they are large, employing about 30% of workers in manufacturing, and (ii) they include both smaller and—for Ugandan standards—larger firms, which allows us to study labor specialization across the size distribution.[10]

We selected a representative sample of 52 sub-counties, stratifying by population and by whether the sub-county is in Kampala, the capital city.[11] We first conducted a complete listing within each sub-county and found close to 3,000 establishments overall. We then randomly sampled about 1,000 establishments from the listing.[12] We interviewed the entrepreneur and all employees in the firm working on pre-specified "core" products that are common in each sector: doors in carpentry, windows in welding, and maize flour in grain milling. Our final sample includes 1,115 entrepreneurs and 2,883 employees.[13] In Appendix A.2, we compare our sample with administrative

[9] Additional results not intended for publication can be found in a Supplemental Appendix posted on the authors' website and available at bit.ly/SEWIF_supp.

[10] The latest Census of Business Establishments shows that these three sectors comprise 32% of total manufacturing employment and 27% in firms with five or more employees (UBOS, 2011).

[11] The average sub-county consists of 5,285 households and spans 4.4 square miles.

[12] We over-sampled firms with more than five workers to ensure enough observations among relatively large firms. All our results are appropriately weighted to reflect our sampling strategy. We use the terms "firm" and "establishment" interchangeably in the paper as in most cases these are single-establishment firms. For the sampling, we considered as one "firm" the entrepreneur and all employees working under their supervision in the same premises. This is the same definition as in typical surveys of informal firms, such as the World Bank Informal Sector Enterprise Surveys.

[13] We use either the term "entrepreneur" or "owner" since they are almost always the same person.

data and show that we properly cover both small and large firms.

The main survey wave was collected in person by our enumerators during 2018–2019. We then followed up with a briefer phone survey in 2022.

2.2 Survey Design

Our key innovation was to collect granular measures of labor specialization inside the firm, which we describe in detail below. In addition, we collected detailed survey modules on the production process of firms and the economic environment in which they operate. Specifically, we asked firms about (i) production steps and machines used to produce the core product; (ii) features of the output market, including prices and customers; and (iii) characteristics of entrepreneurs and employees, including an index of managerial ability for entrepreneurs (as in McKenzie and Woodruff (2017)).[14]

Measuring Labor Specialization. We designed two novel survey modules to measure labor specialization, each directed to both the entrepreneur and the employees.

The first was a time-use module. The respondent was first asked to report all the hours worked for the firm in the last day. For each hour, they were then asked which specific tasks they performed, from a pre-specified list split into "production", "non-production", and "idle" time. On production, we differentiated between working on the core product or another product, and in case of the core product, we also asked about the specific production steps performed. The list of non-production tasks encompasses all other managerial/organizational activities typically needed to run a business, such as customer interactions, supervision and training, sourcing of inputs, book-keeping and financial management, maintenance of machines, or management of stock. Finally, for idle time we recorded the time spent eating/resting or away from the firm for non-business reasons.

The second module complemented this information by asking which production steps the respondent *usually* performs on the core product (not limiting to the last day worked), as well as the hours they spend on each step.

In Appendix A.1, we list all tasks and production steps, together with the share of time the average firm spends on each.

Measuring Customized Production. The follow-up survey collected additional details on labor specialization inside the firm, product characteristics, and interac-

[14]These additional survey modules feature in our previous work and are described in detail in Bassi et al. (2022b). Compliance with the initial survey was over 90%.

tions with customers to shed light on the prevalence of product customization in this context and how this may create a barrier to labor specialization.[15]

2.3 Basic Descriptives

In line with previous studies (Hsieh and Olken (2014)), most firms in our sample employ less than 10 workers. However, they are *not* micro-enterprises: the median firm employs six workers, enough, in principle, for some labor specialization.[16]

Table 1 reports summary statistics by sector for firms below and above median size. The table is divided into three parts. First, Panel A shows that the firms in our sample are well established. They have been in business for about 10 years and make monthly profits of $130-400 (Ugandan GDP per capita was around $60 a month at the time of the study). Firms also offer relatively stable and well-paid jobs.[17]

Second, Panel B describes the nature of demand in the three sectors. In line with the literature, almost no firms export, and the majority of sales are to customers within the district.[18] Most firms sell on order, but the underlying reasons differ across sectors: in carpentry and welding, customers buy custom-made products, whereas in grain milling, customers bring their own maize to be processed into flour. In carpentry and welding, we also find much higher price dispersion for the same product within the firm, which firms report to be a result of customization. Panel B thus highlights a key difference between the sectors: in carpentry and welding, products are customized to the needs of individual consumers, while they are more standardized in grain milling, where firms mostly turn maize into flour. Importantly, both smaller and larger firms produce customized goods in carpentry and welding.

Finally, Panel C presents basic descriptives from our time-use survey. Firms spend about 80% of their non-idle time on production tasks (and 20% on non-production).

[15]The follow-up survey was conducted through phone surveys, and the attrition rate is about 32% for entrepreneurs and 41% for employees. This survey is used to provide qualitative evidence on labor specialization and prevalence of customization. As described in Appendix C, none of the moments used for estimation come from this survey; we rely on it only for one calibrated parameter. See the Supplemental Appendix (available at bit.ly/SEWIF_supp) for details on attrition and a summary of which specific tables and figures from the main text use data from the follow-up survey.

[16]Throughout the paper, we include the entrepreneur in the definition of firm size. The size distribution in the three sectors is reported in Appendix A.2.

[17]In the Supplemental Appendix, we also show that there is substantial dispersion in revenues per worker systematically correlated with managerial ability, suggesting that there could be gains from reallocating resources to higher-ability managers.

[18]See, for instance, Startz (2019), Bassi et al. (2022b), Bassi et al. (2022a) and Vitali (2022).

Remarkably, this split is constant across the size distribution and across sectors. Looking at who does what within the firm, we find substantial task overlap between entrepreneurs and employees: both engage in production as well as non-production tasks, and this is true even in large firms. However, the amount of task overlap is particularly strong in carpentry and welding: in grain milling, there is more specialization of entrepreneurs in non-production tasks, and especially so in large firms.

Given the similarity between carpentry and welding, we first analyze labor specialization by pooling the data for these sectors. We later contrast the results with grain milling to explore potential mechanisms behind the degree of labor specialization.

Table 1: Firm Characteristics and Time Use by Firm Size

	Carpentry		Welding		Grain Milling	
	<=6	>6	<=6	>6	<=6	>6
Number of firms	333	189	254	179	86	74
Panel A. Well-established firms						
Firm age (yrs.)	10.1	11.2	8.2	10.7	13.5	10.0
Monthly profits (USD)	206	260	209	367	131	403
Employee tenure (yrs.)	3.3	4.0	3.2	3.7	4.0	3.6
Monthly wage (USD)	72	79	68	80	42	66
Panel B. Local sales and customization						
Sells outside Uganda (%)	0.0	2.3	1.4	0.1	0.0	0.3
Most sales outside district (%)	9.4	9.3	8.4	14.9	3.1	7.3
Sales made to order (%)	73	80	88	90	73	63
Buy on order to customize (0/1)	0.63	0.71	0.66	0.62	0.08	0.35
Buy on order to bring own inputs (0/1)	0.06	0.00	0.05	0.04	0.72	0.41
Price dispersion w/i firm (same prod.)	1.40	1.51	1.29	1.37	1.08	1.16
Why diff. prices? Customization (0/1)	0.45	0.44	0.54	0.54	0.14	0.19
Why diff. prices? Qty discounts (0/1)	0.23	0.14	0.23	0.35	0.52	0.53
Panel C. Task overlap						
Share of time in prod. (Firm)	0.77	0.78	0.75	0.77	0.82	0.81
Share of time in prod. (Entrepreneur)	0.58	0.50	0.55	0.45	0.46	0.19
Share of time in prod. (Employees)	0.83	0.83	0.81	0.82	0.89	0.90

Notes: Means are reported by median firm size. Monthly profits: average reported profits in the three months preceding the survey (trimmed at top 1%). 1 USD = 3,800 UGX for monetary amounts. Panel B, rows 1-3 and row 6: information based on sales in the last three months. Panel B, rows 4–5: dummies for main reason why customers buy on order (we label as "Customization" the two answer options "Customers want to choose the materials/inputs" and "Each customer wants a different product"). Panel B, rows 7–8: dummies if reason listed among top three for charging different prices for the same product. Panel C, row 1: to compute the firm-level share of time, we sum across the entrepreneur and all surveyed employees.

3 Limited Specialization of Labor

In this section, we analyze the organization of labor inside the firm and how it varies across the size distribution. As a preliminary step, we describe the set of tasks firms do and then turn to who does what within the firm.

3.1 Task Composition: What Do Firms Do?

We document which tasks firms do and show that these do not vary by firm size.

Which Production Steps Do Firms Do? Since we collected data on production steps for the core product only, we limit the sample to the 80% of firms that make that product. For each individual production step, we compute the share of firms that perform that step. We then average across steps to create the share of firms performing the representative step.[19] Panel (a) of Figure 1 shows that: (i) each step is done by most firms, and (ii) this does not vary across the size distribution.[20]

How Do Firms Allocate Time Across Tasks? Panels (b)-(e) of Figure 1 plot, for each firm size, the share of time spent on different tasks.[21] All firms, irrespective of their size, spend about 60% of their time in production activities, 20% in non-production, or "managerial" tasks, and the remaining 20% idle (Panel (b)). Even within managerial activities (Panel (c)) or within production across steps (Panels (d) and (e)), there is very little variation in task composition by firm size.[22]

No Specialization Across Firms. These facts have two broad implications. First, firms do not specialize in different tasks. For instance, we do not find evidence that some firms specialize in production and sell to other firms, which then specialize in customer sales. Second, there is no evidence of scale economies driven by changes in task composition, such as an overhead cost in terms of managerial time. Larger firms

[19]The core product has 10 production steps in carpentry and 7 steps in welding. See Appendix A.1 for details. We average across steps, weighting by the average share of time each production step accounts for in the data, so that steps that represent a larger fraction of total production time get a higher weight. We then average across the two sectors.

[20]We censor firm size at 10 workers as very few firms are larger than that (see Appendix A.2).

[21]Panels (d) and (e) use information from the survey module asking which production steps the respondent usually performs. This survey module was presented only to firms with at least one employee, thus explaining why the x-axis starts at a firm size equal to 2.

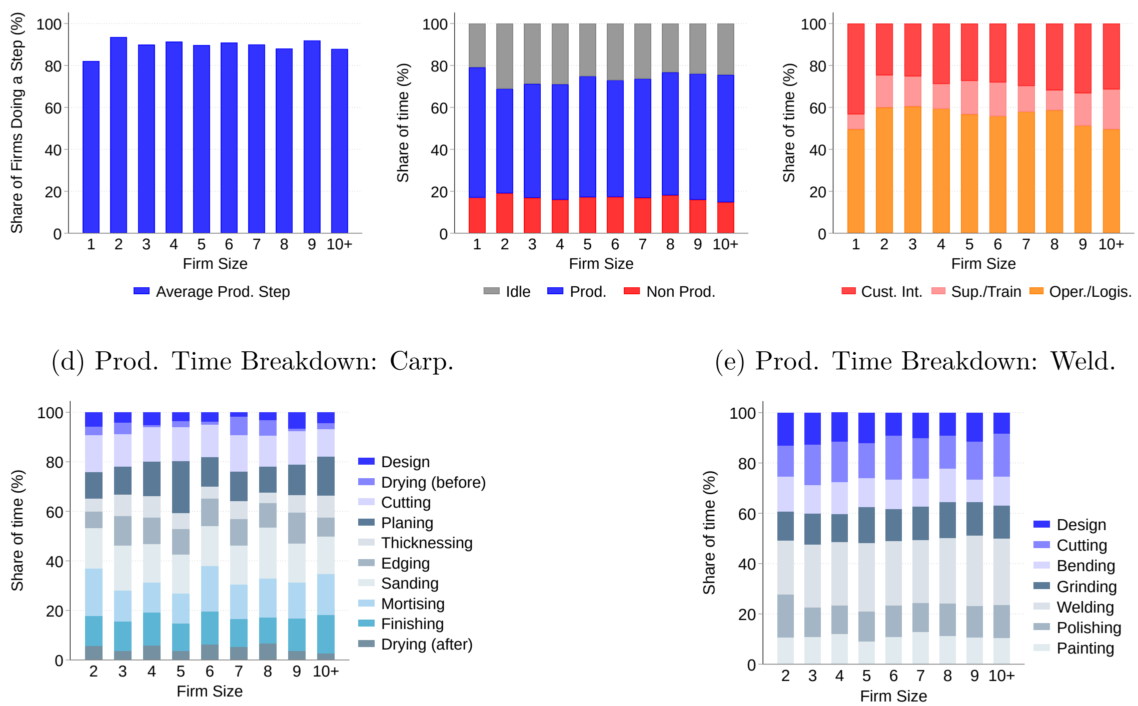
[22]The one exception is that one-person enterprises, reassuringly, spend little to no time on supervision or training (see Panel (c)).

operate as replicas of smaller ones, simply doing more of the same tasks.[23]

Figure 1: Task Composition across the Size Distribution

(a) Average Prod. Step (b) Prod., Non-prod., Idle Time (c) Non-prod. Time Breakdown

(d) Prod. Time Breakdown: Carp. (e) Prod. Time Breakdown: Weld.



Notes: Sample: carpentry and welding. Panel (a): share of firms doing the representative step, computed as described in the text. Panel (b): share of firm-level time in Production, Non-Production, and Idle tasks. Panel (c): breakdown of the non-production time into customer interaction, supervision, and operations/logistics. The category operations/logistics includes all tasks listed between book-keeping and Other non-production tasks from Table A.1. Panels (d) and (e): breakdown of the production time of the core product into the different production steps in carpentry and welding, respectively. Panels (a), (d) and (e): sample is restricted to firms making the core product.

3.2 Task Allocation: Who Does What Within the Firm?

Next, we study the division of labor inside the firm. We focus on two margins of specialization that are relevant in our context: (i) within production across steps, and (ii) between production and non-production tasks. (i) is motivated by the classic "Smithian", or *horizontal*, specialization: as in the pin factory described by Adam Smith, individuals can increase their productivity by specializing in a narrow production task. (ii) is motivated by the fact that non-production tasks are more skill-

[23]In the Supplemental Appendix, we show that the results in Figure 1 hold when we disaggregate the production steps and the time shares completely to reflect all individual production steps, non-production categories, and idle-time categories.

intensive and entrepreneurs are more skilled than employees, as we verify in Appendix A.3. This second margin corresponds to *vertical* specialization based on skill, as in the literature on the organization of knowledge into hierarchies (Garicano (2000); Garicano and Rossi-Hansberg (2006)).

3.2.1 Labor Specialization Between Production Steps

In Figure 2, we plot the share of employees performing the different production steps for the core product by firm size, separately in carpentry and welding.[24] In both sectors, the share of employees working on each step is high and barely decreases with firm size: about 85% of employees work on the representative step in firms of size 6, and the share remains close to 80% even in firms of size 8–10. Further, there is little heterogeneity across steps, especially for the important ones.

To interpret the magnitudes, we build an empirical benchmark corresponding to the share of employees that would work on a production step under full specialization.[25] Comparing the actual allocation with the full specialization benchmark highlights that horizontal specialization is limited even relative to what would be potentially attainable given the firm size distribution and the complexity of the production process. In Appendix A.3 we show that specialization across production steps is also limited for entrepreneurs throughout the size distribution.

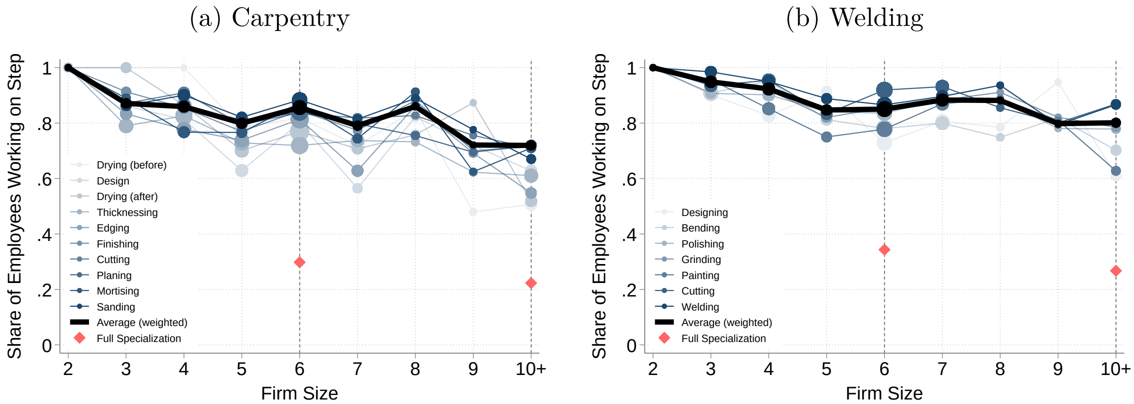
3.2.2 Labor Specialization Between Production and Non-production Tasks

In Figure 3, we compare the time that the entrepreneur and the average employee spend on each task. The y-axis shows the different tasks: blue ones are related to production, red ones to non-production, and grey ones to idle time. Each bar reports the share (normalized to 100%) of that task done by the entrepreneur (the dark portion of the bar) and the average employee (the light portion). If the entrepreneur and the average employee were to spend the same time on a given task, the dark and light bars would each amount to 50%. Figure 3 offers two takeaways. First, entrepreneurs specialize in non-production tasks, and employees in production ones. This shows that there is some (vertical) specialization along this margin, and justifies

[24]Since we sampled employees working on the core product, our sampling strategy cannot directly measure specialization across products. However, we note that despite this sampling restriction, we still interviewed more than 50% of all employees in our sampled firms. This suggests that employee specialization across products is also limited.

[25]To do so, we simply reassign employees across steps to minimize the overlap between employees while keeping the firm-level time on each task constant.

Figure 2: Task Allocation Within Production Across the Size Distribution



Notes: Sample: carpentry (Panel (a)) and welding (Panel (b)). The figures report the share of employees working on each production step, where darker blue colors indicate steps that correspond to a larger share of production time. We also include – in black – the share of employees performing the representative step, which is computed following the same procedure as for Figure 1, Panel (a). The red diamond markers represent the full specialization benchmarks computed for firms of size 6 and 10 (see main text for definition). To build the figures, we use information on which production steps individuals *usually* perform, rather than information from the time-use diary for the last day worked. We do so because not all production steps for one product may be completed on the same day.

our partitioning of tasks into production and non-production. Second, even though there is some specialization, there is also substantial overlap between entrepreneurs and the average employee in terms of time allocation.

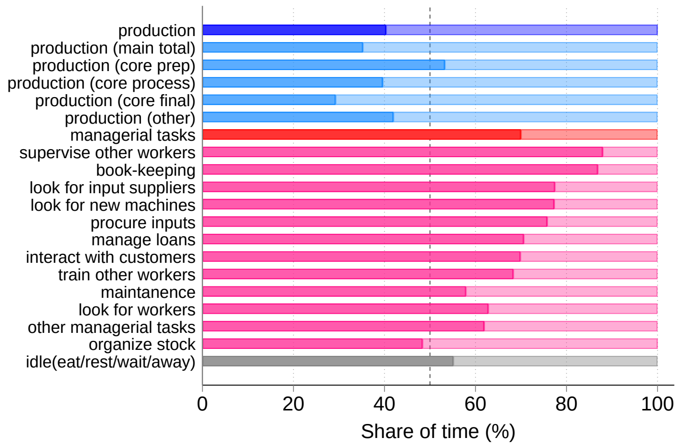
In Appendix A.3, we compare the time allocations of different employees within the same firm and find that the high-skilled spend a bit more time on non-production tasks, but the overlap is substantial across all tasks: overall, differences across employees are less pronounced than differences between employees and entrepreneurs.

More Vertical Specialization of Entrepreneurs in Larger Firms. In Figure 4, we study how vertical specialization of entrepreneurs varies across the size distribution. To do so, we plot the average individual's share of time spent in non-production tasks as a function of firm size, for both employees and entrepreneurs.[26] The figure confirms that specialization among employees is limited and does not vary with firm size. Entrepreneurs, instead, do specialize in non-production tasks, and the gap relative to employees increases in firm size: larger firms are more specialized.

Even in Large Firms, Entrepreneurs Are Not Fully Specialized. Panel (b) of Figure 4 shows that vertical specialization increases weakly with firm size: going from a firm of size one to a firm with five workers, the share of time in non-production activities only increases from about 34% to 45%. So, even in large firms, the entrepreneur

[26]In Figure 4 we only consider production and non-production time and instead drop idle time.

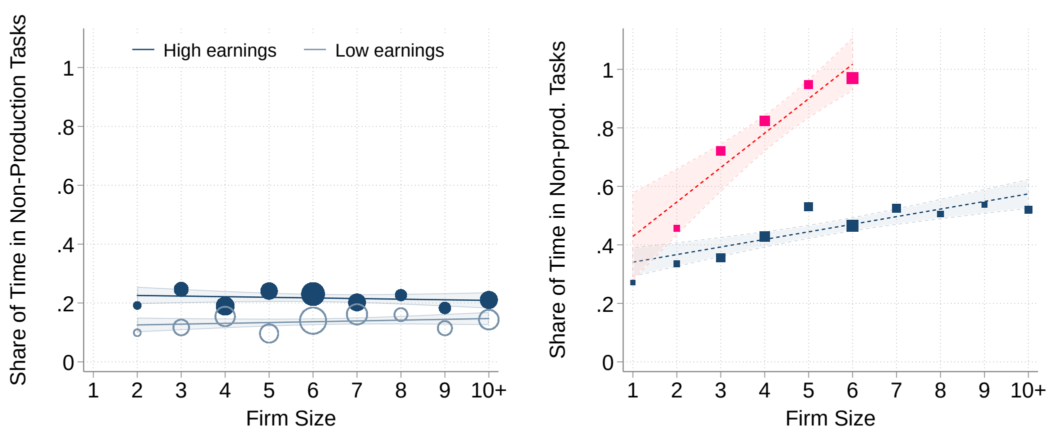
Figure 3: Time Allocation Between Production and Non-production Tasks



Notes: The figure compares the time spent on each task by the entrepreneur (dark bars) and the average employee (light bars). Blue bars: production. Red bars: Non-production. Grey bars: Idle time. "Production (core prep)", "Production (core process)" and "Production (core final)" include the following production steps: "Preparation (core prep)": (i) Carpentry: Design & Drying (before production), (ii) Welding: Design; "Production (core process)": (i) Carpentry: Cutting-Mortising, (ii) Welding: Cutting-Welding; "Production (core final)": (i) Carpentry: Finishing & Drying (after painting), (ii) Welding: Polishing & Painting. Sample: carpentry and welding.

Figure 4: Task Allocation Between Production and Non-production by Firm Size

(a) Employees (b) Entrepreneur



Notes: Sample: carpentry and welding. Shaded areas: 95% confidence intervals. The sizes of dots and squares represent the number of firms in each size group. Time use reported by interviewed entrepreneurs and employees. Idle time is excluded. Panel (a): Employee share of time in non-production tasks. Employees are classified as high and low earners within each firm (above or below the median). Panel (b): Entrepreneur share of time in non-production tasks. The pink squares represent the benchmark of full specialization, as described in the text.

spends only about *half* of her time on non-production activities.[27]

One possibility is that there are simply not enough non-production tasks to keep

[27]In Appendix A.3, we also show that entrepreneurs specialize in the more difficult steps within production, although again only to a limited extent.

entrepreneurs busy. To show that this is not the case, we compute, for each firm, the (hypothetical) share of time that the entrepreneur would spend in non-production tasks if she had fully specialized in these tasks.[28] We see that the observed relationship between specialization and firm size is closer to a flat line than to the empirical full-specialization benchmark (in pink). This highlights that limited vertical specialization is not merely an artifact of firms being small.[29]

In Appendix A.3 we show that the results in Figure 4 are robust to focusing on individual tasks within non-production (e.g., customer interaction). We also show that the results in Panel (a) of Figure 4 are not driven by some workers specializing in production while others specialize in non-production.[30]

In sum, we find that labor specialization in this context is limited overall, but vertical specialization of entrepreneurs in complex non-production tasks is relatively more important than horizontal specialization of labor across production tasks. As a result, we focus on vertical specialization in the model in the next section.

3.3 Why Is There Limited Specialization?

Our results so far naturally raise the question of why is there low specialization in this context. As mentioned, Figure 4 rules out that firms are simply too small: we observe low specialization even in firms that are large enough to specialize. Next, we exploit our survey data to explore other potential drivers of low specialization.

Correlates of Specialization Within Sector. We begin by exploring the correlates of specialization within sector. To do so, we estimate the following regression for firm i in sector s and region r, pooling the data for carpentry and welding:

$$specialization_{isr} = \alpha + \gamma size_i + \beta X_i + \delta_s + \eta_r + \epsilon_{isr}, \tag{3.1}$$

where $specialization_{isr}$ is a firm-level measure of specialization. Following Figures

[28]To do so, we reassign the time spent by all employees in a firm on non-production tasks to the entrepreneur. The counterfactual share of time in non-production tasks stays at 100% in firms with more than six workers.

[29]One direct implication of the limited specialization of entrepreneurs is that most non-production activities in larger firms are done by employees, not the entrepreneur. We verify this in Appendix A.3, where we show that, for instance, in firms of size six close to 70% of non-production activities are done by employees, despite the entrepreneur having enough time to do all of them.

[30]In the Supplemental Appendix, we also show that our measurement of non-production tasks is consistent across the size distribution, and report several pieces of evidence suggesting that more specialized firms are more productive (even conditional on a rich set of controls).

2 and 4, we measure horizontal specialization as the share of employees performing the representative step, and vertical specialization asthe gap between the share of the entrepreneur's and average employee's time in non-production tasks. We regress these on various firm-level characteristics X_i, always controlling for firm size (as larger firms are more specialized), region (η_r) and sector (δ_s) fixed effects.[31]

The results are in Figure 5. Each row shows a separate regression for a different firm characteristic X_i. To interpret the results more easily, we create dummy variables for each characteristic, and report the mean predicted specialization in the two groups of firms, together with 90% confidence intervals of the difference in means.

High ability entrepreneurs (i.e., those scoring above the median on our index of managerial practices) are more specialized, which is in line with the literature on managerial practices and firm productivity (see, e.g., (Bloom et al., 2013)). Firms where employee absenteeism is more prevalent are less specialized (along the horizontal dimension), consistent with absenteeism increasing coordination costs (Atencio-De-Leon et al., 2023).[32] Firms where all employees are hired through family and friends (i.e., "family firms") are less specialized. In principle, we might have expected more or less specialization in family firms, as these firms tend to be less well managed (Bennedsen et al., 2007), but may also have stronger trust between entrepreneurs and employees (Bloom et al., 2013; Akcigit et al., 2021), which could facilitate specialization.[33] While the majority of firms pay only piece rate, those that pay at least some of their employees a fixed salary are more specialized, consistent with moral hazard leading employers to prefer piece-rate contracts, but this hindering specialization as piece rates are easier to implement per product than per task (Holmstrom and Milgrom, 1991, 1994).[34] Finally, firms in Kampala are more specialized (vertically), which is consistent with access to larger markets facilitating standardization and specialization (Piore and Sabel, 1984; Holmes and Stevens, 2014).

On the other hand, there is no significant difference in specialization based on employee tenure. This suggests that lack of specialization is not driven by apprenticeship motives, whereby entrepreneurs spend time in production to train employees (Hardy

[31] Consistent with the analysis in the rest of the paper, we censor firm size at 10 workers.

[32] The average employee is absent 1.8 days per month.

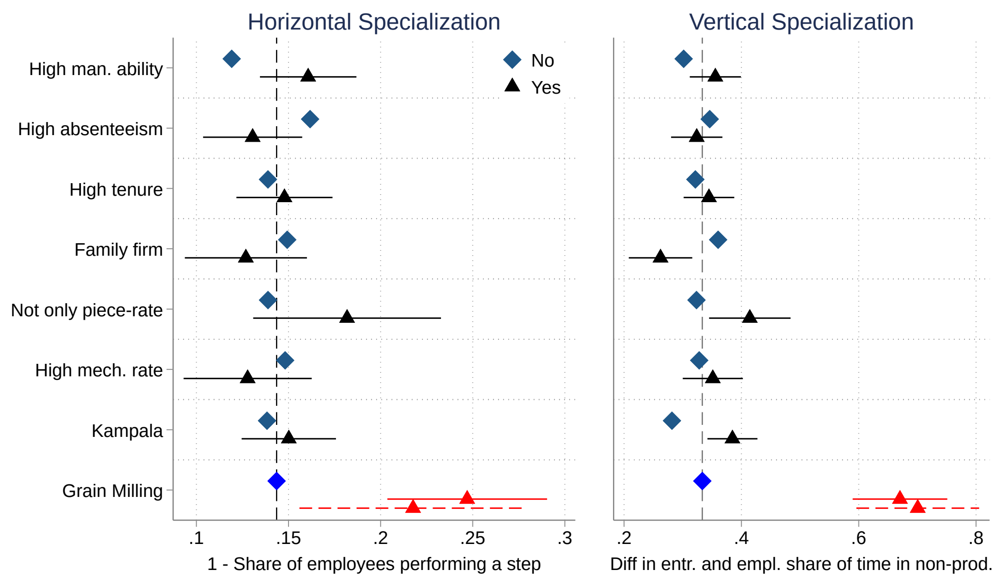
[33] 28% of firms are family firms. To define family firms, we exploit a survey question where for each employee we know if they were hired through family or friends. We compare firms where everyone was hired through family/friends with firms where no employee was hired in this way.

[34] 9% of firms pay at least some employees a fixed salary. For this analysis, we exclude unpaid workers and workers paying the owner of the firm for training (less than 2% of workers in total).

and McCasland, 2022): if this was the case, we would expect less specialization in firms where employees have low tenure and so are more likely to be receiving training.[35] We also find no evidence that more mechanized firms are more specialized.[36]

While not causal, these results do uncover systematic heterogeneity in specialization, for the most part consistent with what the literature suggests may be plausible reasons for the low specialization in this context. At the same time, the magnitude of these differences in specialization is small, implying that limited specialization is a pervasive feature of how firms operate in this setting. Even in the best managed firms in carpentry and welding, workers and entrepreneurs are not very specialized.

Figure 5: Correlates of Specialization



Notes: Sample: rows 1-7: carpentry and welding; rows 8: all sectors. Vertical dotted line: mean horizontal (left panel) and vertical (right panel) specialization in carpentry and welding. Results of OLS estimation of equation 3.1. Definition of horizontal and vertical specialization: see main text. The y-axis lists the independent variables of interest in each regression (see main text for definitions). For managerial ability, absenteeism, tenure and mechanization rate we split firms by below/above median. Diamonds: predicted mean in the comparison group (e.g., below median managerial ability firms). To predict this mean, we subtract from the average specialization in carpentry and welding the coefficient on the relevant characteristic of interest (e.g. dummy for above median managerial ability), weighted by the share of observations with that characteristic. Triangles: predicted mean in the comparison group plus estimated coefficient on the characteristic of interest. Bars: 90% confidence intervals.

[35] See the Supplemental Appendix for additional analysis ruling out that apprenticeship motives can explain the documented limited specialization.

[36] We define the mechanization rate as the share of machines used among the pre-specified list of machines asked in the survey. The literature has shown the importance of mechanization for labor specialization in the industrial revolution in the U.S., thus highlighting that mechanization may play an important role in a different context (Atack et al., 2019, 2023).

Heterogeneity in Specialization across Sectors. We contrast the within-sector heterogeneity in specialization with differences across sectors. To do so, in the the last row of Figure 5 we run a version of Equation (3.1) with the full sample, and comparing grain milling vs. carpentry/welding (solid red bars). The results are striking: grain millers are much more specialized both horizontally and vertically, and the magnitude of these cross-sectoral differences swamps all within-sector differences. For example, while high ability managers in carpentry and welding are 5pp more vertically specialized than low ability managers, grain milling firms are 27pp more specialized than carpentry/welding firms (controlling for firm size). Importantly, the last row also shows that the larger specialization in grain milling is robust to controlling for *all* the firm-level covariates X_i discussed above (dashed red bars).[37]

In Figure 6 we show how labor specialization varies with firm size in the different sectors. The results are again striking: while in small firms, specialization is similar across sectors, larger grain millers are substantially more specialized.[38] In Appendix A.3 we also show that there is less idle time in grain milling and that it decreases faster with firm size, consistent with higher labor specialization due to better time coordination.[39]

Plausible Mechanism: Customization. As highlighted in Section 2, customization is significantly more prevalent in carpentry and welding than in grain milling. The results in Figures 5 and 6 thus suggests that lack of product standardization could explain why firms in carpentry and welding operate with a production technology that makes it difficult to specialize labor. In practice, product customization may make specialization costly by raising communication and coordination costs.[40]

[37]The results of these specifications controlling for all covariates X_i simultaneously are reported in detail in the Supplemental Appendix.

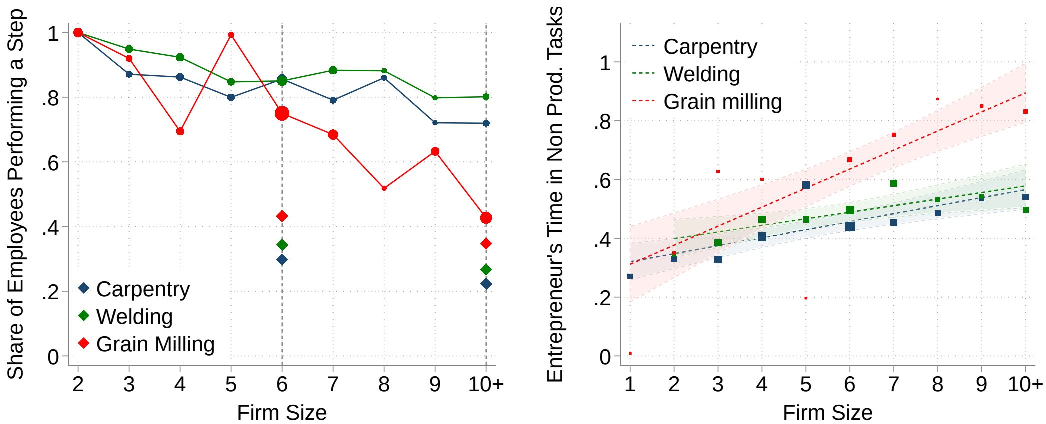
[38]Panel (a) of Figure 6 confirms that in grain milling the empirical benchmark of full horizontal specialization is similar, implying that differences in the shares of employees performing the representative step can be interpreted as differences in horizontal specialization across sectors.

[39]In the Supplemental Appendix we report the average levels of horizontal and vertical specialization for entrepreneurs and employees in the three sectors, and their correlation with firm size. These confirm the results of Figure 6. There we also show that employees in grain milling spend a smaller share of time in non-production tasks than in carpentry/welding and this does not vary with firm size, so that the results in Figure 6, Panel (b), underestimate the actual differences in vertical specialization across sectors. In the Supplemental Appendix we also show that grain milling features more specialization across production steps (with smaller firms doing fewer steps).

[40]This would be consistent with a large literature studying the link between standardization, specialization, and scale of operation (Piore and Sabel, 1984; Holmes and Stevens, 2014; Vickery et al., 1999; Dessein and Santos, 2006).

Figure 6: Heterogeneity in Specialization Across Sectors

(a) Horizontal Specialization (b) Vertical Specialization



Notes: Sample: all sectors. Panel (a): replication of Figure 2 by sector, focusing on the representative step only. See Figure 2 for details. Panel (b): replication of Figure 4 Panel (b) by sector. See Figure 4 for details.

Table 2: Implications and Consequences of Customization across Sectors

	Carpentry	Welding	Grain Milling
Panel A. Consequences of Customization			
Customers want to discuss order with person producing	52%	48%	22%
Customers have phone number of person producing	23%	23%	10%
Workers perform independent orders	49%	53%	26%
Potential varieties of core product	13	7	4
Panel B. Drivers of Customized Production			
Potential number of machine types for main product	24	20	13
Minimal time needed to produce main product (mins.)	433	351	56
Median days to complete typical order	4.0	4.0	0.6

Notes: Means. Panel A, row 1: dummy if discussing details with person producing is among top 3 reasons why customers buy on order. Panel A, row 3: dummy if employees perform independent orders. Panel A, row 4: number of different varieties of doors, windows, and flour in the sample. Rows 1–3 of Panel A are conditional on the firm having at least one employee. Panel B, row 1: number of machine types used to produce doors, windows, and flour.

In Table 2, Panel A, we use our survey to corroborate this hypothesis. First, we show evidence consistent with the idea that customization increases communication and coordination costs: carpenters and welders are twice as likely to report that customers buy on order because they want to discuss the details with the person producing. Direct phone communication with the person producing is also twice as common as in grain milling. Further, "independent orders" are more prevalent in carpentry and welding, an arrangement whereby a single employee manages the entire production of the order as well as the relationship with the customer all by themselves, thereby eliminating any communication costs within the firm.

Second, as each door or window can have different features, this may make it difficult to set up a production line with workers specialized in different tasks. To gauge this, the last row of Panel A shows that, according to our data, there are 13 different types of doors and 7 types of windows.[41] By contrast, in grain milling there are only 4 types of flour, so that setting up standardized processes is likely simpler as firms produce a larger quantity of each product.

Why are products more customized in carpentry and welding than in grain milling? Our data suggests that product complexity is a key difference across sectors. As shown in Panel B, many kinds of machines can be used to make products in carpentry and welding. Products also take several hours to make, usually over multiple days. The scope for customization and quality variation is therefore high.[42] This is not the case in grain milling, as flour is a much simpler and more standardized product.[43]

In sum, the sectoral heterogeneity is consistent with the notion that the limited specialization is a byproduct of firms producing customized products rather than standardized goods. This heterogeneity also reassures us that the limited specialization in carpentry and welding is not simply due to measurement error, as the measurement of time use is the same across the three sectors.

4 Model

We develop a model of vertical specialization within the firm, optimal firm size, and occupational choice. We use it to formalize the relationship between labor special-

[41]Note that these statistics just refer to product varieties (e.g., two-panel vs. four-panel doors), and not to the customization that is conducted on top of this (e.g., the precise size of the two-panel door), and thus provide a substantial underestimate of the number of possible products.

[42]Building codes could facilitate standardization in sectors such as carpentry and welding. Anecdotal evidence from our field visits confirms that building codes are present in Uganda but loosely enforced. For example, one larger carpenter reported that even when they get orders of doors for formal buildings, the size of the door frames usually vary from building to building, and this uncertainty is a key reason why they have not been able to set up a production line. When asked about how the firm is organized, he said: "I wish we had a production line, but now it is more like a big workshop." When asked if and how he would reorganize production if he could be sure that all doors had the same size, he replied: "I would set up a production line. In fact, I also have a snack factory, and there we have a production line".

[43]In exploiting differences in complexity across products, we relate to a literature on the role of product complexity for trade frictions (Juhász and Steinwender, 2018) and for building capabilities and specialization through trade (Atkin et al., 2021).

ization and firm size and to study the implications of barrier to specialization for firm-level and aggregate productivity.

4.1 Environment

We consider a static, closed economy with one sector—manufacturing.

Agents and Demographics. The economy is populated by a measure 1 of agents who differ in their ability $z \in [0, z_{\max}]$, distributed according to $G(z)$. Each agent supplies one unit of labor and has linear utility over consumption. Individuals can start a firm and become entrepreneurs (owners) o, or join the labor market as employees (workers) w. The resulting distributions of ability in the two occupations are F_o and F_w with $G(z) = F_o(z) + F_w(z)$. We refer to the ability of firm owners as $\hat{z}$.

Technology. There is a single good whose price is normalized to 1. Aggregate output is given by:

$$Y = \int Y(\hat{z})\, dF_o(\hat{z}), \tag{4.1}$$

where $Y(\hat{z})$ is the output of a firm owned by an individual of ability $\hat{z}$. Aggregate output is used for consumption and as an intermediate input in production.

All agents in the economy—workers as well as entrepreneurs—can transform their one unit of labor into final goods. The production process consists of a fraction D of complex tasks (e.g. negotiation with customers) and a fraction $1 - D$ of simple tasks (e.g. thicknessing wood). All agents are equally productive at the simple tasks, but their ability to perform the complex ones differs according to z. The complex part of the production process solely determines its value: if an individual with ability z does all D complex tasks, she produces z units of the final good. In addition to labor, production by a single agent requires a fixed amount $\chi(1)$ of intermediate inputs.

If agents get together in a firm of size n (with a fixed requirement $\chi(n)$ of intermediate inputs), then the output produced by each member of the firm may depend on the entrepreneur's ability as well as the assignment of people to tasks. We describe the firm-level production function in detail below.

Labor Market. There is a spot market for labor. Ability is private information at the time of hiring. Therefore, there is a single labor market that randomly matches owners and employees. When an owner chooses employment, she chooses the mass of workers, the composition is determined by the equilibrium distribution $F_w(z)$. Upon matching, types are revealed and employees and workers bargain over the surplus.

Firm-Level Production. When working together in a firm, individuals may trade tasks with one another. The problem of assigning workers to tasks is infinite dimensional: for each pair of individuals $\{z, z'\}$, it specifies the fraction of z's complex tasks that are performed by z'. We describe the full problem in Appendix B and focus here on a special case that we prove arises under two empirically relevant assumptions.

Assumption **1.** Each entrepreneur spends at least some time on simple tasks.

Assumption **2.** Workers' bargaining weight ω satisfies $\omega \leq \left(\frac{\partial(\max_{\boldsymbol{\mu}} y(\hat{z}, z, \boldsymbol{\mu}))}{\partial z}\right)^{-1} \forall\{z, \hat{z}\}$.[44]

Assumption 1 is a joint assumption on parameters of the model, motivated by the empirical evidence discussed in Section 3.[45] Assumption 2 is also motivated by the data, where we show that there is relatively little variation in worker compensation. As we show in Lemma 1 below, Assumption 2 is sufficient for there to be sorting by ability in equilibrium: individuals with high z become owners. This property is consistent with the data, where we show that entrepreneurs are positively selected.

Under Assumptions 1 and 2, owners are the most skilled individuals in the firm and, at the margin, have time to take on more complex tasks. Therefore, any complex task an employee delegates, she delegates to the owner. The assignment simplifies from an infinite-dimensional problem to choosing one number for each employee: the fraction of complex tasks she delegates to the entrepreneur, $\mu(z, \hat{z}) \in [0, 1]$.[46]

Formally, the output of a firm of size n, owned by an individual with ability $\hat{z}$ who chooses task assignment $\boldsymbol{\mu}$, is given by[47]

$$Y(\hat{z}, n, \boldsymbol{\mu}) = y(\hat{z}, \hat{z}, \boldsymbol{\mu}) + (n-1) \int y(z, \hat{z}, \boldsymbol{\mu}) \frac{dF_w(z)}{F_w(z_{\max})} \tag{4.2}$$

$$\text{where} \quad y(\hat{z}, \hat{z}, \boldsymbol{\mu}) = \hat{z}$$

$$y(z, \hat{z}, \boldsymbol{\mu}) = \underbrace{\hat{z}^{\lambda}}_{\text{non-rival}} \underbrace{\left[\hat{z}^{\mu(z,\hat{z})} z^{1-\mu(z,\hat{z})} (1 - \kappa(\mu(z, \hat{z})))\right]^{1-\lambda}}_{\text{net task productivity}}$$

Firm-level output is the sum of the production by the owner and the measure $(n-1)$ of employees. In order for an assignment to be *feasible*, no individual in

[44] $y(\hat{z}, z, \mu)$, formally defined in (4.2), is the output produced by worker z in a firm owned by an entrepreneur $\hat{z}$ who chooses task assignment $\boldsymbol{\mu}$.

[45] In the estimated model, this assumption holds, but we relax it for the counterfactuals.

[46] We refer to the firm-level vector of assignments as $\boldsymbol{\mu}$.

[47] More precisely, output is given by $\min\{Y(\hat{z}, n, \mu), \chi(n)\}$, taking into account the required amount of intermediate inputs.

the firm can spend more than their one unit of time across all tasks. Assumption 2 guarantees that the solution to (4.2) is feasible.[48]

Since the owner is more productive, she completes all her complex tasks and her "production line" yields output $\hat{z}$. The output generated by an employee's production line is a function of two components. First, it directly depends on the ability of the firm owner, $\hat{z}$. This captures the quality of the "idea" or also the reputation of the shop. This component is non-rival: the value of everybody's output benefits from the ability of the entrepreneur, irrespective of who does what within the firm. The relative importance of the idea component is governed by λ.

Second, the output from each employee's production line depends on net task productivity, which is a measure of the average ability with which the complex tasks are performed, net of an *unbundling cost.* The more tasks are delegated, i.e., the larger is $\mu(z, \hat{z})$, the larger the weight on owner ability, $\hat{z}$. Delegating tasks is costly. In order to assign parts of a production line to a different person, tasks must be *unbundled.* For example, if the entrepreneur negotiates all orders, she must then communicate exactly what customers want to the employee producing the order. The cost of unbundling, $\kappa(\mu(z, \hat{z}))$, is increasing in the share of complex tasks delegated by z.

Artisanal Production Technology and Talent Pass-Through. The production technology firms operate with is summarized by two parameters: (λ), determining how important specialization is, and the unbundling cost (κ), modulating how costly it is to specialize. Both determine the extent to which the ability of a firm owner affects her workers' output – i.e. the *pass-through* of entrepreneurial ability to worker productivity:

$$\frac{\partial \log y(z, \hat{z}, \boldsymbol{\mu})}{\partial \hat{z}} = \lambda + (1 - \lambda)\mu(z, \hat{z}). \tag{4.3}$$

This pass-through can be high if either labor specialization, $\mu(z, \hat{z})$, or the non-rival component of ability, λ, are large. In both cases, worker productivity closely tracks entrepreneurial talent, a case we think of as *modern* manufacturing. On the other hand, when λ is small and there is little specialization, pass-through of entrepreneurial ability to worker productivity is close to zero. We refer to this second case as an *artisanal production technology*, since each person's output primarily depends on their own skill.

[48] By Assumption 2, the owner spends less than one unit of time on her complex tasks plus the ones she takes over from her employees. Since all members of the firm have one unit of time, they can exactly take over the firm owner's simple tasks she no longer has time for.

4.2 Choices

We next describe the choices of economic agents: whether to be workers or start a firm, and how many workers to hire as well as the assignment of individuals to tasks.

Profits. An entrepreneur with ability $\hat{z}$ chooses firm size n and task assignment $\boldsymbol{\mu}$ to maximize profits:

$$\pi(\hat{z}) = \max_{\{\boldsymbol{\mu}, n \geq 1\}} Y(\hat{z}, n, \boldsymbol{\mu}) - (n-1) \int w(z, \hat{z}, \boldsymbol{\mu}) \frac{dF_w(z)}{F_w(z_{\max})} - \chi(n) \quad \text{s.t.(4.2)} \tag{4.4}$$

The cost $\chi(n)$ is the required amount of intermediate inputs. It captures all other expenses incurred by the firm, including hiring costs, capital expenditures, credit frictions, and any other auxiliary costs or frictions that scale with firm size. For brevity, we refer to $\chi(n)$ as the hiring cost. Since firm size is at least equal to 1—the owner herself,—$\chi(1)$ corresponds to the fixed cost of setting up a firm.

Wages. As soon as workers and entrepreneurs match, their ability is publicly observed. The wage is determined by a standard Nash bargaining protocol.

A worker's outside option is equal to the wage level $\overline{w}$, which is endogenous and adjusts to clear the labor market. The owner's outside option is equal to profits when producing with one fewer worker. The surplus of the match is therefore a function of worker as well as the entrepreneurial ability and task assignment $\boldsymbol{\mu}$: $S(z, \hat{z}, \mu) = y(z, \hat{z}, \boldsymbol{\mu}) - \overline{w}$.[49] The worker has bargaining power ω, his wage is

$$w(z, \hat{z}, \boldsymbol{\mu}) = (1-\omega)\overline{w} + \omega y(z, \hat{z}, \boldsymbol{\mu}) \tag{4.5}$$

Since task assignment maximizes match surplus, workers and owners agree on the choice of task assignment $\boldsymbol{\mu}$.

Occupational Choice. Each agent observes their ability z and chooses whether to be a worker or an entrepreneur. Profits conditional on entering are known, since firm owners hire a representative sample of workers. Wage earnings, on the other hand, depend on who the worker matches with. An individual with ability z starts a firm if and only if profits are higher than the expected wage in the labor market:

$$\mathbb{I}_o(z) = 1 \quad \iff \quad \pi(z) \geq \int w(z, \hat{z}, \boldsymbol{\mu}) \, \frac{(n(\hat{z}) - 1)\, dF_o(\hat{z})}{\int (n(\hat{z}) - 1)\, dF_o(\hat{z})} \tag{4.6}$$

[49]The hiring cost $\chi(n)$ is sunk and therefore not directly included in the surplus.

4.3 Equilibrium

Finally, we define an equilibrium in our setting, which requires that all agents maximize and the wage level clears the labor market; that is, the total labor demand of entrepreneurs is equal to the mass of individuals choosing not to start a firm.

Definition of Competitive Equilibrium *The competitive equilibrium is a wage level $\overline{w}$, size and task assignment for each ability $\hat{z}$ $\{n(\hat{z}), \boldsymbol{\mu}(\hat{z})\}_{\forall \hat{z}}$, an occupational choice function $\mathbb{I}_o(z)$, and distributions $F_o(z)/F_o(z_{max})$, $F_w(z)/F_w(z_{max})$ such that:*

1. *firm owners choose size and task assignment to maximize profits as in (4.4);*
2. *individuals choose their occupation according to (4.6);*
3. *the labor market clears: $\int (n(z) - 1)dF_o(z) = \int dF_w(z)$;*
4. *$F_o(z)/F_o(z_{max})$, $F_w(z)/F_w(z_{max})$ are consistent with the occupational choice—that is, $F_w(z) = \int (1 - \mathbb{I}_o(z))dG(z)$ and $F_o(z) = \int \mathbb{I}_o(z)dG(z)$.*

4.4 Characterization

In this section, we analyze how the production technology, as summarized by the costs and benefits of specialization (i.e., $\kappa(.)$ and λ), affects the allocation of talent within firms and consequently how it shapes firm size and aggregate productivity. We start by describing the occupational choice and then turn to the within-firm assignment problem and its implications for firm size and productivity. Finally, we discuss properties of the economy's equilibrium. We maintain Assumptions 1 and 2 throughout. All proofs are in Appendix B.

Parameterizing the Unbundling Cost. We assume that the unbundling cost μ takes on the functional form specified in Assumption 3, which guarantees closed-form solutions and allows us to parameterize the unbundling cost by a key parameter, κ_0 .

ASSUMPTION **3.** The cost of unbundling a fraction μ of complex tasks is given by $\kappa(\mu) = 1 - \exp\{-\hat{\kappa}(\mu)\}$, where $\hat{\kappa}(\mu) = {\kappa_0}^{1/\kappa_1} \frac{\mu^{1+1/\kappa_1}}{(1+1/\kappa_1)}$.

Occupational Choice. The model yields a familiar sorting of talent into occupations as a function of their skill sensitivity.

LEMMA **1** (Occupational Choice)**.** *In equilibrium, there is a cutoff z_0 such that an individual z chooses to become an entrepreneur if and only if $z \geq z_0$.*

Labor Specialization. Each worker delegates complex tasks until the marginal unbundling cost equals the marginal benefit—the difference in abilities between worker and entrepreneur. Using (4.2), the optimal share delegated by employee z thus solves:

$$\log \hat{z} - \log z \ = \kappa_0^{1/\kappa_1} \mu(z, \hat{z})^{1/\kappa_1} \tag{4.7}$$

The solution to the assignment problem highlights the specific nature of labor specialization in our model: specialization happens along the vertical dimension. The level of specialization in the firm is governed by κ_0, while the curvature, κ_1, modulates the extent to which delegation depends on the ability gap between worker and owner. To directly map model and data, we now characterize the resulting time use of entrepreneurs and workers.

Definition **1** (Average Labor Specialization)**.** Let the total time the entrepreneur $\hat{z}$ spends on complex tasks be $\hat{\theta}(\hat{z}) \equiv D\left(1 + (n-1)\int \mu(z', \hat{z}) \frac{dF_w(z')}{F_w(z_{max})}\right)$ and that of one of her workers z be $\theta(z, \hat{z}) \equiv D(1 - \mu(z, \hat{z}))$. We define the *average labor specialization* in the firm, $\overline{\theta}(\hat{z})$, to be the difference between the time spent on complex tasks by the entrepreneur and her average employee:

$$\overline{\theta}(\hat{z}) \ \equiv \hat{\theta}(\hat{z}) - \int \theta(z', \hat{z}) \frac{dF_w(z')}{F_w(z_{max})}.$$

Equipped with this definition, Lemma 2 formalizes the degree of labor specialization and its relationship with firm size.

Lemma **2** (Labor Specialization)**.** *Consider a firm of size n.*

1. *The time spent on complex tasks by a worker z and entrepreneur $\hat{z}$ is equal to*

$$\theta(z, \hat{z}) = D\left(1 - \frac{1}{\kappa_0}(\log \hat{z} - \log z)^{\kappa_1}\right) \tag{4.8}$$

$$\hat{\theta}(\hat{z}) = D\left(1 + \frac{n-1}{\kappa_0}\int (\log \hat{z} - \log z)^{\kappa_1} \frac{dF(z)}{F_w(z_{max})}\right). \tag{4.9}$$

2. *Average labor specialization in the firm is equal to*

$$\overline{\theta}(\hat{z}) = D\left(\frac{n}{\kappa_0}\int (\log \hat{z} - \log z)^{\kappa_1} \frac{dF(z)}{F_w(z_{max})}\right) \tag{4.10}$$

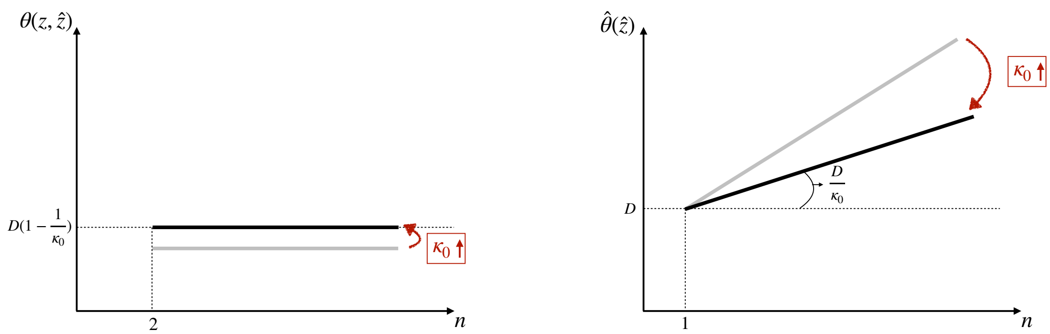
   It is declining in the unbundling cost κ_0 and increasing in firm size n at a rate that decreases in κ_0.

Figure 7 illustrates the relationship between specialization, firm size, and the unbundling cost κ_0. For ease of exposition, we set $\kappa_1 = 0$, implying that the share of complex tasks each worker delegates to the entrepreneur is independent of ability. Both panels of Figure 7 plot the share of time spent on complex tasks as a function of firm size for workers of any z (left), and for entrepreneurs of any $\hat{z}$ (right).

The share of time each worker spends on complex tasks is independent of firm size. Since the entrepreneur has capacity left to take on complex tasks (guaranteed by Assumption 1), optimal delegation only depends on the unbundling cost. Entrepreneurs' time on complex tasks, however, is increasing in firm size. This relationship between size and specialization is mechanical: the bigger the firm, the more "low-hanging" complex tasks there are for the entrepreneur to take on.

Figure 7: Labor Specialization, Firm Size, and Unbundling Cost κ_0

(a) Workers Time in Complex Tasks (b) Entrepreneurs Time in Complex Tasks



When the unbundling cost is higher ($\kappa_0 \uparrow$), each worker delegates fewer tasks to the entrepreneur and spends more time on complex tasks. For entrepreneurs, a higher unbundling cost only affects the *slope* of $\theta(n)$ with size. In a firm of size one, the unbundling cost of course has no impact on time allocation, since the entrepreneur is the sole worker. But with a higher delegation cost, each employee she hires delegates fewer tasks, and hence her share of time spent on complex tasks rises more slowly with firm size. Average labor specialization—the difference between the right and the left panels—is therefore decreasing in κ_0, especially for large firms.

Firm Productivity. Conditional on the distribution of worker ability, firm productivity is pinned down by the within-firm assignment of tasks.

LEMMA **3** (Firm Productivity)**.** *The output of a firm of size n, run by an entrepreneur of ability $\hat{z}$, can be written as $Y(\hat{z},n) = \mathbb{Z}(\hat{z},n,\boldsymbol{\mu})\,n$ where*

$$
\begin{aligned}
\mathbb{Z}(\hat{z}, n, \boldsymbol{\mu}) &= \underbrace{\hat{z}^{\lambda}}_{\textit{non-rival}} \quad \underbrace{\tilde{Z}(\hat{z}, n, \boldsymbol{\mu})^{1-\lambda}}_{\textit{aggregate task-productivity}} \\
\tilde{Z}(\hat{z}, n, \boldsymbol{\mu}) &= \left(\frac{1}{n}\hat{z}^{1-\lambda} + \underbrace{\frac{n-1}{n}\int \tilde{z}(z, \hat{z}, \boldsymbol{\mu})^{1-\lambda} \frac{dF_w(z)}{F_w(z_{max})}}_{\textit{dilution from firm size}} \right)^{\frac{1}{1-\lambda}}, \\
\tilde{z}(z, \hat{z}, \boldsymbol{\mu}) &= \hat{z}^{\mu(z,\hat{z})} z^{1-\mu(z,\hat{z})} \left(1 - \kappa(\mu(z, \hat{z}))\right),
\end{aligned}
$$

$\mathbb{Z}(\hat{z}, n, \boldsymbol{\mu})$ is strictly decreasing in n as long as $\lambda < 1$ and $\kappa_0 > 0$.

Lemma 3 isolates the two components of firm productivity. The first term, $\hat{z}^{\lambda}$, captures the unique role of the entrepreneur. As long as $\lambda < 1$, ability passes through to firm productivity in a non-rival way, that is, independently of time use.

The second term, firm-level task-productivity $\tilde{Z}(\hat{z}, n, \mu)^{1-\lambda}$, is a geometric average of the ability of all individuals doing the complex tasks. Since the entrepreneur completes all her own tasks, her productivity is $\hat{z}$. The task productivity of each employee, however, is lower than the entrepreneur's—as long as there is less than full specialization ($\kappa_0 > 0$). The entrepreneur's and her workers' task productivity is aggregated to the firm level with weights of $1/n$ and $(n-1)/n$. Increasing the size of the firm would therefore decrease its productivity: more weight is given to the lower task productivity of workers. This highlights that low pass-through of entrepreneurial ability leads to stronger decreasing returns to scale.

Optimal Firm Size. Labor specialization and firm size are closely intertwined. Lemma 2 showed one side of this two-way relationship: there is less labor specialization in small firms. Lemma 4 shows that there is also a reverse relationship: barriers to labor specialization reduce the optimal firm size.

LEMMA **4** (Firm Size)**.** *The optimal firm size n of each entrepreneur $\hat{z}$ solves*

$$
\left[\mathbb{Z}(\hat{z}, n, \boldsymbol{\mu}) + \underbrace{\frac{\partial \mathbb{Z}(\hat{z}, n, \boldsymbol{\mu})}{\partial n} n}_{\textit{prod. dilution}<0} \right] = \overline{w}(\hat{z}, \boldsymbol{\mu}) + \underbrace{\chi'(n)}_{\textit{hiring cost}},
$$

It is declining in the marginal hiring cost $\chi'(n)$ and, as long as $\lambda < 1$, in the unbundling cost κ_0.

At the optimal size, the marginal cost of hiring is equal to marginal revenues. The marginal cost is equal to the average wage plus the additional hiring cost. The first component of the marginal benefit is the standard increase in firm output from hiring an additional worker. The second component is unique to our framework. As shown in Lemma 3, firm-level productivity is decreasing in size, since each additional worker is less skilled than the entrepreneur. In choosing firm size, the entrepreneur takes into account the decreasing returns arising from productivity dilution.

Two frictions keep firms small. The hiring cost $\chi(n)$ directly reduces optimal firm size by making expansion costly. The unbundling cost κ_0 reduces firm size through productivity dilution and because it reduces average productivity for any firm size bigger than 1. There is also an apparent complementarity between the two. The benefit from relaxing the external friction $\chi'(n)$ is limited if internal barriers to labor specialization lower firm productivity and generate strong decreasing returns to scale.

Why Do Firms Exist? Two Polar Cases. To complete the intuition behind our model of the firm, Lemma 5 characterizes two polar cases that span different production technologies from modern manufacturing to fully artisanal firms.

LEMMA **5** (What is a Firm?)**.** *The weight of non-rival entrepreneurial talent in production (λ) and the size of the unbundling cost (κ_0) span two polar types of firms:*

1. ***Scalable Entrepreneurial Talent.*** *If $\lambda = 1$ or $\kappa_0 = 0$, then $\frac{\partial \log y(z,\hat{z},\boldsymbol{\mu})}{\partial \hat{z}} = 1$, $Y(\hat{z}, n, \boldsymbol{\mu}) = \hat{z}\, n$, and optimal firm size is increasing in $\hat{z}$.*

2. ***Self-Employment within the Firm.*** *If $\lambda = 0$ and $\kappa_0 \to \infty$, then $\frac{\partial \log y(z,\hat{z},\boldsymbol{\mu})}{\partial \hat{z}} = 0$, then $Y(\hat{z}, n, \boldsymbol{\mu}) = \overline{z}(\hat{z})\, n$, with $\overline{z}(\hat{z}) \equiv \frac{1}{n}\left(\hat{z} + \frac{n-1}{n}\int z \frac{dF_w(z)}{F_w(w_{max})}\right)$, and optimal firm size is constant in $\hat{z}$.*

When delegation is costless ($\kappa_0 = 0$) or entrepreneurial talent is entirely non-rival ($\lambda = 1$), entrepreneurs fully pass through their ability to workers and firm productivity is equal to their ability. This benchmark resembles the typical firm problem dating back to Lucas (1978), in which labor is a commodity and firms are vehicles for leveraging the entrepreneur's talent. In this world, organizing labor into few large firms run by talented entrepreneurs yields large aggregate productivity gains.

In the opposite extreme, delegation is prohibitively costly ($\kappa_0 \to \infty$). All individuals in the firm effectively work on their own, completing all tasks required for their production line. If in addition talent is fully rival—that is, output depends only on the individual performing the complex tasks—then entrepreneurs cannot pass-through any of their ability to workers. Firms are *artisanal*: productivity is simply the average ability of all their members. In this benchmark, the only reason for firms to exist is to share fixed costs. As a result, who starts a firms is indeterminate and all firms are identical in size. Importantly, irrespective of the firm size distribution, aggregate productivity closely tracks the overall distribution of talent in the population rather than the right tail of entrepreneurs.

Equilibrium and Aggregate Implications. So far, we have considered the solution to the problem of one entrepreneur. Next, we turn to the overall economy. We prove the main proposition for the case of $\kappa_1 = 0$, where no assumptions on the population distribution of talent, $G(z)$, are required. The estimated model confirms that κ_1 is small in our environment and that the proposition holds.

PROPOSITION **1** (Aggregate Effects of the Unbundling Cost κ_0)**.** *Suppose that $\lambda < 1$ and $\kappa_1 = 0$. As long as the aggregate labor supply curve is increasing in the wage level and ω is sufficiently small, a decline in κ_0 leads to an increase in:*

1. *average labor specialization $\overline{\theta}(\hat{z})$ in all firm sizes;*
2. *the slope of the relationship between average labor specialization and firm size;*
3. *the average ability of firm owners;*
4. *the average firm size $\overline{n} \equiv \int n(z) \frac{dF_o(z)}{F_o(z_{max})}$, where $n(z)$ is the optimal firm size;*
5. *the average firm productivity $\overline{\mathbb{Z}} \equiv \int \mathbb{Z}(z, n(z), \boldsymbol{\mu}(z))n(z) \frac{dF_o(z)}{F_o(z_{max})}$;*
6. *the wage $w(z, \hat{z}, \boldsymbol{\mu})$ of all workers z in all firms $\hat{z}$.*

Proposition 1 shows that reducing the unbundling cost transforms the way firms are organized internally with effects that ripple through the economy in equilibrium. Higher labor specialization increases firm productivity and thus the demand for labor. As a result, wages increase, leading some marginal firm owners to become workers. This further increases aggregate productivity through a classic selection effect. Overall, managerial ability is highly priced in the economy, as talent can be leveraged by taking over more and more complex tasks.

5 Bringing the Model to the Data

To make the model suitable for quantitative analysis, we add a few features discussed below and parameterize the model. Then, we discuss the identification and estimation results. In Appendix C.1, we use heterogeneity across sectors and regions to validate the theoretical predictions from Section 4.

5.1 Extensions and Parameterization

We extend the model along three dimensions. First, to match the joint distribution of firm sizes and revenues, we allow entrepreneurs to differ not only in their managerial ability z but also in the hiring cost χ_0.[50] We assume that z is drawn from a generalized Pareto distribution with scale and location normalized to one and shape given by σ_z, and that χ_0 follows a normal distribution with mean $\overline{\chi_0}$ and standard deviation σ_χ.

Second, to match the time use within firms, we allow for a firm-level overhead of non-production tasks d. This overhead time must be supplied by the entrepreneur and does not affect productivity.[51]

Third, we specify the functional form of the hiring cost. We assume that the entrepreneur has to pay a fixed cost to operate a firm χ_f, and a hiring cost for hired labor $(n-1)$. The overall "hiring" cost for a firm of size n is therefore $\chi(n) = \chi_f + \chi_0^{1/\chi_1}\,(n-1)^{1+1/\chi_1}\,(1+1/\chi_1)^{-1}$. For simplicity, we still refer to the composite cost $\chi(n)$ as the hiring cost.

Last, we assume that the variable "managerial ability index" discussed in Section 3 is a noisy proxy of true managerial ability, denoted $s(z)$. Specifically, we let the (normalized) managerial index be equal to the (normalized) log of managerial ability plus an additive, normally distributed term.[52]

Table 3 summarizes the economic environment that we take to the data and links each economic block to the main parameters modulating it.

5.2 Targeted Moments and Identification

The model has 12 parameters. We specifically designed our survey to measure firms' start-up and fixed operating costs. We can thus directly calibrate χ_f.[53] The remaining

[50]It is important to match this joint distribution since the dispersion of talent across individuals is a key driver of the aggregate losses from the barriers to labor specialization. If all potential entrepreneurs were of similar skills, the inability of relatively high-skilled entrepreneurs to leverage their talent would not be very consequential.

[51]We do not include d when calculating firm-level specialization, which we now define as $\overline{\theta}(\hat{z}) - d$, where $\overline{\theta}(\hat{z})$ is as previously defined.

[52]This assumption allows us to accommodate enough heterogeneity in managerial ability to match the empirical distribution of log revenues while also matching the observed empirical relationship between firm revenue, workers' earnings, and the managerial index.

[53]See Appendix C.2 for details.

Table 3: Summary of the Economic Environment and Parameters

	Equation	Parameters
Final Output	$Y = \int Y(\hat{z}) dF_o(\hat{z})$	
Firm Output	$Y(\hat{z}) = \mathbb{Z}(\hat{z}, n(\hat{z}), \boldsymbol{\mu})\, n(\hat{z})$	
Firm Productivity	$\mathbb{Z}(\hat{z}, n, \boldsymbol{\mu}) = \hat{z}^{\lambda} \left(\frac{1}{n} \hat{z}^{1-\lambda} + \frac{n-1}{n} \int \tilde{z}(z, \hat{z}, \boldsymbol{\mu})^{1-\lambda} dF_w(z) \right)^{\frac{1}{1-\lambda}}$	λ
Net Task Productivity	$\tilde{z}(z, \hat{z}, \boldsymbol{\mu}) = \hat{z}^{\mu(z,\hat{z})} z^{1-\mu(z,\hat{z})} \left[1 - \kappa\left(\mu(z, \hat{z})\right)\right]$	κ_0, κ_1
Heterogeneity	$\log z \sim N(1, \sigma_z),\ \chi_0 \sim N(\overline{\chi_0}, \sigma_\chi)$	$\sigma_z, \overline{\chi_0}, \sigma_\chi$
Unbundling Cost	$\kappa(\mu) = 1 - \exp\left\{ -{\kappa_0}^{1/\kappa_1}\, \mu^{1+1/\kappa_1} (1 + 1/\kappa_1)^{-1} \right\}$	κ_0, κ_1
Hiring Cost	$\chi(n) = \chi_f + \chi_0^{1/\chi_1}\, n^{1+1/\chi_1}\, (1 + 1/\chi_1)^{-1}$	$\chi_f, \overline{\chi_0}, \sigma_\chi, \chi_1$
Worker Earnings	$w(z, \hat{z}, \boldsymbol{\mu}) = (1-\omega)\overline{w} + \omega \hat{z}^{\lambda} \tilde{z}(z, \hat{z}, \boldsymbol{\mu})^{1-\lambda}$	ω
Measurement Error	$s(z) = \log z + \epsilon,\ \epsilon \sim N(0, \sigma_\epsilon)$	σ_ϵ
Complex Share (Workers)	$\theta(z, \hat{z}) \equiv D(1 - \mu(z, \hat{z})) = D\left(1 - \frac{1}{\kappa_0} (\log \hat{z} - \log z)^{\kappa_1}\right)$	D, κ_0, κ_1
Complex Share (Entrepr.)	$\hat{\theta}(\hat{z}) = d + D\left(1 + (n-1)\frac{1}{\kappa_0} \int (\log \hat{z} - \log z)^{\kappa_1} \frac{dF_w(z)}{F_w(z_{max})}\right)$	d, D, κ_0, κ_1

11 parameters do not have direct empirical counterparts and are jointly estimated.

Targeted moments. We target 150 moments, computed using pooled data for carpentry and welding, as explained in details in Appendix C.2. Table 4 lists 21 summary moments that capture the main relationships we are targeting.[54]

Our choice of moments is guided by two principles. First, the model should be consistent with the key features of the economic environment, as described in Sections 2 and 3. Therefore, we target a rich set of moments describing time allocation within the firm as well as heterogeneity across firms in terms of size and productivity.[55]

[54] For example, while we target the deciles of the distributions of firm sizes and revenue, we include in Table 4 only their means and standard deviations.

[55] Computing the moments does not pose any complications either in the model or in the data. Only a few simple decisions are to be made. First, we need to define what complex tasks are in the data. We assume, following the evidence discussed, that non-production tasks are more complex. Second, we need to decide whether to purge the data of some variation. Here, again, we closely follow the empirical section and use the same set of controls. Finally, when calculating the distribution of firm revenue and workers' earnings, we trim the top and bottom 5% to get rid of excessive variation plausibly driven by measurement error.

Second, we need to include enough targets to be able to identify the parameters modulating the returns to labor specialization. For this purpose, as we explain below, it is important to include moments on the distribution of workers' earnings within and between firms, and their relationship with managerial ability.

Estimation Procedure. We estimate the model using indirect inference and simulated method of moments. We minimize the distance between data moments and their exact model counterparts using a routine that we developed in Bassi et al. (2022b). Details are in the Supplemental Appendix, where we also show that the parameters are well-identified: the likelihood function is single-peaked around the estimates, and we verify that our estimation procedure recovers the true parameters when we run it on a synthetic set of moments generated by the model itself.

Identification. While all the parameters are jointly estimated, we can provide a heuristic identification argument, which we verify by computing the Jacobian matrix that traces out how each moment is affected by each parameter. The matrix is in the Supplemental Appendix, but in the last column of Table 4, we include the *key parameters* that are linked to each moment.

As Lemma 2 highlights, the within-firm allocation of time is tightly linked to the share of complex tasks in production (D), the overhead time (d), and the parameters of the unbundling cost (κ_0, κ_1). Our unique data on the relationship between firm size and the entrepreneur's time spent on complex tasks identifies κ_0. This same relationship, but estimated for employees, helps to pin down κ_1. In equilibrium, larger firms are managed by more skilled entrepreneurs; hence, if κ_1 is large, workers in large firms should spend less time on complex tasks. In the data, however, the relationship is flat, suggesting that κ_1 is small.

The biggest identification challenge is to pin down the degree of the non-rivalry of entrepreneurial talent, λ. We use the fact that, conditional on labor specialization, λ modulates the pass-through of entrepreneurial ability to worker productivity. When λ is large, workers inherit the ability of their entrepreneurs, and there is a lot of heterogeneity in worker productivity across firms but little within-firm heterogeneity.[56] In our data, we do not directly observe worker productivity. We can, nonetheless, rely on a key feature of our setting: workers' earnings are an increasing function of

[56]It is important to emphasize that a low κ_0 has the same effect on pass-through as a high λ. Therefore, our identification strategy relies on the assumed relationship between time spent on complex tasks and productivity.

their productivity, modulated by workers' bargaining weight ω (see equation (4.5)).

The second block of moments therefore includes several statistics on workers' earnings, which allow us to separately identify λ and ω. The intuition is as follows. When ω is high, the variance of wages is high overall, both across and within firms. With a high λ, on the other hand, only the variance across firms is high, but the one within firms is low. In practice, since earnings are likely measured with error, we do not directly match their variance. Rather, we target the relationships between worker earnings and firm characteristics, as well as the average earnings gap, normalized by their standard deviation, across more versus less productive firms.

The third block of moments includes the distribution of firm revenue and its relationship with the managerial ability index. These moments discipline the variance of managerial talent (σ_z) and the noise term (σ_ϵ) in our empirical proxy. σ_z increases the variance of productivity and revenues. Given σ_z, a large σ_ϵ flattens the relationship between revenue per worker and the managerial index due to attenuation bias.

Finally, the last block of moments pin down the parameters of the hiring cost (χ_0, χ_1, σ_χ) since—as shown in Lemma 4— these parameters directly map to the firm size distribution and its relationship with managerial ability.

Importance of Time Use Data. Time use data is crucial for identifying barriers to labor specialization within the firm separately from any other constraints that keep firms small. Even observing aggregate measures of specialization would not be enough, since it would be impossible to distinguish whether firms are small because they are not specialized or whether they are not specialized because there is not enough scope for specialization given their small size. Our unique data shows that specialization increases weakly with firm size, which allows us to directly pin down the barriers to specialization (κ_0). Then, given κ_0 and the other parameters, all other constraints keeping firms small—the distribution of χ_0—is chosen to match the firm size distribution.

5.3 Estimation Results and Model Fit

The model matches the data well, as Table 4 shows. Figure 8 illustrates the fit for some key moments: the model matches the heterogeneity between firms in terms of size and revenue, as well as the time allocation within firms.[57]

Table 5 includes the estimated values of all parameters. A few are worthwhile to

[57]We describe the model fit for all 150 moments in the Supplemental Appendix.

Table 4: Summary of Targeted Moments and Model Fit

Moments	Data	Model	Param.
A. Allocation of Time to Complex Tasks			
(i) Average Time on Complex Tasks	0.234	0.229	D
(ii) Average of Entrepreneurs	0.457	0.447	d, D
(iii) Average for Self-Employed	0.341	0.341	d, D
(iv) Average of Low-Skilled Workers	0.137	0.173	D
(v) Average of High-Skilled Workers	0.217	0.177	D
(vi) Slope w/ Size (Entrepreneur)	0.021	0.021	κ_0, κ_1
(vii) Slope w/ Size (Low-Skilled Workers)	0.002	-0.001	κ_1, ω, χ_1
(viii) Slope w/ Size (High-Skilled Workers)	0	-0.001	κ_1, ω, χ_1
(ix) Slope w/ Log(Earn) (All Workers)	0.033	0.009	κ_1
B. Distribution of Earnings w/i and b/w Firms			
(i) Log(Earn) on Man. Ability (Normalized)	0.187	0.196	$\sigma_\epsilon, \lambda, \omega$
(ii) Log(Earn) on Log(Rev p.w.)	0.191	0.196	$\lambda, \omega, \sigma_\chi$
(iii) Norm. Earn Gap by Rev p.w.	0.389	0.718	$\lambda, \chi_1, \overline{\chi_0}$
(iv) Norm. Earn Gap by Man. Ability	0.137	0.327	$\omega, \chi_1, \sigma_\epsilon$
C. Distribution of Firm Revenues			
(i) Std of Log(Rev)	0.726	0.637	ω, χ_1, σ_z
(ii) Log(Rev p.w) on Man. Ability	0.145	0.145	$\sigma_\epsilon, \sigma_z, \overline{\chi_0}$
(iii) Log(Rev) Gap by Man. Ability	0.305	0.385	$\sigma_\epsilon, \omega, \overline{\chi_0}, \sigma_z$
D. Firm Size Distribution			
(i) Average Size	5.701	5.894	$\omega, \chi_1, \overline{\chi_0}$
(ii) Std of Log(Size)	0.489	0.586	$\sigma_\chi, \overline{\chi_0}$
(iii) Std of Size	2.263	2.537	σ_χ, χ_1
(iv) Log(Size) on Man. Ability	0.1	0.089	$\chi_1, \omega, \sigma_\epsilon$
(v) Size Gap by Man. Ability	0.275	0.339	$\omega, \chi_1, \sigma_\epsilon$

Notes: Empirical moments used in estimation and corresponding values in the model, together with the key parameters relating to each moment. For details of the computation of the empirical moments, see Appendix C.2.

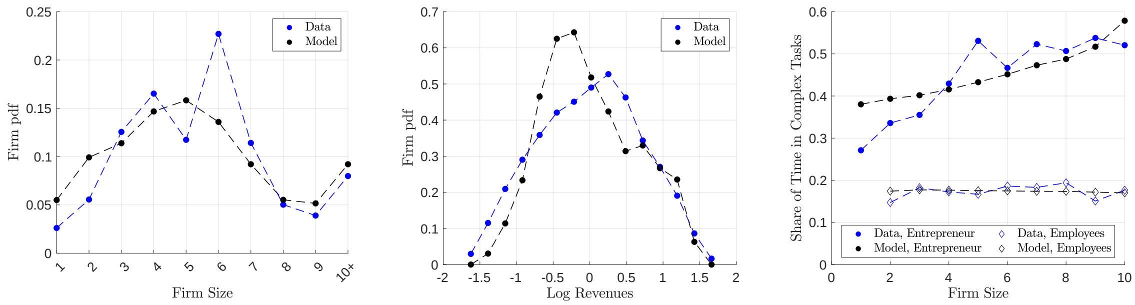
Table 5: List of Parameters and their Estimated Values

Param.	Value	Param.	Value	Param.	Value
χ_f	$0.1\overline{\pi}(z)$	κ_0	0.078^{-1}	κ_1	0.684
λ	0.223	ω	0.373	$\overline{\chi_0}$	14.608
χ_1	0.47	σ_χ	4.371	σ_z	0.966
D	0.189	d	0.181	σ_ϵ	2.28

discuss. First, the value of λ implies that the entrepreneur is able to pass through approximately 22% of her ability to her workers. To put this number in perspective, we can compare it with the productivity pass-through due to vertical specialization.

Figure 8: Model Fit for Firm Heterogeneity and Time Allocation

(a) Firm Sizes (b) Firm Revenues (c) Time in Complex Tasks



Notes: The figure compares empirical moments, in blue, with their model-generated counterparts.

In the estimated model, we find that, on average, the typical worker completes more than 90% of her complex tasks. Given the value of λ, this means that the productivity pass-through due to vertical specialization is $\sim 6\%$—that is, about a quarter of the direct pass-through due to λ.

Second, the value of ω implies a prominent role for the piece-rate component of workers' earnings, consistent with the evidence described in Section 3: more productive workers are compensated for around 40% of their higher output.[58]

Third, we estimate large heterogeneity in managerial ability at the top of the distribution. The estimated value of the shape parameter σ_z implies that ability at the 98^{th} percentiles is approximately 9 times that at the 80^{th} percentiles.[59]

Finally, we find that κ_1 is small, which shows that Proposition 1, which characterized the equilibrium for $\kappa_1 = 0$, considers an empirically relevant case.[60]

6 Quantification

We use the estimated model for three purposes. First, we provide a quantitative assessment of the production technology firms operate with by measuring how close the estimated equilibrium is to *self-employment within the firm*. Second, we study the

[58]Importantly, we verify that the estimated value of ω is small enough to satisfy Assumption 2, making the single-crossing hold in our estimated model.

[59]The 80^{th} percentiles of the ability distribution correspond roughly to the marginal entrepreneur, given an average firm size ~ 6.

[60]One way to assess the magnitude of κ_1 is to calculate the average implied gap in the share of complex tasks completed by low- and high-skilled workers. We find that, on average, a worker at the 10^{th} percentile of the distribution completes $\sim 91\%$ of his complex tasks, whereas a workers at the 90^{th} percentile completes $\sim 94\%$.

mechanisms through which firm-level pass-through of entrepreneurial ability affects aggregate productivity. Third, we show that barriers to within-firm labor specialization limit the returns to other interventions aimed at spurring firm growth.

6.1 Quantifying the Internal Organization of Firms

The technology governing the organization of labor in the firm and its implications for aggregate productivity are modulated by two parameters: (i) λ, which determines the extent to which labor specialization is necessary to leverage entrepreneurial talent; and (ii) κ_0, which determines how costly such specialization is. Both parameters affect the ability of entrepreneurs to pass on their talent to workers – i.e., what we defined in Section 4 as an *artisanal production technology*.

We use the estimated model to perform four counterfactual exercises with different combinations of κ_0 and λ. The results are in Table 6, where we compare each counterfactual to the benchmark economy (column 1). In this section, we focus on the first four rows of the Table which report labor specialization, average firm size, total output (or labor productivity), and aggregate consumption.[61]

In column 2, we shut down labor specialization entirely ($\kappa_0 \to \infty$). In column 3, we use a low value of κ_0 calibrated to match the relationship between firm size and specialization we observe in grain milling.[62] We choose this value of κ_0 to represent a degree of labor specialization that is, at least in principle, attainable in our setting. In columns 4 and 5, we compute the two polar cases of Lemma 5: *self-employment within the firm* ($\lambda = 0$ and $\kappa_0 \to \infty$) and *scalable entrepreneurial talent* ($\lambda = 1$).

This exercise offers two key takeaways. First, shutting down any specialization, and even going as far as the extreme case of column 4, has only a relatively modest impact on firm size, output, and consumption.[63] This result provides a quantitative answer to the question, "why do firms exist?" Our baseline economy is not far from the polar case of self-employment within the firm, implying that, in our setting, firms seem to exist more in order to share fixed costs and less as vehicle to leverage entrepreneurial talent.

[61]Consumption is equal to value added, that is, output minus resources spent on hiring costs.

[62]Recall from Section 5 that the parameter κ_0 is closely tied to the slope of the regression of labor specialization on firm size. We can thus interpret this counterfactual as a hypothetical economy in which the unbundling cost is as small in carpentry and welding as it is in grain milling.

[63]Even in this case, firms are not of size one because of the fixed operating cost. The presence of the fixed cost also implies that there are still some returns to operating as a unit.

Second, the degree of artisanality in carpentry and welding in Uganda, as measured by the estimated values of κ_0 and λ, leads to sizable aggregate losses. For example, column 3 shows that even an "attainable" reduction in κ_0 would increase aggregate productivity by 30%. The average firm size would also increase, by almost one employee, showing that firms are small, at least in part, because of their lack of specialization. Column 5 shows that in an economy with fully scalable talent, which could resemble modern manufacturing, the average firm size would be more than 20 employees, and both productivity and consumption would increase dramatically.[64]

Table 6: Model Counterfactuals for Artisanality (κ_0, λ) and Hiring Cost ($\overline{\chi_0}$)

Moment	(1) Bench	(2) $\kappa_0 \to \infty$	(3) Low κ_0	(4) $\lambda = 0, \kappa_0 \to \infty$	(5) $\lambda = 1$	(6) High $\overline{\chi_0}$	(7) Low $\overline{\chi_0}$
Specialization	0.09	0	0.29	0	0	0.08	0.11
Firm Size	5.89	5.38	6.84	3.08	21.46	5.11	7.03
Output	1	0.86	1.3	0.41	23.52	0.85	1.23
Consumption	1	0.91	1.2	0.56	11.96	0.9	1.13
Pass-through of Man. Ability	0.28	0.22	0.39	0	1	0.28	0.28
Log(Size) on Man. Ability	0.36	0.31	0.42	0	0.83	0.3	0.44
Average Man. Ability	1	0.94	1.1	0.64	2.1	0.91	1.12
Workers' Earnings	1	0.91	1.17	0.56	2.16	1.47	1.12
Entrepreneurs' Profits	1	0.9	1.2	0.56	12.48	0.9	1.13

Notes: Statistics are created from model counterfactuals. Average managerial ability, output, consumption, workers' earnings, and entrepreneurs' profits are normalized to 1 for the benchmark values.

6.2 Mechanism: Low Pass-Through and Allocation of Labor

The degree of artisanality shapes the relationship between the exogenous distribution of talent and the endogenous distribution of firm productivity via two channels.

First, either a decrease in κ_0 or an increase in λ amplify the pass-through of entrepreneurial talent to worker productivity. This can be seen in row 5 of Table 6 and in the left panel of Figure 9, where we plot average worker productivity as a function of entrepreneurial ability.[65] In the estimated equilibrium (blue), average worker productivity increases in managerial ability, but the pass-through is small. The pass-through is zero in the case of self-employment within the firm (gray), while it would be one with scalable entrepreneurial talent (pink).

[64] We should, of course, take this case with a grain of salt since we are entirely changing the production technology. Nonetheless, it is a useful benchmark to show that the artisanality of manufacturing could play a major role in understanding cross-country differences.

[65] Average worker productivity is computed as $\hat{z}^{\lambda} \int \tilde{z}(z, \hat{z}, \mu)^{1-\lambda} \frac{dF_w(z)}{F_w(z_{\max})}$.

Second, a decline in artisanality affects the allocation of labor across firms. A higher λ or a lower κ_0 cause an increase in firm-level productivity and thus wages, leading marginal entrepreneurs to shift into wage work. Moreover, as we just discussed, the productivity pass-through also increases, which leads more talented entrepreneurs to grow their firms more. Labor is thus reallocated toward talented entrepreneurs through an extensive as well as an intensive margin, as can be noticed in rows 6 and 7 of Table 6 and in the right panel of Figure 9, which plots average firm size as a function of managerial ability.

Overall, if λ is low and κ_0 is high, the distribution of firm productivity mirrors the ability distribution $G(z)$. If λ is high or κ_0 is low, it instead reflects the right tail of the talent distribution as the most skilled entrepreneurs hire more workers and pass on their ability. In this second case, wages and profits are higher (rows 8 and 9).

The mechanism through which barriers to labor specialization affect the economy is different from other frictions keeping firms small. To illustrate this, we compare the effects of changing the unbundling cost κ_0 and the hiring cost $\overline{\chi_0}$. In Figure 9, we consider an increase (green) and a decrease (orange) in the average hiring cost $\overline{\chi_0}$, which we calibrate to generate changes in firm size similar to those of the κ_0 counterfactuals (see columns 2, 3, 6, and 7 of Table 6). The left panel of Figure 9, as well as rows 1 and 5 of Table 6, show that the effects of the two parameters on worker productivity and labor specialization are quite different. A change in $\overline{\chi_0}$ has only a minimal impact on worker productivity and pass-through (solely operating through the selection of entrepreneurs) and a small effect on labor specialization that is purely compositional, since larger firms are more specialized.

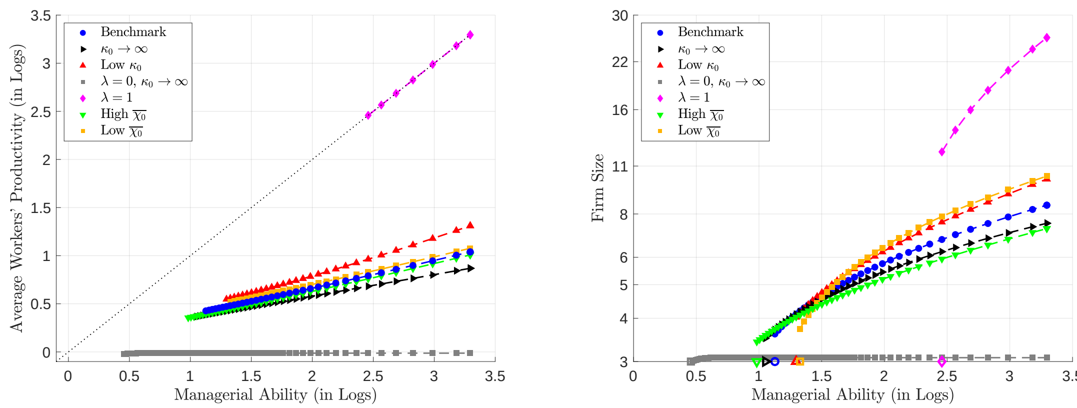
This last result is interesting by itself since it shows that, while our model allows for both a causal relationship from labor specialization to firm size and from firm size to specialization, the former is quantitatively stronger. In this sense, our analysis is more consistent with the notion that firms are small because they are not specialized than the notion that they are not specialized because they are small.

6.3 Returns to Development Interventions are Dampened

Finally, we show that the returns from development interventions depend on barriers to labor specialization within the firm. In practice, we study the effect of reducing the hiring cost $\overline{\chi_0}$, which could be interpreted as a policy aimed at relaxing credit or hiring constraints, and show how it varies as a function of the unbundling cost κ_0.

Figure 9: Firm-Level Effects of Changing λ, κ_0, and $\overline{\chi_0}$

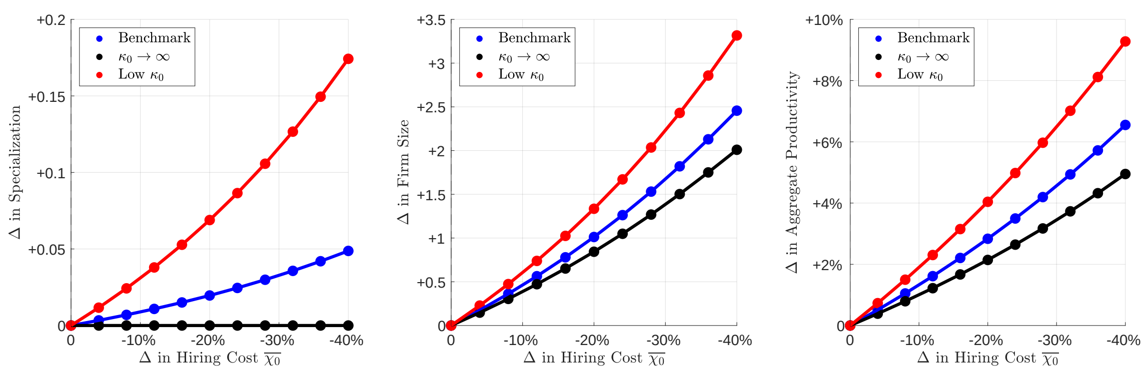
(a) Workers' Productivity | (b) Firm Size



Notes: The figure shows average worker productivity (left panel) and firm size (right panel) as a function of managerial ability. The right panel also marks the ability of the lowest entrepreneur on the x-axis. The blue circles are for the estimated model. The other lines represent different model counterfactuals, as explained in the text.

Figure 10: Aggregate Effects of Changing the Hiring Cost $\overline{\chi_0}$

(a) Specialization | (b) Average Firm Size | (c) Aggregate Productivity



Notes: The figure shows changes in labor specialization (left panel), average firm size (middle), and aggregate productivity (right) as a function of changes in the hiring cost ($\overline{\chi_0}$). Each lines corresponds to different values of the unbundling cost (κ_0). Changes are expressed relative to the κ_0-specific baseline values.

We start from the three alternative values of κ_0: the one estimated for carpentry and welding (in blue), a benchmark with no specialization—that is, $\kappa_0 \to \infty$ (in black)—and the "attainable" value $\kappa_0 = \overline{\kappa_0}$ of grain milling (in red). We then vary the average hiring cost $\overline{\chi_0}$. Figure 10 shows the results of this exercise.

The unbundling cost has a large impact on the return to development policies. Relative to our benchmark, calibrating κ_0 to match the larger specialization observed in grain milling would increase the effect of a reduction in the hiring cost on productivity by 60% and on firm size by 35%.

This exercise highlights a key takeaway of our paper. Artisanal manufacturing is a business model that is difficult to scale. As a result, the returns from policy interventions aimed at spurring firm growth may be limited because, given the estimated production technology, organizing labor into larger firms does not significantly improve the allocation of talent: workers would effectively transition from self-employment to *self-employment within the firm*.

7 Conclusion

This paper offers a new perspective on how firms operate in low-income countries. Combining a novel time use survey of manufacturing firms in Uganda with an equilibrium model, we demonstrate that even large firms resemble a collection of self-employed individuals sharing a production space more than a modern firm with workers specialized in different tasks. As a result, there are small productivity gains in our setting from organizing labor into few large firms run by the most talented entrepreneurs. This new understanding of firms could significantly reshape strategies and policies for economic development.

First, to understand the allocation of talent in low-income countries, we should shift the focus from who starts a firm to what people do within firms. In a world with self-employment within the firm, the firm size distribution is less important for aggregate productivity. Second, the returns to development interventions are likely to vary across sectors and countries, depending on the internal organization of firms and their implied scalability.[66] Third, demand-side policies, such as connecting firms with larger markets or promoting product standards, could be key to foster development (Goldberg and Reed, 2022). These policies could help to reduce barriers to labor specialization and limit the prevalence of the artisanal business model. In turn, this would create an opportunity for entrepreneurs to scale up their business and leverage the capabilities they already possess, thus increasing productivity and, ultimately, reducing poverty.

[66] In our context, supply-side interventions to help firm growth (such as credit or hiring subsidies) would have a larger aggregate impact if targeted toward grain milling rather than carpentry or welding. This underscores the importance of designing context-specific industrial policies (Juhász et al., 2023).

References

Adhvaryu, A., V. Bassi, A. Nyshadham, J. Tamayo, and N. Torres (2023): "Organizational Responses to Product Cycles," *Available at SSRN 4403515*. 5

Akcigit, U., H. Alp, and M. Peters (2021): "Lack of selection and limits to delegation: firm dynamics in developing countries," *American Economic Review*, 111, 231–275. 1, 3.3

Anderson, S. J. and D. McKenzie (2022): "Improving business practices and the boundary of the entrepreneur: A randomized experiment comparing training, consulting, insourcing, and outsourcing," *Journal of Political Economy*, 130, 157–209. 1

Atack, J., R. A. Margo, and P. Rhode (2023): "De-skilling: Evidence from Late Nineteenth Century American Manufacturing," Tech. rep., National Bureau of Economic Research. 7, 36

Atack, J., R. A. Margo, and P. W. Rhode (2019): ""Automation" of manufacturing in the late nineteenth century: The hand and machine labor study," *Journal of Economic Perspectives*, 33, 51–70. 7, 36

Atencio-De-Leon, A., M. Lee, and C. Macaluso (2023): "Does Turnover Inhibit Specialization? Evidence from a Skill Survey in Peru," . 3.3

Atkin, D., A. Chaudhry, S. Chaudry, A. K. Khandelwal, and E. Verhoogen (2017): "Organizational barriers to technology adoption: Evidence from soccer-ball producers in Pakistan," *The Quarterly Journal of Economics*, 132, 1101–1164. 4

Atkin, D., A. Costinot, and M. Fukui (2021): "Globalization and the Ladder of Development: Pushed to the Top or Held at the Bottom?" Tech. rep., National Bureau of Economic Research. 43

Bandiera, O., A. Elsayed, A. Heil, and A. Smurra (2022): "Economic Development and the Organisation of Labour: Evidence from the Jobs of the World Project," *Journal of the European Economic Association*, 20, 2226–2270. 7

Bassi, V., M. E. Kahn, N. Lozano Gracia, T. Porzio, and J. Sorin (2022a): "Searching for Customers, Finding Pollution," Tech. rep., mimeo. 18

Bassi, V., R. Muoio, T. Porzio, R. Sen, and E. Tugume (2022b): "Achieving scale collectively," *Econometrica*, 90, 2937–2978. 1, 14, 18, 5.2, D.3, D.6

Bassi, V., T. Porzio, R. Sen, and E. Tugume (2021): "The Impact of the COVID-19 Lockdown on SMEs and Employment Relationships in Uganda," Tech. rep., International Growth Centre Policy Brief UGA-20112. 90

Becker, G. S. and K. M. Murphy (1992): "The division of labor, coordination costs, and knowledge," *The Quarterly journal of economics*, 107, 1137–1160. 1

Bennedsen, M., K. M. Nielsen, F. Pérez-González, and D. Wolfenzon (2007): "Inside the family firm: The role of families in succession decisions and performance," *The Quarterly Journal of Economics*, 122, 647–691. 3.3

Bloom, N., B. Eifert, A. Mahajan, D. McKenzie, and J. Roberts (2013): "Does Management Matter? Evidence from India," *The Quarterly Journal of Economics*, 128, 1–51. 1, 3, 3.3

Bloom, N., L. Iacovone, M. Pereira-López, and J. Van Reenen (2022): "Management and misallocation in Mexico," Tech. rep., National Bureau of Economic Research. 6

Bloom, N., A. Mahajan, D. McKenzie, and J. Roberts (2010): "Why do firms in developing countries have low productivity?" *American Economic Review*, 100, 619–23. 1

Boehm, J. and E. Oberfield (2023): "Growth and the Fragmentation of Production," Tech. rep., mimeo. 7

Bold, T., S. Ghisolfi, F. Nsonzi, and J. Svensson (2022): "Market Access and Quality Upgrading: Evidence from Four Field Experiments," *American Economic Review*, 112, 2518–52. 1

Bolton, P. and M. Dewatripont (1994): "The firm as a communication network," *The Quarterly Journal of Economics*, 109, 809–839. 1

Bruhn, M., D. Karlan, and A. Schoar (2018): "The impact of consulting services on small and medium enterprises: Evidence from a randomized trial in Mexico," *Journal of Political Economy*, 126, 635–687. 1

Caliendo, L., F. Monte, and E. Rossi-Hansberg (2015): "The anatomy of French production hierarchies," *Journal of Political Economy*, 123, 809–852. 7

Caliendo, L. and E. Rossi-Hansberg (2012): "The impact of trade on organization and productivity," *The quarterly journal of economics*, 127, 1393–1467. 5

Chandler, A. D. (1990): *Scale and scope: The dynamics of industrial capitalism*, Harvard University Press. 1

De Mel, S., D. McKenzie, and C. Woodruff (2008): "Returns to capital in microenterprises: evidence from a field experiment," *The quarterly journal of Economics*, 123, 1329–1372. 3

——— (2019): "Labor Drops: Experimental Evidence on the Return to Additional Labor in Microenterprises," *American Economic Journal: Applied Economics*, 11, 202–235. 3

Dessein, W. and T. Santos (2006): "Adaptive organizations," *Journal of political Economy*, 114, 956–995. 2, 5, 40

Dupas, P. and J. Robinson (2013): "Savings constraints and microenterprise development: Evidence from a field experiment in Kenya," *American Economic Journal: Applied Economics*, 5, 163–92. 91

Freund, L. (2022): "Superstar Teams: The Micro Origins and Macro Implications of Coworker Complementarities," *Available at SSRN 4312245*. 7

Garicano, L. (2000): "Hierarchies and the Organization of Knowledge in Production," *Journal of Political Economy*, 108, 874–904. 1, 3.2

Garicano, L. and E. Rossi-Hansberg (2006): "Organization and inequality in a knowledge economy," *The Quarterly journal of economics*, 121, 1383–1435. 1, 3.2

Ghosh, A. (2022): "Religious divisions and production technology: Experimental evidence from India," *Available at SSRN 4188354*. 4

Goldberg, P. K. and T. Reed (2022): "Demand-side constraints in development: The role of market size, trade, and (in) equality," Tech. rep., Yale University Working Paper, New Haven, CT. 1, 7

Hardy, M. and J. McCasland (2022): "Are small firms labor constrained? experimental evidence from ghana," *American Economic Journal: Applied Economics*. 3.3

——— (2023): "Are Small Firms Labor Constrained? Experimental Evidence from Ghana," *American Economic Journal: Applied Economics*. 3

Hjort, J. (2014): "Ethnic divisions and production in firms," *The Quarterly Journal of Economics*, 129, 1899–1946. 4

Hjort, J., V. Iyer, and G. de Rochambeau (2020): "Informational Barriers to Market Access: Experimental Evidence from Liberian Firms," Working Paper 27662, National Bureau of Economic Research. 1

Holmes, T. J. and J. J. Stevens (2014): "An alternative theory of the plant size distribution, with geography and intra-and international trade," *Journal of Political Economy*, 122, 369–421. 2, 3.3, 40

Holmstrom, B. and P. Milgrom (1991): "Multitask principal–agent analyses: Incentive contracts, asset ownership, and job design," *The Journal of Law, Economics, and Organization*, 7, 24–52. 3.3

——— (1994): "The firm as an incentive system," *The American economic review*, 972–991. 3.3

Hsieh, C.-T. and B. A. Olken (2014): "The Missing "Missing Middle"," *The Journal of Economic Perspectives*, 28, 89–108. 1, 1, 2.3

Jensen, R. and N. H. Miller (2018): "Market Integration, Demand, and the Growth of Firms: Evidence from a Natural Experiment in India," *American Economic Review*, 108, 3583–3625. 1, 8

Juhász, R., N. J. Lane, and D. Rodrik (2023): "The New Economics of Industrial Policy," Tech. rep., National Bureau of Economic Research. 66

Juhász, R. and C. Steinwender (2018): "Spinning the web: Codifiability, information frictions and trade," *NBER working paper*. 43

Kohlhepp, J. (2023): "The Inner Beauty of Firms," . 7

Lucas, R. (1978): "On the Size Distribution of Business Firms," *Bell Journal of Economics*, 9, 508–523. 4.4

Macchiavello, R., A. Menzel, A. Rabbani, and C. Woodruff (2020): "Challenges of change: An experiment promoting women to managerial roles in the bangladeshi garment sector," Tech. rep., National Bureau of Economic Research. 4

McKenzie, D., N. Assaf, and A. P. Cusolito (2017): "The additionality impact of a matching grant programme for small firms: experimental evidence from Yemen," *Journal of Development Effectiveness*, 9, 1–14. 91

McKenzie, D. and C. Woodruff (2008): "Experimental evidence on returns to capital and access to finance in Mexico," *The World Bank Economic Review*, 22, 457–482. 91

——— (2014): "What are we learning from business training and entrepreneurship evaluations around the developing world?" *The World Bank Research Observer*, 29, 48–82. 91

——— (2017): "Business Practices in Small Firms in Developing Countries," *Management Science*, 63. 2.2

——— (2021): "Training Entrepreneurs," Tech. rep., VoxDev Lit. 3

Piore, M. J. and C. F. Sabel (1984): "The second industrial divide: possibilities for prosperity," . 2, 3.3, 40

Startz, M. (2019): "The Value of Face-to-Face: Search and Contracting Problems in Nigerian Trade," *mimeo*. 1, 18

UBOS (2011): *Census of Business Establishments, 2010/11*, Uganda Bureau of Statistics. 10, A.2

Vickery, S., C. Dröge, and R. Germain (1999): "The relationship between product customization and organizational structure," *Journal of Operations Management*, 17, 377–391. 2, 40

Vitali, A. (2022): "Consumer Search and Firm Location: Theory and Evidence from the Garment Sector in Uganda," *mimeo*. 1, 18

Yang, X. and J. Borland (1991): "A microeconomic mechanism for economic growth," *Journal of political economy*, 99, 460–482. 1

A Online Appendix - Empirical Evidence

A.1 Measuring Labor Specialization: Details

Panel A of Table A.1 lists the 17 tasks elicited in our time use module, together with the share of time spent in each task by the average firm. Panel B shows the production steps for the core product in the three sectors with the share of production time accounted for by each step.

Table A.1: Measuring Time Use

Panel A: All Tasks					
(i) Production	**(58.9%)**	Book-keeping	(0.5%)	Other non-prod. tasks	(0.8%)
Producing Core prod.	(17.6%)	Maintanence	(0.4%)		
Producing other prod.	(41.3%)	Organizing stock	(4.6%)	**(iii) Idle**	**(25.6%)**
		Procuring inputs	(2.0%)	Eating/Resting	(13.5%)
(ii) Non-prod. Tasks	**(15.5%)**	Looking for input supp.	(0.6%)	Waiting for customers	(11.4%)
Interacting with customers	(3.5%)	Looking for new mach.	(0.1%)	Away not for business	(0.7%)
Supervising	(2.2%)	Looking for workers	(0.0%)		
Training	(1.0%)	Managing loans	(0.0%)		

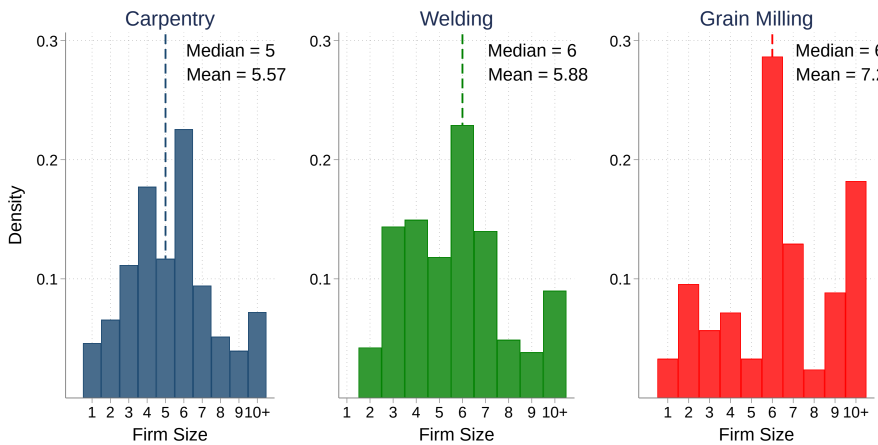
Panel B: Production Steps					
(i) Carpentry		**(ii) Welding**		**(iii) Grain milling**	
Design	(3.7%)	Design	(7.0%)	Cob shelling	(0.5%)
Drying (before prod.)	(3.0%)	Cutting	(17.9%)	Drying	(1.6%)
Cutting	(13.3%)	Bending	(10.8%)	Cleaning/Destoning	(14.1%)
Planing	(14.0%)	Grinding	(12.9%)	Conditioning	(12.1%)
Thicknessing	(6.8%)	Welding	(28.0%)	De-hulling	(23.5%)
Edging	(10.3%)	Polishing	(11.5%)	Milling	(40.4%)
Sanding	(16.3%)	Painting	(11.9%)	Sealing	(7.8%)
Mortising	(15.4%)				
Finishing	(12.5%)				
Drying (after painting)	(4.8%)				

Notes: The table reports the average share of firm-level time in each task, computed by summing the time spent by the entrepreneur and all employees within a firm on a given task. Panel A uses information from the time use module, asking about time spent hour by hour on the last day worked. For firms not producing the core product, the category "Producing Core prod." corresponds to the production of their main product. Panel B breaks down production time on the core product into time in each step. Steps are listed in typical order of implementation. The statistics in Panel B are conditional on doing a given step for the core product. The data from Panel B comes from the survey module asking the entrepreneur and each employee whether they usually work on each step. This information is available for entrepreneurs and employees but only in firms with at least one employee.

A.2 Firm Characteristics and Representativeness: Details

Firm Size Distribution. Figure A.1 plots the size distribution in the three sectors (see the Supplemental Appendix for a version without top coding at 10 workers).

Figure A.1: Firm Size Distribution in the Three Sectors



Notes: Sample: all surveyed firms. Firm size is defined as the entrepreneur plus all employees. Firms with more than 10 workers are grouped together in the category "10+". Vertical lines represent the median.

Representativeness. We assess the representativeness of our sample by comparing it to two sources of administrative data on firms available for Uganda: (i) the 2010 Census of Business Establishments (UBOS, 2011), and (ii) the Corporate Income Tax (CIT) data collected by the Uganda Revenue Authority (URA), which is available for 2013—2020. The Census is meant to cover the entire firm population, including both formal and informal establishments. The CIT data should include all firms with more than $40,000 in yearly revenues, the threshold required to pay the CIT. Throughout the analysis, we keep all the firms in our 52 sampled sub-counties, and focus on carpentry and welding, as these are our two main sectors of interest.

In Panel (a) of Figure A.2, we first compare the number of firms in our initial survey (conducted in 2018/19) with the number of firms in the Census and in the URA data. The figure shows two key results. First, we find that our data includes twice as many firms as the Census. This reassures us that our survey thoroughly covered our sampled sub-counties.[67] Second, even when restricting our sample to firms above the CIT revenue threshold, our data still includes about 8 times more firms than the

[67]Since the UBOS census is from 2010, some of this difference can reflect net firm entry until 2018/19. Of course, it is also possible that there was some non-compliance in the UBOS census.

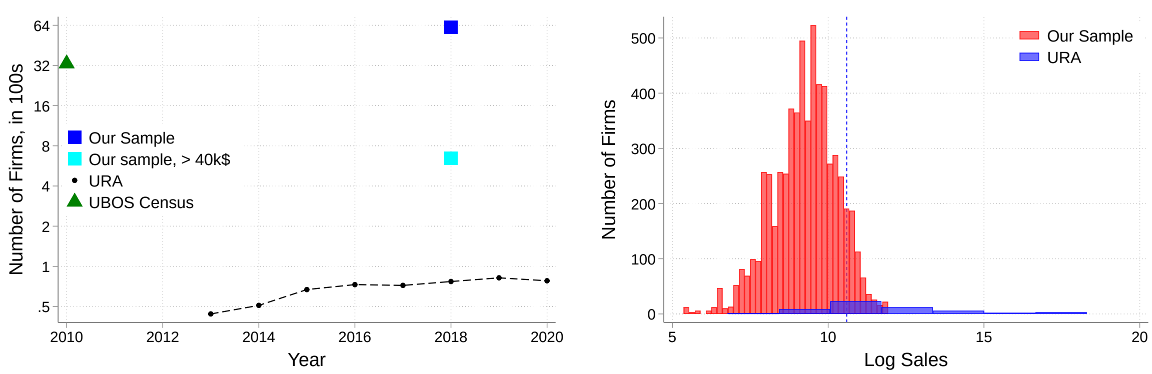
URA data. This is important because it shows that our data also includes many "large" firms above the URA threshold (it also suggests that compliance with CIT could be relatively weak in this setting).

In Panel (b) we narrow in on the comparison with the URA data, focusing on 2018/19, the same year as our initial survey. The figure shows two key results. First, there is significant overlap in the distribution of revenues in our data and the URA data.[68] This is reassuring, because it implies that our results apply also to the typical "large" and formal firm in these sectors. Second, the URA data includes a handful of firms with very large yearly revenues above $1 million, which are not covered in our survey. However, we note that these firms at the top of the sales distribution in the URA data have a wage bill-to-sales ratio of less than 5% (and in some cases close to 1%), thus suggesting that they may be large importers, plausibly foreign owned, rather than manufacturers.

Overall, this analysis shows that our sample is representative of both small and large firms. While we have not been able to reach some of the very large formally registered firms, we notice that those are so few that in the aggregate they still constitute just a relatively small share of total sales, and an even smaller share of total employee earnings.

Figure A.2: Comparison with Firm Census and Corporate Income Tax Datasets

(a) Number of Firms (b) Distribution of Revenues



Notes: Left panel: number of firms in carpentry and welding: (i) in the 2010 UBOS census, (ii) in our sample, both overall and restricting to firms with yearly sales above the CIT threshold (i.e., $40,000), and (iii) in the URA data. Right panel: distribution of log yearly revenues in our sample and in the firms in the 2018/19 URA data. The vertical line represents the threshold to be included in the URA data ($40,000).

[68] As Panel (b) of Figure A.2 shows that many of our firms are close to the URA threshold, this can help explain why the number of firms in our data above the threshold is so much larger than in the URA data (as firms right around the threshold may be less likely to register for CIT).

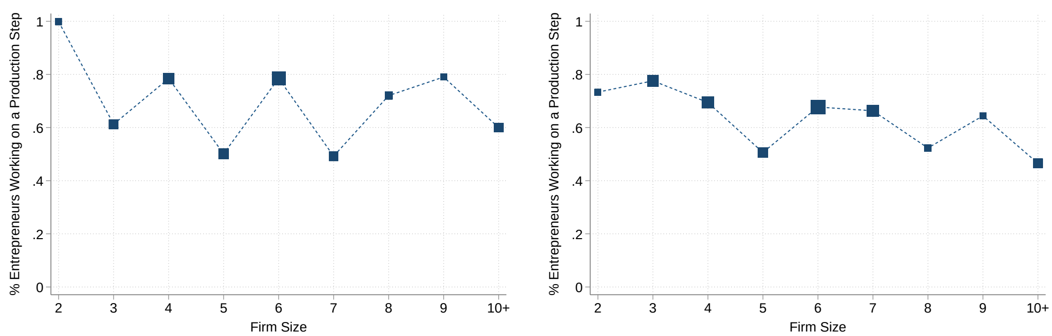
A.3 Additional Evidence on Labor Specialization

In this section, we report several additional results and robustness checks on labor specialization that are mentioned in Section 3 of the main text.

Labor Specialization of Entrepreneurs across Production Steps. Figure A.3 shows the share of entrepreneurs working on the representative step, as defined in Figure 2. As we have shown that entrepreneurs are less likely to work on production (Figure 4), the share of entrepreneurs working on the typical step is naturally lower than for employees. However, we again find no strong evidence of specialization increasing with firm size: comparing Figures 2 and A.3, we see that the gap between the share of employees and entrepreneurs performing the typical step is roughly constant.

Figure A.3: Task Allocation Within Production: Entrepreneurs

(a) Carpentry (b) Welding

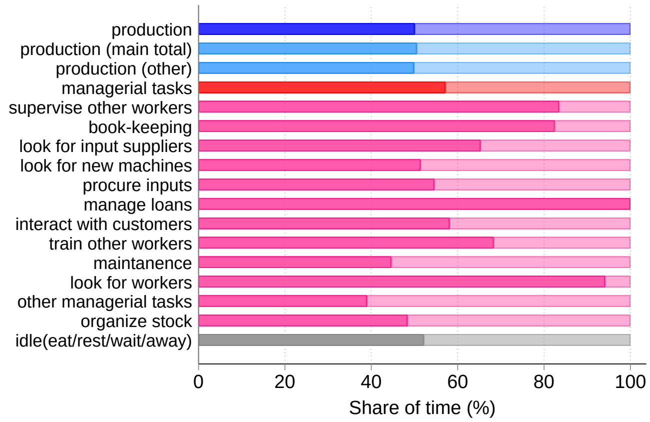


Notes: Replication of Figure 2 for entrepreneurs, focusing on the representative production step (see Figure 2).

Limited Specialization in Non-production Tasks Between Employees. Figure A.4 replicates Figure 3 but comparing employees above and below median earnings. The Figure shows much higher overlap and substantially less evidence of specialization in non-production tasks for more skilled employees: when focusing on the headline summary categories of "production" and "managerial tasks", we clearly see that the time allocation of higher and lower skilled employees is more similar than the time allocation of entrepreneurs and the average employee in Figure 3.

Robustness to Focusing on Non-production Sub-categories. In Table A.2 we test the robustness of Figure 4 by focusing only on the share of time spent in the three most complex non-production tasks: supervision/training, customer interactions, and input procurement (see Table A.3 and related discussion on the complexity of different non-production tasks). For comparison, the first row reports the average share of time

Figure A.4: Task Allocation Between Production and Non-production: Employees



Notes: Replication of Figure 3 but comparing skilled and unskilled employees. Dark bars: skilled employees. Light bars: unskilled employees. Sample: carpentry and welding. The classification between skilled and unskilled employees is based on whether an employee's monthly earnings are above the median among the employees in each firm.

in all non-production tasks combined (using the same definition as in Figure 4) and the correlation with firm size for both entrepreneurs (columns 1 and 2) and employees (columns 3 and 4). In the second row, we focus instead only on the share of time in any of supervision/training, customer interactions, and input procurement. Finally, in the last three rows, we focus on each of these sub-categories individually. Three key findings emerge. First, comparing columns 1 and 3, we confirm that entrepreneurs are specialized in all complex non-production tasks, regardless of their exact definition. Second, the slope with firm size is always positive for entrepreneurs and close to zero for employees (comparing columns 2 and 4). Third, comparing across rows in column 2, we confirm that the positive relationship with firm size for entrepreneurs is very similar when focusing on all non-production tasks (row 1) or only on the most complex non-production tasks (row 2), and that this relationship is driven primarily by customer interactions and supervision/training (rows 3-5).[69]

Limited Heterogeneity Across Workers Not Varying with Firm Size. We explore whether the findings in panel (a) of Figure 4 that there is little heterogeneity in specialization among employees can mask the fact that some workers may spend significant time in non-production tasks, while others very little. Figure A.5 reports the distribution of time shares in non-production tasks among workers (left panel) and entrepreneurs (right panel). Since our measurement of time use refers to the

[69] In the Supplemental Appendix, we conduct this analysis separately by sector, including also grain milling.

Table A.2: Task Allocation and Firm Size: Robustness

	Entrepreneur Mean (1)	Entrepreneur Slope (2)	Employees Mean (3)	Employees Slope (4)
All Non-Production Tasks	0.457	0.021	0.178	0.000
		(0.005)		(0.003)
Cust. Int. + Superv. + Input Proc.	0.322	0.021	0.088	0.004
		(0.005)		(0.002)
Customer Interactions	0.091	0.004	0.036	0.001
		(0.002)		(0.001)
Supervision/Training	0.151	0.014	0.028	0.003
		(0.004)		(0.001)
Input Procurement	0.081	0.003	0.024	-0.000
		(0.002)		(0.001)

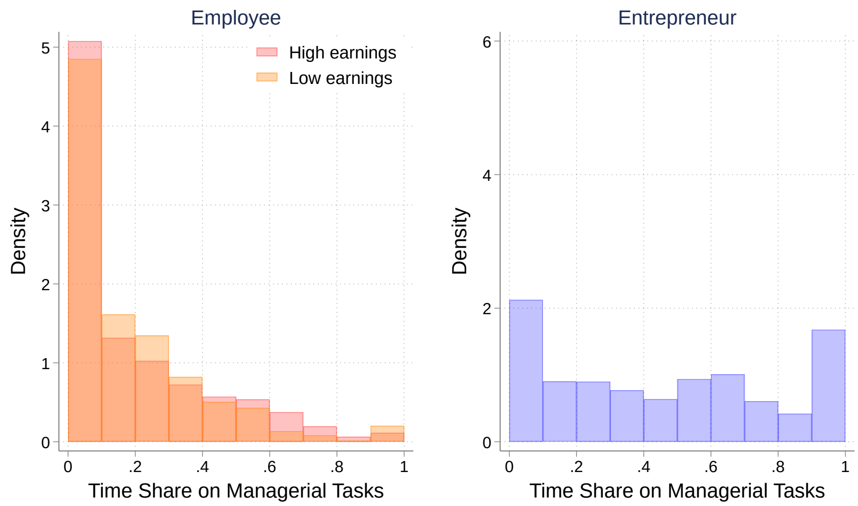
Notes: Sample: carpentry and welding. Non-Production Tasks refer to non-production tasks (same definition as in Figure 4). Columns 1 and 3: means. Columns 2 and 4: OLS regression results of the share of time in various non-production categories on firm size (top coded at 10 workers), controlling for region and sector dummies. Robust standard errors clustered at the firm level in parentheses. Superv./Train. represents supervising or training other workers; Cust. Int. represents interacting with customers; Inp. Proc. represents looking for input suppliers, looking for new machines, looking for workers or procuring inputs; Cust. Int. + Superv. + Input Proc. represents all three categories together (Customer Interaction, Supervision/Training, Input Procurement).

last day worked, naturally we expect some variation across workers in the share of time spent in non-production tasks. Despite this, the Figure shows that there is very limited heterogeneity among workers, with most workers spending little time in non-production.[70] We farther validate this in Figure A.6, where we split employees by whether their share of time in non-production tasks is above or below the median within each firm-size group. The figure shows that: (i) even workers that spend above median time in non-production activities spend just over 20% of their time in non-production; (ii) the gap between the two types of workers does not increase sharply with firm size. This confirms that heterogeneity across workers is limited, especially considering that our measurement of time use refers to the last day worked, and that there is no organizational change with firm size with respect to employees' time use.

Non-Production Tasks Are More Complex. In Appendix Table A.3 we provide evidence to support the claim that non-production tasks are more complex. We do so by studying whether employees more involved in non-production tasks earn more, controlling for firm fixed effects and other worker characteristics. Excluding entrepreneurs from this analysis is important to verify that non-production tasks are

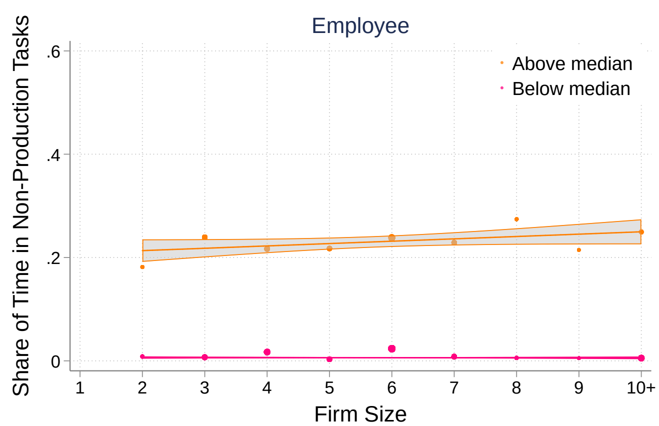
[70] The right panel shows that there is more variation among entrepreneurs, and this is consistent with panel (b) of Figure 4, where we see that entrepreneurs in larger firms spend more time in non-production tasks.

Figure A.5: Distribution of Time Allocation of Employees and Entrepreneurs



Notes: Distribution of share of time spent on non-production tasks. Left panel: Employees, classified as high and low earnings by above/below median earnings within each firm. Right panel: Entrepreneurs. Sample: carpentry and welding.

Figure A.6: Limited Increase in Specialization Across Employees with Firm Size



Notes: Share of time employees spend on non-production tasks by firm size. Orange lines correspond to employees that spend an above-median share of time on non-production tasks within each firm-size group; pink lines correspond to those that spend a below-median share. Sample: carpentry and welding.

indeed more complex tasks, but not a different kind of task altogether, which may be specific to entrepreneurs. The inclusion of firm fixed effects is critical as it allows us to compare employees within the same firm, thus perfectly controlling for other firm-level determinants of employee earnings or involvement of workers in different types of tasks. In addition, we also control for worker characteristics including age, years of education, tenure at the firm, and whether the worker received vocational training, to narrow in the comparison between workers with similar observables, but who differ in their involvement in non-production activities.

The results in column 1 show that those employees spending a higher share of time on non-production tasks earn substantially more: going from no involvement in non-production to spending all working time in non-production tasks is associated with an increase in earnings of 30%. As this regression controls for firm fixed effects and worker characteristics, this result shows that there are sizeable returns from involvement in non-production tasks, thus suggesting that they are more complex: the higher earnings are consistent with the idea that workers are compensated to be able to complete more challenging tasks that not everyone is able to perform well.[71] In column 2 we then unpack which specific non-production tasks are correlated with higher earnings, by including separate dummies for whether the employee is involved in the different non-production categories. We find that supervision/training, interaction with customers and input procurement drive the earnings gains (and so are particularly complex).

Variation in Task Difficulty Within Production. In column 3 of Table A.3 we show that even within production there is evidence of vertical differentiation in terms of task difficulty. We exploit a survey question where each employee working on the core product was asked to state their ability to perform each production step (regardless of whether they work on the step), using a 1 to 5 scale. Using this information, we rank steps in each sector by average reported difficulty, and then create a variable that for each employee captures the average difficulty of the steps they perform. We find that employees working on more difficult steps earn more, even controlling for firm fixed effects and other worker characteristics.[72]

Entrepreneurs Are More Skilled than Employees. In Appendix Table A.4 we show that entrepreneurs are on average more skilled than employees. In columns 1, 3, and 5 we regress years of schooling, age and experience in the firm on a dummy for whether the individual is the entrepreneur or an employee, with firm fixed effects. Entrepreneurs on average have 0.6 more years of education, are 10.7 years older, and

[71] Note also that in Figure 4, Panel (a), we have shown that higher skilled employees (as measured by earnings) spend a larger share of time in non-production tasks, which is again consistent with non-production tasks being more complex.

[72] Consistent with this result, in Appendix Figure A.7 we show that higher-skilled employees (as measured by earnings) spend a larger share of their time on difficult production steps.

Table A.3: Heterogeneity in Skill Intensity of Tasks

	(Log) Employee Earnings		
	(1)	(2)	(3)
Time Share Non-prod. Tasks	0.302		0.270
	(0.107)		(0.114)
Supervise/Train (0/1)		0.213	
		(0.086)	
Customer Int. (0/1)		0.088	
		(0.065)	
Input Procurement (0/1)		0.102	
		(0.047)	
Org. Stock (0/1)		0.005	
		(0.056)	
Other Managerial Tasks (0/1)		-0.047	
		(0.094)	
Avg. Difficulty of Prod. Steps Performed			0.308
			(0.086)
Firm FE	Yes	Yes	Yes
Demographic Ctrl.	Yes	Yes	Yes
Adjusted R^2	0.518	0.525	0.530
Observations	1,976	1,976	1,677

Notes: OLS regression coefficients, standard errors clustered at the firm level in parentheses. Sample: employees in carpentry and welding. Dependent variable: log of monthly employee earnings. Column 1: we include the employee share of time on non-production tasks as a continuous variable). Column 2: we include dummy variables taking value one if the employee performs each task (the reference group are employees who do not perform any non-production tasks). Supervise/Train represents supervising or training other workers; Customer Int. represents interacting with customers; Input Procurement represents looking for input suppliers/new machines/workers or procuring inputs; Org. Stock represents organizing stock; Other Managerial Tasks represents book-keeping, looking for new loans, maintenance or managing loans. Column 3: the variable "Avg. Difficulty of Prod. Steps Performed" is computed as the weighted average of the difficulty levels of the steps performed by each employee (as described in the text), where the weights are the time spent on each step. Demographic controls: age, years of education, tenure at the firm, and a dummy for whether the worker received vocational training.

have 6.3 more years of experience than employees in their firm, thus confirming that entrepreneurs are significantly more skilled. For comparison, in columns 2, 4 and 6 we limit the sample to employees and create a dummy for whether the employee has above median salary within the firm. We find that more skilled employees within the firm (as proxied by salary) also have more schooling, are older and have longer tenure; however, differences between employees are overall less pronounced, compared to differences between entrepreneurs and employees, apart from education, where the

Table A.4: Heterogeneity in Skill Distribution within the Firm

	Yrs. schooling		Age		Tenure	
	(1)	(2)	(3)	(4)	(5)	(6)
Entrepreneur (0/1)	0.626		10.658		6.348	
	(0.182)		(0.501)		(0.355)	
Skilled (0/1)		0.739		3.892		1.562
		(0.276)		(0.802)		(0.328)
Sample	Ent.+Emp.	Emp.	Ent.+Emp.	Emp.	Ent.+Emp.	Emp.
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.228	0.318	0.440	0.335	0.491	0.402
Observations	3,237	2,299	3,220	2,281	3,280	2,316

Notes: OLS regression coefficients, standard errors clustered at the firm level in parentheses. Sample: entrepreneurs and employees (odd columns); employees (even columns). Carpentry and welding sectors only. The classification between skilled and unskilled employees is based on whether an employee's salary is above the median among employees in each firm. The variable "Tenure" measures the years of experience of the individual in the firm.

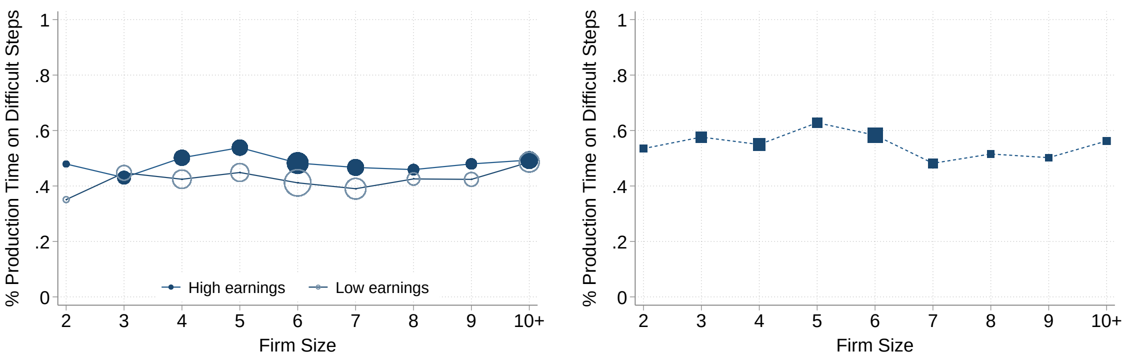
gaps are similar in columns 1 and 2.[73]

Labor Specialization Between Difficult and Simple Steps. We study specialization across production steps of different difficulty by exploiting a survey question where each employee ranked (on a scale 1 to 5) their ability to perform each production step conducted by the firm (regardless of whether the particular employee performs that step). We use this to rank production steps and then we split them by above/below median difficulty. In Figure A.7, we study how employees and entrepreneurs allocate their production time to simple and difficult steps. If an individual only works on difficult steps, the share of time in difficult steps would be 100%. The figure shows that: (i) high skilled employees are more likely to work on difficult steps than low skilled employees, but the gap between the two groups is small and does not vary with firm size; (ii) entrepreneurs spend slightly more time than employees on difficult steps, but again their share of time in difficult steps is close to 50% and there is no gradient with firm size. We conclude that while there is some evidence of entrepreneurs and more highly skilled employees specializing in more difficult steps, this is limited and there is no organizational change with firm size in this dimension.

[73] Note however that since entrepreneurs are on average more than 10 years older than employees (column 3) there are large cohort effects at play, and controlling for such trends in education would increase farther the gap between entrepreneurs and employees in column 1.

Figure A.7: Specialization between Simple and Difficult Production Steps

(a) High & Low Earning Employees (b) Entrepreneurs



Notes: Sample: carpentry and welding. Panels (a) and (b) represent the share of worker and entrepreneur production time spent on difficult production steps. Definition of difficult steps: see main text.

In Larger Firms, Most of Non-production Done by Employees A direct implication of the limited vertical specialization is that most non-production activities in larger firms are done by employees, not the entrepreneur. This is shown in Figure 4. Panel (a) confirms that the share of firm-level time in non-production tasks is constant across the size distribution at around 20% (in line with Figure 1, Panel (b)). However, Panel (b) shows that *who does* the non-production tasks varies dramatically with firm size: in firms with no employees or just one employee, naturally most of the non-production time in the firm is supplied by the entrepreneur. However, in larger firms, most of the non-production tasks are in fact done by employees: for instance, in firms of size eight, 70% of non-production activities are done by employees.[74]

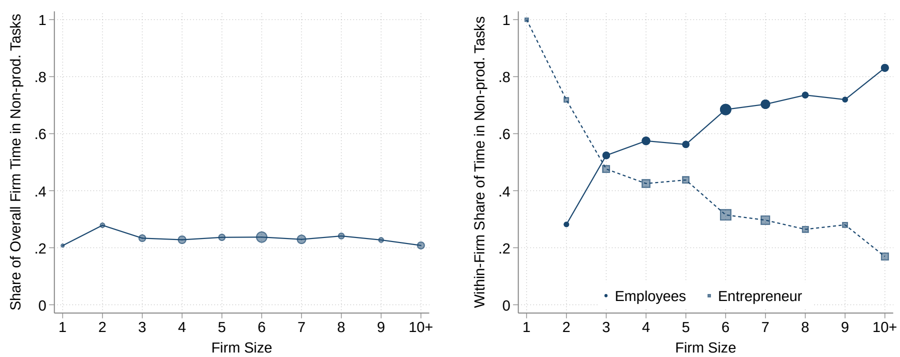
Evidence on Coordination Costs from Idle Time Data. In Figure A.9 we compare the distribution of idle time across hours of the day, by sector and size. We do so by reporting for each time slot, the share of firms where at least one worker is idle, splitting the sample by below and above median firm size. The figure shows two main results. First, there is significantly more idle time in carpentry and welding. Second, while in grain milling employees in larger firms are significantly less idle (apart from around lunch time), this is not the case in carpentry and welding, where there is effectively no relationship between idleness and firm size.

The results in this figure relate to our main empirical results in two ways. First,

[74]In line with this, in the Supplemental Appendix, use a separate set of questions from the follow-up survey to show that in larger firms, employees play a more prominent role in customer generation and interaction, a key non-production activity.

Figure A.8: Task Allocation Between Entrepreneur and Employees by Firm Size

(a) Employees + Entrepreneur (b) Employee vs. Entrepreneur



Notes: Sample: carpentry and welding. The sizes of dots and squares represent the number of firms in each size group. Time use reported by interviewed entrepreneurs and employees. Idle time is excluded. Panel (a): The total (entrepreneur + all employees) share of firm-level time in non-production tasks. Panel (b): Breakdown of the total firm-level non-production time between the share supplied by the entrepreneur and that supplied by all employees.

firms with higher labor specialization likely exhibit lower idle time as a result of better coordination of work. Therefore, if we take idle time as another proxy of labor specialization, this evidence is again in line with grain milling firms being more specialized, and with the relationship between specialization and firm size being steeper in grain milling. Second, as idle time could reflect the presence of coordination and communication costs, the larger idle time in carpentry and welding is consistent with the prevalence of customization creating sizable communication and coordination costs.[75]

B Online Appendix - Model

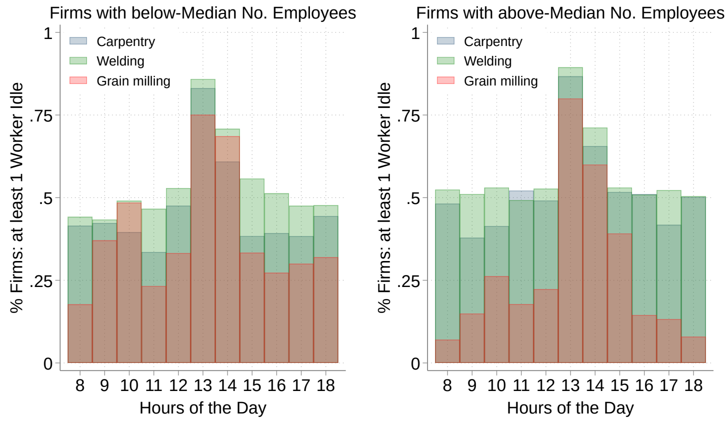
B.1 Firm Problem - General Setup

We describe firm output in the general case and prove that it simplifies to the setup in the main text under Assumptions (1) and (2). Let $\mathcal{W}$ denote the set of workers, so that $\{\mathcal{W} \cup \hat{z}\}$ is the set of all individuals in the firm.

Task assignment is summarized by $\boldsymbol{\mu}$, which consists of two functions. For all pairs of employees $\{z, z'\} \in \{\mathcal{W} \times \mathcal{W}\}$, $\mu_c(z, z')$ and $\mu_s(z, z')$ specify the fraction of z's complex (c) and simple (s) tasks that are performed by z'. In order to economize on notation, we use the same function to denote the share of complex and simple

[75]In the Supplemental Appendix, we show robustness of this Figure A.9 by considering the share of firms where more than 50% of workers are idle at the same time.

Figure A.9: Heterogeneity in the Share of Idle Workers in a Time Slot



Notes: In both panels, the bars depict the share of firms with at least 1 worker being idle in a time slot. The navy, green, and red colors correspond to the carpentry, welding, and grain milling sectors, respectively. Left panel: sample is firms with below median firm size. Right panel: sample is firms with above median firm size.

tasks delegated to and by the entrepreneur $\hat{z}$.[76] For example, $\mu_c(z, \hat{z})$ is the share of an employee z's complex tasks that are performed by the entrepreneur, while $\mu_c(\hat{z}, z')$ is the share of the entrepreneur's complex tasks performed by z'. Output is given by:

$$Y(\hat{z}, n, \boldsymbol{\mu}) = y(\hat{z}, \hat{z}, \boldsymbol{\mu}) + (n-1) \int y(z, \hat{z}, \boldsymbol{\mu}) \frac{dF_w(z)}{F_w(z_{\max})} \tag{B.1}$$

$$\text{where,} \quad \forall z \in \{\mathcal{W} \cup \hat{z}\}$$

$$y(z, \hat{z}, \boldsymbol{\mu}) = \hat{z}^{\lambda} \quad \tilde{z}(z, \hat{z}, \boldsymbol{\mu})^{1-\lambda} \quad \mathbb{I}_{y(z,\hat{z},\boldsymbol{\mu})}$$

$$\tilde{z}(z, \hat{z}, \boldsymbol{\mu}) = \exp\left\{\mu_C(z, \hat{z}) \log(\hat{z}) + (n-1) \int \mu_C(z, z') \log(z') \frac{dF_w(z')}{F_w(z_{\max})}\right\} (1 - \kappa\,(1 - \mu_C(z, z)))$$

$$\mathbb{I}_{y(z,\hat{z},\boldsymbol{\mu})} = \mathbb{I}_{\left[\mu_C(z,\hat{z}) + (n-1)\int \mu_C(z,z') \frac{dF_w(z')}{F_w(z_{\max})} \geq 1\right]} \quad \mathbb{I}_{\left[\mu_S(z,\hat{z}) + (n-1)\int \mu_S(z,z') \frac{dF_w(z')}{F_w(z_{\max})} \geq 1\right]},$$

where the indicator function guarantees that, for each output line $y(.)$, all simple and complex tasks are performed by *someone* in the firm.

In order for an assignment $\boldsymbol{\mu}$ to be *feasible*, no individual in the firm can spend more than their one unit of time across all tasks. Formally, $\boldsymbol{\mu}$ is feasible if and only if

$$\begin{aligned} \forall z \in \{\mathcal{W} \cup \hat{z}\} : \quad & D\mu_C(\hat{z}, z) + (1-D)\mu_S(\hat{z}, z) \\ & + (n-1) \int (D\mu_C(z', z) + (1-D)\mu_S(z', z)) \frac{dF_w(z')}{F_w(z_{\max})} \quad \leq 1 \end{aligned} \tag{B.2}$$

[76] In terms of the notation in the main text, $\mu(z, \hat{z}) = 1 - \mu_c(z, \hat{z})$.

In its general form, the problem of assigning workers to tasks is highly complex. The entrepreneur needs to choose, for all possible pairs of workers as well as combinations of herself and a worker, what fraction of one individuals' simple and complex tasks are performed by the other, and vice-versa. We now show that, under assumptions (1) and (2), the general problem (B.1) simplifies to choosing only the fraction of complex tasks each worker delegates to the entrepreneur.[77] This necessitates two conditions: (i) the entrepreneur performs all her complex tasks, and (ii) all tasks that are delegated are given to the entrepreneur.

PROPOSITION 2. *Under Assumptions (1) and (2), the task assignment that maximizes (B.1) satisfies (i) $\forall z' : \mu_c(\hat{z}, z') = 0$ and (ii) $\forall z' \neq \hat{z} : \mu_c(z, z') = 0$. Hence $\mu_c(z, \hat{z}) = 1 - \mu(z, \hat{z})$ where $\mu(z, \hat{z})$ maximizes (4.4).*

PROOF OF PROPOSITION **2.**

Assumption (1) guarantees that the feasibility condition is slack, that is, a local increase in $\mu_c(z, \hat{z})$ is feasible. Assumption (2) guarantees that $\forall z \in \mathcal{W} : \hat{z} \geq z$. We prove parts (i) and (ii) by contradiction.

(i) Suppose the optimal assignment has $\mu_c(\hat{z}, z') > 0$ for some z'. Consider an alternative assignment $\boldsymbol{\mu})^*$ with $\mu_c^*(\hat{z}, z') = \mu_c(\hat{z}, z') - \varepsilon$ and $\mu_c^*(\hat{z}, \hat{z}) = \mu_c(\hat{z}, \hat{z}) + \varepsilon$. Note that under $\boldsymbol{\mu}^*$, all complex tasks are performed. Then, $\tilde{z}(z, \hat{z}, \boldsymbol{\mu})^*) > \tilde{z}(z, \hat{z}, \boldsymbol{\mu})$ since both the weight on $\hat{z}$ relative to z' has increased, and the higher $\mu_c^*(\hat{z}, \hat{z})$ reduces the unbundling cost. All other production lines are unaffected. Since $\boldsymbol{\mu}^*$ yields higher firm-level output, $\boldsymbol{\mu}$ could not have been optimal.

(ii) Suppose the optimal assignment has $\mu_c(z, z') > 0$ for some $z' \neq \hat{z}$. Consider an alternative assignment $\boldsymbol{\mu}^*$ with $\mu_c^*(z, z') = \mu_c(z, z') - \varepsilon$ and $\tilde{\mu}_c^*(z, \hat{z}) = \mu_c(z, \hat{z}) + \varepsilon$. Again, all complex tasks are performed under $\boldsymbol{\mu}^*$. Then, $\tilde{z}(z, \hat{z}, \boldsymbol{\mu})^*) > \tilde{z}(z, \hat{z}, \boldsymbol{\mu})$ since the weight on $\hat{z}$ relative to z' has increased and the unbundling cost is unchanged ($\mu_c^*(z, z) = \mu_c(z, z)$). All other production lines are unaffected. Since $\boldsymbol{\mu}^*$ yields higher firm-level output, $\boldsymbol{\mu}$ could not have been optimal.

■

[77]Problem (4.4) further suppresses $\mu_S(.)$, the share of simple tasks delegated. This is w.l.o.g: since output is independent of who performs the simple tasks and the total number of tasks is fixed, there exist a—possibly large—set of $\mu_s(.)$ for any set of $\mu_c(.)$ such that the assignment is feasible and all tasks are completed.

B.2 Proofs

Proof of Lemma 1. We want to show that $\exists z_0 \geq 0$ such that

- $\forall z < z_0$, $\pi(z) < \int w(z, \hat{z}, \boldsymbol{\mu}) \frac{dF_o(\hat{z})}{F_o(z_{\max})}$
- $\forall z \geq z_0$, $\pi(z) \geq \int w(z, \hat{z}, \boldsymbol{\mu}) \frac{dF_o(\hat{z})}{F_o(z_{\max})}$

The proof proceeds in three steps

1. We show that $\frac{\partial \pi(z)}{\partial z} > \frac{\partial}{\partial z} \int w(z, \hat{z}, \boldsymbol{\mu}) \frac{dF_o(\hat{z})}{F_o(z_{\max})} \equiv \frac{\partial \mathbb{E}_{\hat{z}}(w(z,\hat{z},\boldsymbol{\mu})}{\partial z}$
2. $\pi(0) \leq \int w(0, \hat{z}, \boldsymbol{\mu}) \frac{dF_o(\hat{z})}{F_o(z_{\max})}$
3. $\pi(z_{\max}) \geq \int w(z_{\max}, \hat{z}, \boldsymbol{\mu}) \frac{dF_o(\hat{z})}{F_o(z_{\max})}$

Together, (1)-(3) guarantee the existence of such a threshold.

1. From Equation (4.4) combined with the solution to the wage bargaining in Equation (4.5), we can write the derivative of profits wrt to owner ability as
$$\frac{\partial \pi(x)}{\partial x} = \frac{\partial y(\hat{z}, x, \boldsymbol{\mu})}{\partial x} + (n-1)(1-\omega) \int \frac{\partial y(z, x, \boldsymbol{\mu})}{\partial x} \frac{dF_w(z)}{F_w(z_{\max})} \tag{B.3}$$
Here, we used the fact that n and $\boldsymbol{\mu}$ are optimal choices and hence the envelope theorem applies. Since the owner performs all her own complex tasks, $\frac{\partial y(\hat{z},x,\boldsymbol{\mu})}{\partial x} = 1$ and therefore $\frac{\partial \pi(x)}{\partial x} \geq 1$.

   Turning to expected wages,
$$\frac{\partial \mathbb{E}_{\hat{z}}(w(z, \hat{z}, \boldsymbol{\mu})}{\partial z} = \omega \int \frac{\partial y(z, \hat{z}, \boldsymbol{\mu})}{\partial z} \frac{dF_o(\hat{z})}{F_o(z_{\max})} \leq 1 \tag{B.4}$$
by Assumption 2.

2. Suppose instead that $\pi(0) > \int w(0, \hat{z}, \boldsymbol{\mu}) \frac{dF_o(\hat{z})}{F_o(z_{\max})}$. From above, the derivative of profits is always larger than the derivative of expected wages. Then, the set of workers would be the empty set and the labor market would not clear.

3. Suppose instead that $\pi(z_{\max}) < \int w(z_{\max}, \hat{z}, \boldsymbol{\mu}) \frac{dF_o(\hat{z})}{F_o(z_{\max})}$. From above, the derivative of profits is always larger than the derivative of expected wages. Then the set of entrepreneurs would be the empty set and the labor market would not clear.

■

Proof of Lemma 2.

1. The share of time each worker spends on complex tasks is equal to D – the total amount of complex tasks in his production line – minus the share of tasks delegated to the entrepreneur. Using Equation (4.7), this can easily be rewritten as $\theta(z,\hat{z}) = D\left(1 - \frac{1}{\kappa_0}(\log \hat{z} - \log z)^{\kappa_1}\right)$. The share of time the entrepreneur spends on complex tasks is equal to D – the time it takes her to complete her own complex tasks – plus the time to complete all her $n-1$ workers' complex tasks that were delegated to her. $\hat{\theta}(\hat{z}) = D\left(1 + \frac{n-1}{\kappa_0}\int(\log \hat{z} - \log z)^{\kappa_1}\frac{dF(z)}{F_w(z_{max})}\right)$

2. The expression for $\overline{\theta}(\hat{z})$ follows directly from using the expressions above in the definition of average labor specialization.

$$\frac{\partial\overline{\theta}(\hat{z})}{\partial\kappa_0} = -D\frac{n}{\kappa_0^2}\int(\log \hat{z} - \log z)^{\kappa_1}\frac{dF(z)}{F_w(z_{max})} \qquad \leq 0$$

$$\frac{\partial\overline{\theta}(\hat{z})}{\partial n} = D\frac{1}{\kappa_0}\int(\log \hat{z} - \log z)^{\kappa_1}\frac{dF(z)}{F_w(z_{max})} \qquad \geq 0$$

$$\frac{\partial^2\overline{\theta}(\hat{z})}{\partial\kappa_0\,\partial n} = -D\frac{1}{\kappa_0^2}\int(\log \hat{z} - \log z)^{\kappa_1}\frac{dF(z)}{F_w(z_{max})} \qquad \leq 0$$

■

Proof of Lemma 3. Rearranging Equation (4.2) gives the result.

■

Proof of Lemma 4.

Let $\overline{w}(\hat{z},\boldsymbol{\mu}) \equiv \int w(z,\hat{z},\boldsymbol{\mu})\frac{dF_w(z)}{F_w(z_{\max})}$. The equation in Lemma (4) follows from taking the first-order condition of (4.4) with respect to n. Further,

$$\frac{\partial\mathbb{Z}(\hat{z},n,\boldsymbol{\mu})}{\partial n} = \hat{z}^{\lambda}\frac{1}{n^2}\left[-\hat{z}^{1-\lambda} + \int\tilde{z}(z,\hat{z},\boldsymbol{\mu})^{1-\lambda}\frac{dF_w(z)}{F_w(z_{\max})}\right] \leq 0$$

where the last inequality follows from the definition of $\tilde{z}(z,\hat{z},\boldsymbol{\mu})$.

Solving for n,

$$n = \frac{1}{\chi_0}\left[\hat{z}^{\lambda} + \int\tilde{z}(z,\hat{z},\boldsymbol{\mu})^{1-\lambda}\frac{dF_w(z)}{F_w(z_{\max})}\right]^{\chi_1}$$

which is declining in χ_0.

Using the envelope theorem,

$$\frac{\partial \tilde{z}(z,\hat{z},\boldsymbol{\mu})}{\partial \kappa_0} = z^{\mu(z,\hat{z})}\hat{z}^{1-\mu(z,\hat{z})}\frac{\partial(1-\kappa(\mu(z,\hat{z})))}{\partial \kappa_0} \leq 0$$

and hence $\frac{\partial n}{\partial \kappa_0} < 0$ as long as $\lambda < 1$.

■

Proof of Lemma 5.

1. When $\lambda = 1$, $Y(\hat{z}, n, \boldsymbol{\mu})$ directly collapses to $\hat{z}\, n$. When $\kappa_0 = 0$, then $\mu(z,\hat{z}) = 1\ \forall z$. Note that Assumption (1) guarantees that the entrepreneur has capacity to take on all complex tasks of her workers. With $\mu(z,\hat{z}) = 1$, we have again that $Y(\hat{z}, n, \boldsymbol{\mu}) = \hat{z}\, n$. Optimal firm size is then simply given by

$$\hat{z} = \overline{w}(\hat{z}, \boldsymbol{\mu}) + \chi'(n)$$

   and is increasing in $\hat{z}$ since $\chi'(n) = (\chi_0 n)^{\frac{1}{\chi_1}}$ is increasing in n

2. When $\kappa_0 \to \infty$, no tasks are unbundled and $\mu(z,\hat{z}) = 0 \forall z$. Hence $\tilde{z}(z,\hat{z},\boldsymbol{\mu}) = z$. Moreover, if $\lambda = 0$, we get that $Y(\hat{z}, n, \boldsymbol{\mu}) = \hat{z} + (n-1)\int z \frac{dF_w(z)}{F_w(w_{max})}$ and optimal firm size solves

$$\chi'(n) + (1-\omega)\overline{w} + \omega \int z \frac{dF_w(z)}{F_w(w_{max})} = \int z \frac{dF_w(z)}{F_w(w_{max})}$$

   which is independent of $\hat{z}$.

■

Proof of Proposition 1.

Consider an increase in $1/\kappa_0$ (decrease in κ_0). With $\kappa_1 = 0$, firm-level output simplifies to

$$Y(\hat{z}, n) = \hat{z} + (n-1)\, \hat{z}^{\lambda + \frac{1-\lambda}{\kappa_0}} \int_0^{z_0} z^{(1-\lambda)(1-\frac{1}{\kappa_0})} \frac{dF(z)}{F(z_0)} \tag{B.5}$$

To simplify notation, let average output per worker in a firm owned by an individual with ability $\hat{z}$, when the marginal entrepreneur in the economy is given by z_0, be denoted $\mathbb{Z}(\hat{z}, z_0)$. That is,

$$\mathbb{Z}(\hat{z}, z_0) \equiv \hat{z}^{\lambda + \frac{1-\lambda}{\kappa_0}} \int_0^{z_0} z^{(1-\lambda)(1-\frac{1}{\kappa_0})} \frac{dF(z)}{F(z_0)} \tag{B.6}$$

Profits of an entrepreneur with ability $\hat{z}$ can then be written as:

$$\pi(\hat{z}; z_0) = \hat{z} + (n-1)(1-\omega)\left[\mathbb{Z}(\hat{z}, z_0) - \overline{w}\right] - \chi(n) \tag{B.7}$$

where n is equal to

$$n = \frac{1}{\chi_0}\left[(1-\omega)\left(\mathbb{Z}(\hat{z}, z_0) - \overline{w}\right)\right]^{\chi_1} \tag{B.8}$$

The expected wage of a worker z is equal to

$$\mathbb{E}\left(w(z; \boldsymbol{\mu})\right) = (1-\omega)\bar{w} + \omega \mathbb{Z}_w(z; z_0) \tag{B.9}$$

where $\mathbb{Z}_w(z; z_0)$ is, analogously to $\mathbb{Z}(\hat{z}, z_0)$, the average output that a worker of ability z would get given the equilibrium distribution of entrepreneurs in the economy:

$$\mathbb{Z}_w(z_0) \equiv z^{(1-\lambda)(1-\frac{1}{\kappa_0})} \int_{z_0}^{z_{\max}} \hat{z}^{\lambda + \frac{1-\lambda}{\kappa_0}} \frac{n(z)dF(z)}{\int_{z_0}^{z_{\max}} n(z)dF(z)} \tag{B.10}$$

The two equations that pin down the aggregate equilibrium objects—z_0 and $\overline{w}$—are given by

$$z_0 + (n-1)(1-\omega)\left[\mathbb{Z}(\hat{z}, z_0) - \overline{w}\right] - \chi(n) = (1-\omega)\bar{w} + \omega \mathbb{Z}_w(z_0), \tag{B.11}$$

$$\int_{z_0}^{\bar{z}} n(z) f(z) dz = 1. \tag{B.12}$$

The structure of the proof then is as follows: We find the level of the wage $\overline{w}^*$ such that, given a marginal increase from $1/\kappa_0$ to $1/\kappa_0^*$, the marginal entrepreneur z_0 is unchanged. For small enough ω, as we assumed, $\overline{w}^* > \overline{w}$.

We then show that at this wage level, aggregate labor demand exceeds aggregate supply. Thus, the new equilibrium wage level must be bigger than $\overline{w}^*$, implying that z_0 is higher in the new equilibrium as well. The last part of the argument follows from our assumption on the slope of aggregate labor demand wrt the wage.

Let $n^*(z_0)$ be the level of employment of the cut-off type z_0 under κ_0^* and $\overline{w}^*$.

$$z_0 + (n-1)(1-\omega)\left[\mathbb{Z}(z_0, z_0, \kappa_0^*) - \overline{w}^*\right] - \chi(n) = (1-\omega)\bar{w}^* + \omega \mathbb{Z}_w(z_0, \kappa_0^*) \tag{B.13}$$

$$n^*(z_0) = \frac{1}{\chi_0}\left[(1-\omega)\left(\mathbb{Z}(z_0, z_0, \kappa_0^*) - \overline{w}^*\right)\right]^{\chi_1} \tag{B.14}$$

Combining the two equations:

$$n^* = \frac{1}{\chi_0}\left[\frac{(1-\omega)\bar{w}^* + \omega\mathbb{Z}_w(z_0,\kappa_0^*) - z_0 + \chi(n^*)}{n^*-1}\right]^{\chi_1} \tag{B.15}$$

We want to show that $\frac{\partial n^*}{\partial w^*} > 0$. Totally differentiating, we get

$$\begin{aligned}\chi_0 dn = \chi_1 &\left[\frac{(1-\omega)\bar{w}^* + \omega\mathbb{Z}_w(z_0,\kappa_0^*) - z_0 + \chi(n^*)}{n^*-1}\right]^{(\chi_1-1)} \\ \times &\left[\frac{(1-\omega)d\bar{w}^* + \omega\frac{\partial\mathbb{Z}_w(z_0,\kappa_0^*)}{\partial 1/\kappa_0}d(1/\kappa_0) + \chi'(n)dn}{n-1} - dn\frac{(1-\omega)\bar{w}^* + \omega\mathbb{Z}_w(z_0,\kappa_0^*) - z_0 + \chi(n^*)}{(n-1)^2}\right]\end{aligned} \tag{B.16}$$

$$\chi_0 dn = \chi_1 (\chi_0 n)^{\frac{\chi_1-1}{\chi_1}} \frac{(1-\omega)d\bar{w}^* + \omega\frac{\partial\mathbb{Z}_w(z_0,\kappa_0^*)}{\partial 1/\kappa_0}d(1/\kappa_0)}{n-1} \tag{B.17}$$

For small enough ω, implies that $\frac{\partial n^*}{\partial w^*} > 0$, that is, the cut-off entrepreneur z_0 chooses to run a larger firm under $\overline{w}^*$ and κ_0^*. Note that if firm size increases for the cut-off entrepreneur, it also increases for all entrepreneurs with higher ability. Therefore, the labor market cannot clear.

In equilibrium therefore, we must have that $\overline{w}$ increase to a *higher* level than $\overline{w}^*$. Together with the fact that aggregate labor demand declines in the wage level, it must be that z_0 increases.

1. With $\kappa_1 = 0$, average specialization simplifies to $\bar{\theta} = D\frac{n}{\kappa_0}$, which is increasing in $1/\kappa_0$.

2. $\frac{\partial\bar{\theta}}{\partial n} = \frac{D}{\kappa_0}$ which is increasing in $1/\kappa_0$.

3. Shown above.

4. Implied by the fact that z_0 increases and the labor market clears.

5. The output of the production line associated to each individual either stays constant (for entrepreneurs who stay entrepreneurs under κ_0^*) or increases. To see this, recall that

$$y(z,\hat{z},\boldsymbol{\mu}) = \hat{z}^{\lambda}\left(z^{\mu(z,\hat{z})}\hat{z}^{1-\mu(z,\hat{z})}[1-\mu(z,\hat{z})]\right) \tag{B.18}$$

and consider that all individuals are matched – on average – with more skilled entrepreneurs, and also acquire more of their higher productivity due to the stronger specialization ($\mu(z,\hat{z})$ is lower). As a result, total output increases, implying that average firm productivity must increase as well since the total amount of labor is constant.

6. The wage is given by $w(z,\hat{z},\boldsymbol{\mu}) = (1-\omega)\overline{w} + \omega z^{(1-\lambda)(1-\frac{1}{\kappa_0})}\hat{z}^{\lambda+\frac{1-\lambda}{\kappa_0}}$ which increases for all $\{z,\hat{z}\}$ since $\overline{w}$ increased and the increase in $1/\kappa_0$ increases the wage as long as $\hat{z} > z$. Further, the set of entrepreneurs becomes more productive, so in the new equilibrium, the $\hat{z}$ any worker matched with is at least as high.

■

C Online Appendix - Estimation

C.1 Empirical Validation of the Theoretical Predictions

We provide two qualitative tests to support the model predictions of Section 4.4.

Heterogeneity across Sectors. Proposition 1 is in principle testable using market-level variation in the unbundling cost κ_0. In the absence of credible exogenous variation, we rely on cross-sectoral heterogeneity. As discussed in Section 3, the degree of standardization is remarkably similar in carpentry and welding, but is larger in grain milling, suggesting a lower κ_0 in that sector.

In Table C.1, we show that the key predictions of Proposition 1 hold across sectors. Carpentry and welding are almost identical in terms of labor specialization, average size, returns to managerial ability, and selection into entrepreneurship. In grain milling, on the other hand, there is more specialization, firms are larger, and the returns from managerial ability as well as the skill gap between entrepreneurs and their employees are larger.[78]

Heterogeneity across Regions. Our model has one unique implication, shown in Lemma 3: all else equal, entrepreneurial ability is less important for firm productivity in larger firms since employees are responsible for a larger share of the "firm management". To test this prediction, we would ideally find a credible instrument for firm size. In the absence of such exogenous variation, we provide suggestive evidence exploiting heterogeneity across sub-counties. We proceed as follows. First, we drop

[78]We do not test the prediction on wages because the model-consistent wage level is not directly observable in the data. A simple comparison of average wage would not hold since employees in grain milling are (in both the model and the data) less skilled.

Table C.1: Cross-Sectoral Heterogeneity

	Carpentry	Welding	Grain milling
	(1)	(2)	(3)
Panel A. Average Specialization & Firm Size			
Specialization	0.32	0.35	0.62
Firm Size	5.6	5.9	7.2
Panel B. Reg. Coeff's on Man. Ability (Std.)			
Log Revenues	0.24	0.25	0.57
Log Revenues per Worker	0.14	0.15	0.35
Log Size	0.10	0.10	0.23
Panel C. Reg. Coeff's on Entrepreneur (0/1)			
Years of Education	0.87	-0.10	3.29
Age	10.4	11.5	19.0
Log Earnings	0.72	0.94	1.00

Notes: Panel A: Sample: all firms. Average specialization: gap in the share of time in non-production tasks between the entrepreneur and her employees. Panel B: Sample: all firms. Coefficients from the regression of three dependent variables on the (standardized) index of managerial ability. Panel C: Sample: all entrepreneurs and employees. Regressions on a dummy equal to 1 if the individual is the entrepreneur, and zero if they are an employee. Regressions for Panels B and C include region fixed effects. Earnings are labor income for workers and firm profits for entrepreneurs.

all firms in grain milling.[79] We calculate the average firm size in each sub-county, rank them based on this statistic, and then divide them in two groups with roughly equal numbers of firms.[80] Finally, within each group of sub-counties, we estimate the return to managerial ability by regressing log revenues on sector dummies and either the managerial ability index or the years of education of the entrepreneur.

The results are shown in Table C.2. Consistent with Lemma 3, we find higher returns to managerial ability within the set of sub-counties with the smallest firms.

C.2 Details on Empirical Moments and Calibration

We describe the computation of the 150 moments targeted in the model estimation, and of the calibrated fixed costs. We use pooled data from carpentry and welding. All moments are computed from the initial survey. The calibrated fixed cost, instead,

[79]We restrict our focus to carpentry and welding since we have shown in Table C.1 that grain milling has larger returns to managerial ability, and we want to ensure that sectoral composition across regions is not driving our estimates. The results are unaffected by the restriction, however.

[80]The "marginal" sub-county is one of the largest ones, implying that we end up with 40% of the firms in one group and 60% in the other.

Table C.2: Returns to Managerial Ability in Locations with Different Firm Size

	Dep. Var: (Log) Revenues			
	(1)	(2)	(3)	(4)
Manager Ability (Std.)	0.388	0.177		
	(0.056)	(0.041)		
Yrs. of Education			0.060	0.036
			(0.016)	(0.012)
Subcounty by Firm Size	Small	Large	Small	Large
(Average Firm Size)	(4.80)	(6.15)	(4.80)	(6.15)
Sector FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.152	0.044	0.081	0.029
Observations	360	583	360	583

Notes: OLS regression coefficients. Sample: carpentry and welding. Robust standard errors are in parentheses.

is from the follow-up survey. We start by describing the moments, and organize the discussion by dividing them into four groups, following the four panels of Table 4.

Allocation of Time to Complex Tasks (Table 4, Panel A). The Average Time on Complex Tasks (Panel A, row (i)) is the average firm-level share of time in non-production tasks, including the entrepreneur and all employees. Rows (ii) and (iii) report, respectively, the average share of time in non-production tasks for all entrepreneurs, and for entrepreneurs in firms of size 1 (so with no employees). The statistic in row (ii) is computed exactly as in Table A.2, column 1. Rows (iv) and (v) report the average share of time in non-production tasks for employees, split by below and above median salary (we use salary as a proxy of skill).[81] The slope for entrepreneurs in row (vi) is taken from column 2 of Table A.2, where we regress the share of time of the entrepreneur in non-production tasks on firm size. Rows (vii) and (viii) report the coefficients from a similar regression for high- and low-skilled employees separately, where again we split them by below and above median salary. The results are reported in columns 2 and 3 of Table C.3. Finally, row (ix) reports the coefficient from a regression of the share of time in non-production tasks on log employee earnings, with firm fixed effects, shown in column 1 of Table C.3.

We also target several moments related to the distribution of specialization in complex tasks across the size distribution (shown in Figure 8). Specifically, we calcu-

[81] To preserve the full sample, employees with missing salary are assigned the lowest salary in the sample, and so are included in the low-skilled group. Employees are ranked by salary and split above and below median within each firm size group.

late the share of entrepreneurs' time in non-production tasks in each firm size group, from firms with no employees to firms with 10 or more employees (10 moments), and, similarly, the share of time in non-production tasks for employees in each firm size group (other 9 moments). Finally, we also target the share of time in non-production tasks for employees with below median earnings in each firm size group (again splitting employees by below and above median within each firm size group). This yields other 9 moments.[82]

Distribution of Earnings (Table 4, Panel B). The coefficient in row (i) of Panel B is from a regression of employee log monthly earnings on the index of managerial ability, reported in column 4 of Table C.3. We then standardize this coefficient by dividing it by the standard deviation of employee log earnings.[83] The coefficient in row (ii) is from a regression of employee log monthly salary on log revenues per worker, reported in column 5 of Table C.3. Row (iii) shows the normalized average earnings gap of employees across firms below and above median revenues per worker. To compute this, we regress log employee earnings on region and sector fixed effects, keep residuals, and then normalize these residuals by their mean and standard deviation.[84] In the last row of Panel B we do the same but splitting employees by below/above median managerial ability index of their firm owner.[85]

Distribution of Firm Revenues (Table 4, Panel C). The standard deviation of log revenues reported in the first row of Panel C is after trimming revenues at the 5^{th} and 95^{th} percentiles to reduce the incidence of outliers, and after removing region and sector fixed effects. The coefficient in row (ii) comes from a regression of log revenues per worker on the index of managerial ability, shown in column 1 of Table C.4. In row (iii), we show the average gap in revenues between firms with below and above median managerial ability. To compute this, we regress log revenue on region and sector fixed effects, keep the residual, and then normalize by subtracting the weighted

[82] The full list of moments related to the distribution of specialization in complex tasks across the size distribution is reported in the Supplemental Appendix.

[83] The standard deviation is computed after trimming log earnings at the 5^{th} and 95^{th} percentiles to reduce the incidence of outliers, and after removing region and sector fixed effects.

[84] In the actual estimation, we target the 5, 15, 25, 35, 45, 55, 65, 75, 85, 95 percentiles of the distribution of (normalized) residual salary by above/below median log revenue per worker (so 20 moments, all included in the Supplemental Appendix).

[85] This produces other 20 moments (again shown in the Supplemental Appendix). To preserve the full sample, whenever we split the sample by below and above median managerial ability, we replace missing values in managerial ability by assigning them the lowest value in the sample, so that they are assigned to the low managerial ability group.

average of the residual.[86] In addition, we also target the pdf of residualized log firm revenues (visualized in Figure 8).[87]

Firm Size Distribution (Table 4, Panel D). Average size in the first row of Panel D is uncensored. The standard deviation of log size and of size in rows (ii) and (iii) is after top coding firm size at 10 workers. The coefficient in row (iv) is from a regression of log size on the managerial ability index, shown in column 2 of Table C.4. Finally, row (v) shows the average gap in firm size between entrepreneurs above and below median managerial ability. To compute this, we create the distribution of firm size (censored at 10 workers), separately for above and below median managerial ability firms.[88] In addition, we also target the pdf of firm size (top coded at 10 workers). This gives the final 10 moments used in the estimation (Figure 8).

Calibration of Start-up Cost. In Table C.5 we show estimates of the start-up capital (column 1), and compare this with monthly profits in the first year of operation (column 2) and just before the initial survey (column 3).[89] To calculate the start-up capital, we exploit a unique survey module where entrepreneurs were asked to report: (i) all personal savings and (ii) all external sources of funds (e.g., loans, gifts) used to start the business. We sum (i) and (ii) to create a measure of the start-up capital. The average and median of the start-up capital are \$903 and \$657.9. We can benchmark these values by comparing them to the the average and median monthly profit in the first year of operation, which are \$106.7 and \$65.79. Considering monthly discount rates of 1-2%, which seem appropriate for the context, and converting monthly profits to present values, the average start-up cost represents about 8-14% of the present discounted value of profits. We thus calibrate the start-up cost χ_f as 10% of average profits (as shown in Table 5).

[86]In the actual estimation, we target the 5, 15, 25, 35, 45, 55, 65, 75, 85, 95 percentiles of the distribution of (normalized) log revenues by above/below median managerial ability (so 20 moments, shown in the Supplemental Appendix).

[87]To compute this, we regress log revenues per worker on region and sector fixed effects, keep the residual, and then subtract from the residual value its weighted average, and finally trim this value at the 5^{th} and 95^{th} percentile. To estimate the density, we let the program choose 15 points with default settings. So this yields other 15 moments (shown in the Supplemental Appendix).

[88]In the actual estimation, we target the 5, 15, 25, 35, 45, 55, 65, 75, 85, 95 percentiles of the distribution of firm size by below and above median managerial ability (so 20 moments, shown in the Supplemental Appendix).

[89]The number of observations is around 300 in columns 1 and 2 because the survey module on start-up costs was only asked to a random subset of the sample by design, to limit survey length.

Table C.3: Moments, Employee Level Regressions

Dep. Var.:	Worker Share of Time in Non. Prod.			log(Salary)	
Sample:	All	Skilled	Unskilled	All	All
	(1)	(2)	(3)	(4)	(5)
log(Salary)	0.033				
	(0.012)				
Firm Size		0.002	0.000		
		(0.003)	(0.004)		
Managerial Ability (Std.)				0.089	
				(0.028)	
log(Revenue per Worker)					0.191
					(0.037)
Firm FE	Yes	No	No	No	No
Region and Sector FE	No	Yes	Yes	Yes	Yes
Obs.	2324	1154	1170	1904	1979

Notes:: Sample: Carpentry and Welding. In Col (2) and (3), employees are classified as Skilled an Unskilled within sector by size groups. Firm size is top coded at 10 workers. Standard errors are robust in column 1, and clustered at the firm level in the other columns. The Managerial ability variable is standardized.

Table C.4: Moments, Firm Level Regressions

	log(Revenue)	log(Size)
	(1)	(2)
Managerial Ability (Std.)	0.145	0.100
	(0.030)	(0.021)
Region and Sector FE	Yes	Yes
Obs.	894	897

Notes:: Sample: Carpentry and Welding. Robust standard errors. The Managerial ability variable is standardized.

Table C.5: Start-up Capital and First Year Profit

	Start-up Capital	Monthly Profit (first year)	Monthly Profit (time of survey)
	(1)	(2)	(3)
Mean	902.996	106.606	233.749
Median	657.895	65.789	153.509
Obs.	308	303	930
Sample	Follow-up		Initial survey

Notes: Sample: carpentry and welding. All numbers are in USD. Column (1) and (2) show data from the follow-up survey, Column (3) from the initial survey. Start-up Capital definition: see text. We trimmed the top 1% and excluded all 0 values. Monthly profits are trimmed at the top 1%.