Achieving Scale Collectively:

Evidence from Manufacturing Firms in Urban Uganda*

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Abstract

Firms in developing countries enter small and struggle to grow large. This paper studies whether the small firm size prevents them from exploiting economies of scale, thus further hindering their productivity. We design and implement a novel survey to measure how firms produce output in three manufacturing sectors in urban Uganda. We find strong direct evidence that most firms operate at a scale that is too small to justify investment in modern high-capacity machines. However, an active inter-firm rental market has emerged in response, allowing firms to achieve economies of scale *collectively*. Interpreted through the lenses of an equilibrium model of firm behavior, our data reveals that the rental market for machines limits substantially the productivity losses due to the small scale of production. Taken together, our results show that, while the small size of firms remains a concern, the design of effective development policies should take into account market level interactions between firms as a powerful mean to mitigate the cost of small scale.

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1 Introduction

Firms in developing countries are small. As an example, the average establishment in manufacturing has four employees in Uganda and more than twenty in the United States.[1]

An extensive literature has shown that firms in developing countries are constrained to remain small due to difficulties in accessing credit, weak market integration, labor market frictions, limited contract enforceability and low trust beyond the family or ethnic group.[2] In addition, firms remain small due to lack of managerial talent or distorted regulatory incentives to remain small.[3] This evidence has led to a plethora of policy interventions targeted at helping firms in developing countries grow their size.

The extent to which the small firm size in developing countries limits aggregate productivity however depends on the magnitude of economies of scale in production. If economies of scale are limited, then relaxing constraints to expansion can lead to productivity gains only indirectly, through the exit of the low skilled entrepreneurs.[4] Instead, in the presence of large economies of scale, overcoming barriers to growth can directly increase firm productivity. While the literature has mostly focused on identifying the constraints that keep firms small, direct evidence on the presence of economies of scale in developing countries is scarce, at best.[5]

In this paper, we make two contributions that refine our understanding of the role of scale for development.

First, we design a new survey to measure how firms produce output in three prominent manufacturing sectors in urban Uganda, and we use the data to provide direct evidence for economies of scale. In our context, scale economies are driven by the indivisibility and large capacity of modern (and expensive) production machines..

Second, and most surprisingly, we document that firms engage in a very active inter-firm rental market for such modern machines. Interpreted through the lenses of a model of firm behavior, our data reveals that the rental market substantially mitigates the costs of small scale. In other words, while it is true that each individual firm is too small to benefit from scale economies by itself, firms go a long way in exploiting economies of scale *collectively* thanks to firm to firm interactions in the input market which effectively widen the firm boundaries. This result shows that the focus on firm size – common in the literature and in the policy space alike

[1] See Bento and Restuccia (2017), Bento and Restuccia (2018).

[2] See, for instance, Banerjee and Duflo (2014), Jensen and Miller (2018), Hardy and McCasland (2017), and Akcigit et al. (2016).

[3] See for example Lucas Jr (1978), La Porta and Shleifer (2014), Bloom et al. (2010), and Poschke (2018).

[4] If firms are small, in equilibrium the economy will be populated by many of them in each sector, thus diluting the ability of the average entrepreneur and reducing aggregate productivity. See for instance Buera et al. (2011) and Acemoglu et al. (2018). These studies are not concerned with identifying scale economies or the impact of increasing firm size *per se*.

[5] One notable exception is Jensen and Miller (2018), who shows in the context of small scale boat producers in India that larger firms manage to use labor more effectively by specializing workers across production tasks.

– is partially misplaced; more attention should be given instead to the size and connectedness of firm clusters if we wish to understand the role of scale economies for development.

Our work comprehends three parts: i) survey design and implementation; ii) empirical analysis; iii) model and estimation. Next, we outline each one.

We design the survey with the aim of measuring how firms produce output and whether they use different combinations of production inputs. We restrict the focus to manufacturing due to ease of output and input measurement. Within manufacturing we select the three sectors that have the largest number of firms and that represent the largest share of overall Ugandan employment in firms with more than five employees. The three sectors are: carpentry, metal fabrication, and grain-milling. For practical reasons, we exclude from the analysis rural areas, where the firm density is much lower, and the less densely populated Northern region. Our survey is thus representative of urban and semi-urban areas in the Eastern, Central, and Western regions of Uganda. We interview 1,115 firms: 516 in carpentry, 433 in metal fabrication and 166 in grain-milling.

The survey is extremely detailed: our enumerators spent three days at the median firm, with multiple survey hours every day. A number of features of our data make it unique in this context. We separately interview both the owner and the employees of the firm. For each sector, we select one core product, and we dissect its production process into a series of steps.[6] For each step, we collect information on the exact combination of inputs used: we ask which modern machines or manual tools (if any) are used and for how long, which workers perform the step, and which other inputs are used. We also collect data at the machine-level, in particular, whether they are owned or rented, their price, and multiple proxies of their quality. Finally, we collect time-diaries for both owners and employees.

We organize the empirical results in two parts. We first describe the overall organization of production and the market level outcomes. We then zoom inside the firm and use data on the production process to understand the determinants of labor productivity. In doing this, we highlight differences across our sectors, and how these contribute to testing our core hypothesis.

Our survey reveals that firms are small and spatially concentrated. In carpentry and metal fabrication, the median firm size is five (including one manager and four workers), and there are approximately six firms of each sector per square mile. Grain-milling has similar size distribution, but much lower density. Moreover, while most firms are of similar size and produce the same products following very similar production steps, they differ dramatically in their labor productivity and profitability.

We use our data to understand the drivers of these documented productivity differences and whether the scale of production plays an important role. Since firms produce similar products

[6]Core products are selected ex-ante for each sector before the start of the survey. The core products are doors for carpentry, sliding windows for welding, and maize flour for grain-milling.

using similar production steps, differences in labor productivity might be generated by a better or more intense use of either capital or labor. We explore both possibilities.

In our context, the main capital inputs are modern electrically-powered machines, such as thickness planers in carpentry. We document that firms vary considerably in how mechanized their production process is: while the great majority of firms complete the same production steps, some rely heavily on machines, while others mostly on manual tools and labor. In carpentry, the median firm uses 6 different types of machines, but some firms use only one and others as many as 20 different types, to produce the same product. Metal fabrication and grain-milling have similar dispersion. Machine usage is also the single most important statistical correlate of labor productivity and profitability. Controlling for number of machines used in production decreases the interquartile range of profits per worker by almost half.

However, relative to firm revenues and profits, machines are very expensive, especially in carpentry and grain-milling. In carpentry, one of the most used machines is the thickness planer, which costs on average $4,280 – more than 30 times the median monthly profit ($125). In grain-milling, instead, many firms use the hammer mill, which cost $2,230 – almost 20 times the median monthly profit ($121). Machines in metal fabrication are less expensive: a welding machine costs on average around $300, or only two months worth of profits ($157).

Modern machines are not only expensive, they also have a production capacity that is too large for the needs of the typical firm. In fact, most firms, even if they use a machine, do so for only a few hours per week. Excluding the zeros, the median (average) machine in carpentry is used by one single firm for 4 (8.5) hours per week. In welding, for 9 (18) hours per week. In grain-milling instead, machine capacity is more aligned with firms' needs: each firm uses a machine for 48 (45) hours per week.

These results show that one single firm, especially in carpentry, is too small relatively to the large capacity of the expensive, yet useful, machines: in other words, there seem to be very large, though unexploited, returns from scale. The complete picture, however, is more nuanced. In fact, we document that in carpentry most firms do not own the machines they use, but rather they rent them only when needed, and they do so mostly from other carpentry firms in the same area. For example, while almost 60% of firms use a thickness planer, less than 7% own one. In other words, we document that an inter-firm rental market has emerged to mitigate the cost of firms being too small. The rental market successfully increases the average capacity utilization of machines: for example, while firms use a thickness planer on average for less than 9 hours per week, each thickness planer is operated for more than 50 hours per week, that is, almost at full capacity. On the contrary, the rental market is almost absent in metal fabrication and grain-milling, which is not surprising since our evidence reveals that the cost of being small is much smaller in those sectors.[7]

[7]Machines in metal fabrication are relatively inexpensive, while in grain-milling they do not have much excess

While the rental market clearly improves the allocation of capital to firms and increases capacity utilization, it may still be hampered by transaction costs. In fact, most firms access rented machines at the premise of the machine owner, requiring them to move intermediate inputs between locations, and often leading to long waits for machine access.

We next turn to labor, and show that differences across firms are less marked than for capital. As expected, owners of more productive firms are more skilled and hire more skilled workers. However, even flexibly controlling for all our measures of skills, the residual productivity dispersion remains substantially higher than simply controlling for machines used.

Most importantly, our survey allows us to study whether firms use labor differently and to search for direct evidence of economies of scale driven by the labor market. For instance, scale could allow firms to specialize labor across production steps. In our data, we find only weak evidence for this channel. Scale could also allow workers to form production teams to increase efficacy. The data however does not support this channel either: most workers work by themselves, both in large and small firms. Finally, scale might allow for a more effective use of workers' time. However, while we find that workers spend a large share of their time idle (approximately 25%), this number does not vary substantially across the size distribution.

The data suggests that returns to scale driven by the labor input are at most minor. In fact, the average cost of labor *increases* with size. We show that even conditional on a very rich set of controls larger and more profitable firms pay higher wages to workers. Furthermore, most firms rely on referrals, often from family members, to hire their workers, which is a difficult recruitment method to scale up. This is in line with information and recruitment frictions creating diseconomies of scale in the labor input.[8]

Overall, we find evidence of sizable returns to scale due to capital, but not labor, and especially in carpentry. At the same time, we argue that such returns to scale are unlikely to be generating poverty traps. In the sector with the largest returns to scale, carpentry, a thick inter-firm rental market has emerged allowing firms to reap the benefits of scale collectively. The data alone is, however, not enough to quantify the overall cost of small scale, and how this is mediated by the rental market. In the last part of the paper we build a model that allows us to quantify to what extent firms are able to exploit economies of scale collectively, and to run policy counterfactuals.

We model an economy inhabited by managers and workers. Managers differ along two dimensions: their managerial ability and their cost of capital. High skilled managers face a higher demand for any given price. Managers choose how much to produce and the input mix to minimize the cost of production. Specifically, production requires to fulfill a series of steps and for each one the manager chooses the combination of labor and machines. Machines can

capacity to be leased out.

[8] A recent literature has emphasized the importance of hiring and screening frictions in urban labor markets in developing countries. See Abel et al. (2019), Abebe et al. (2018) and Bassi and Nansamba (2019).

be either purchased or rented. Owned machines can be leased in the rental market, which is in equilibrium. Workers are hired subject to a firm-specific increasing labor supply function which captures, in reduced firm, labor market frictions. The rental market for machines is also distorted by reduced form frictions, or wedges, which guide the choice to mechanize, the aggregate capacity utilization of each machine, and whether each firm decides to buy or rent a machine.

We use our data from the carpentry sector to estimate the model. One of the key outcome of interest is the size of the wedges, which tells us how distorted the rental market has to be in order to justify the observed distribution of machines and capacity utilization. If we estimate the wedges to be small, then we would conclude that the rental market manages to reap most of the benefits of scale.

The rental market wedges are estimated comparing the utilization of rented and owned machines. In the absence of any friction, the marginal cost of one extra hour of machine is identical for owners and renters, which should therefore use similar amounts of capital and labor in production. If there are transaction costs in the market, instead, we would expect machine renters to use fewer hours since their marginal cost of machine time would be higher. We show that rented machines, conditional on a rich set of controls, are used for approximately 50% fewer hours. This result holds even looking at machine utilization within the firm – i.e. when including firm fixed effects in the regression. The results imply that renters face large transaction costs to access machines, consistent with evidence of cumbersom transport cost and long waiting time to access machines.

We then use the estimated model to do counterfactuals and policy experiments. Specifically, we compute aggregate profits under two hypothetical scenarios: i) closing down the rental market, thus forcing firms to buy all the machines they wish to use; ii) consolidating firms, thus allowing managers to get together to buy machines without being subjects to any of the frictions of the rental market. We show that the existing rental market manages to reap a large share of the gains from scale that could be achieved in scenario (ii) relative to (i). We also show that the existence of the rental market has sharp implications for policy effectiveness and optimal targeting. In particular, we show that subsidizing capital for the most productive firms could be the most effective policy even if we are interested in targeting the least productive ones. In fact, the most productive firms are those more able to sustain the new capital investment, while the benefits from the new capital trickle down to other firms through the rental market. Finally, we show that frictions in the rental and labor market interact: frictions in the labor market make the frictions in the rental market less costly for aggregate labor productivity.

We conclude with two cautionary notes. First of all, the nature of our exercise is descriptive, and thus causal inference must rely on the specific structure, and assumptions, that we bring to the data. Nonetheless, we notice that experimentally varying the scale of production is, at

best, extremely difficult and costly. Increasing the scale of a firm would require possibly solving multiple constraints at once, providing a firm with more labor, more capital, more managerial skills, and – importantly – more demand.[9] Therefore, rather than trying to engineer a big-push shock, we followed a different path, and used careful measurement to overcome the lack of causal inference.

Second, we remark that this paper is silent on the fundamental reasons that lead some managers to be more skilled and to have more demand than others. Our focus instead is to understand how these primitive productivity differences map into labor productivity through mechanization choices, and the role played by economies of scale and by the presence of a rental market for capital inputs.

Related Literature. Our work is closely related to two important recent papers that study the role of small scale of production for development: Jensen and Miller (2018) and Foster and Rosenzweig (2017).

Jensen and Miller (2018) study the boat-building industry in Kerala, India, and show that the introduction of cellphones led to the exit of less productive boat builders and to reallocation of their market share towards more productive ones, thus leading to an increase in aggregate productivity. In other words, Jensen and Miller (2018) provide credible evidence that the small average firm size leads to aggregate productivity losses due to lack of competitive selection of the most skilled entrepreneurs. Our paper, instead, focuses on economies of scale. We show that, in addition to the selection margin emphasized by Jensen and Miller (2018), the small average firm size can have direct productivity costs due to economies of scale, which we show are mostly due to the indivisibility and large capacity of modern production machines.[10] Nonetheless, our main contribution is to show that focusing on the size of individual firms in isolation is partly misleading since economies of scale are achieved collectively through the rental markets for machines. To the best of our knowledge, this is a new insight.

Foster and Rosenzweig (2017) study economies of scale in farming. Consistent with our results, they argue that economies of scale are driven by the indivisibility of modern machineries. Our study is complementary to Foster and Rosenzweig (2017) due to our focus on firms, where – a priori – the source of the economies of scale might have been very different. Most importantly, our study provides two new insights: i) we show direct evidence that the scale economies are driven by the capacity of machines being too large for any single firm; ii) we document the presence of a inter-firm rental market, and we analyze its ability to help firms achieve scale

[9]Some recent work has managed to evaluate the impact of very big push interventions, but dealing with self-employed individuals rather than firms – see Banerjee et al. (2015) and Bandiera et al. (2017).

[10]Although it is not the main focus of their work, Jensen and Miller (2018) also provide some evidence on economies of scale at the firm level. In particular, they show consistently with our results that labor is more specialized in large firms. They also speculate that larger firms might be using capital more effectively, but do not show direct evidence for this.

collectively.[11]

2 A New Survey of Manufacturing Firms in Uganda

In this Section we describe a new representative survey of manufacturing firms that we implemented across urban areas of Uganda. The survey was run together with our partner NGO, BRAC Uganda, between September 2018 and July 2019.[12] The goal of the survey was to collect new firm-level data on production, in order to quantify differences in output per worker across firms, and then shed light on how these relate to differences in usage of: i) the capital input, ii) the labor input, and iii) the specific production processes through with such inputs are combined.

2.1 Sampling

We next describe our sampling strategy focusing on the following key aspects: i) sectoral coverage; ii) geographical coverage; iii) firm coverage and final sample. We highlight the main aspects of the sampling strategy that are relevant for the analysis in this paper, and leave additional details to Appendix A.

Sectoral coverage We focus on manufacturing, where output is easier to measure, and where both capital and labor are relevant inputs. Within manufacturing, we aimed to target sectors that: i) are economically relevant for Uganda, that is, employ a large share of workers; and ii) include a sizable share of relatively "large" firms, that we define as firms with at least five employees. The first criteria means we target sectors that are important for policy; the second criteria allows us to focus on sectors where both smaller and larger firms co-exist, and that are not dominated by subsistence entrepreneurs with little potential to grow beyond micro enterprises.

To select the sectors for the study, we use the latest Census of Business Establishments (COBE) for Uganda from 2010, and compute for each ISIC code the number of workers employed in firms with five or more employees (or in "large" firms).[13] We then rank sectors based on their share of total manufacturing employment in large firms. From this list we exclude those sectors

[11] Foster and Rosenzweig (2017) notice (i) as a promising channel. However, they do not have direct data on machines' time use and capacity for most machines, thus cannot validate the hypothesis in general. Their work has inspired us to design a survey to properly measure capacity utilization.

[12] BRAC is a large non-profit organization founded in Bangladesh in 1972, currently active in 12 developing countries in Asia, Sub-Saharan Africa and the Caribbean. BRAC was launched in Uganda in 2006 and is currently one of the largest development organizations and micro-finance institutions in the country. BRAC has extensive experience running surveys of firms in Uganda. For instance, BRAC has run the surveys described in Alfonsi et al. (2019) and Bassi and Nansamba (2019).

[13] The Census of Business Establishments is conducted by the Ugandan Bureau of Statistics (UBOS).

that include farms and that are dominated by a small number of very large firms, such as manufacturing of sugar. This is because we wanted to keep the focus on sectors not involving agriculture and with a sufficiently large number of firms. We then choose the top three sectors among the remaining ones in this list, that is: Manufacturing of structural metal products (ISIC 2511), Carpentry (ISIC 3100), and Manufacture of grain mill products (ISIC 1061). As shown in Table A1A1, these are all sectors with many firms, and with a substantial fraction of large firms, in all three cases around 20%. Focusing on more than one sector allows us to exploit heterogeneity across sectors, something that we do later in the paper. We limit the number of sectors to three for budgetary constraints.

Geographical coverage The survey was implemented in a representative sample of urban and semi-urban areas across three of the four macro-regions of Uganda: Central, Western, and Eastern region.[14] We do not include rural areas purely for cost-effectiveness reasons due to the lower firm density. Similarly, we do not include the Northern region for cost-effectiveness reasons, as that is the area with the lowest population and firm density. The geographical distribution of firms in Uganda is spatially concentrated, and so despite these sampling restrictions as many as 70% of the firms in the 2010 Census are located in areas eligible for our survey.

Our sampling units are sub-counties. We extracted our final sample of sub-counties stratifying by total population and by whether the sub-county is in the broader Kampala area. Our stratification ensures that our sample includes enough sub-counties in the Kampala area, which is richer and more densely populated, and reduces the risk that we draw a high number of sparsely populated sub-counties, which would have prevented us from surveying a sufficient number of firms.[15] We extracted 52 sub-counties, as calculations based on the 2010 Census revealed this was the number of sub-counties needed to achieve (in expectation) our target sample size of 1,000 firms in the survey. The size of the target sample of firms was dictated by budget considerations. Figure A1 shows the final sample of sub-counties included in the survey. This confirms that our sample extends throughout the three target regions. The actual survey was then conducted within all urban and semi-urban parishes of each of the 52 selected sub-counties, for a total of 177 parishes .

Firm coverage and final sample To identify the firms eligible for our survey, we conducted a full listing of all the firms in our three sectors of interest in the sampled parishes.[16] We then

[14]Following the definition in the U.S. population census, we define a geographical area to be urban or semi-urban if it has density higher than 288 individuals per squared kilometer.

[15]To implement the stratification procedure, we first split the 129 subcounties into two groups – the ones that are in the broader Kampala area, which comprises the districts Kampala and Wakiso, and all the rest. Then, we divide each group into two strata, of equal number of subcounties, based on total population of the subcounty.

[16]We decided not to use the existing Census of Business Establishments for the listing because it would not have allowed us to capture firm entry since 2010 and because we suspect the Census might have under-sampled

randomly extracted firms from the listing to be included in the final survey sample. To make sure our final sample included enough large firms, we oversampled firms with five or more employees from the listing.[17]

Column 1 of Table 1 reports the number of firms identified through our listing, by sector. In total, we identified 2,916 firms across the three sectors. We note that the number of firms is highest in Carpentry, followed by Metal fabrication and Grain milling. This is reassuring as it corresponds to the same ordering in terms of number of firms across sectors that is shown in Appendix Table A1 for the 2010 Census, where Carpentry is also the sector with the highest firm number, again followed by Metal fabrication and Grain milling. Figure A3 shows the result of the listing exercise in one sampled sub-county. The green dots correspond to firms in our three sectors from the 2010 Census. The dots of the other colors are the firms identified in our own listing. Reassuringly, we note that: i) the spatial distribution of firms is similar in our listing and in the 2010 Census, and ii) few firms in our data fall outside the corresponding sub-county limits, and the ones that do so are located in the immediate proximity of the sub-county limits. This is true for all our sample sub-counties, and confirms that measurement error in our firm listing is limited.[18]

Each firm identified in the listing was then asked to participate in a few "screening" questions to determine eligibility in the final survey, including primarily firm size. Reassuringly, comparing columns 1 and 2 of Table 1, we see that the number of firms that completed the screening is around 93%.[19] This is does not vary substantially across sectors.

Figure 1 reports the firm size distribution (in terms of number of workers) for all the firms that completed the screening questions, that is represented by the black dotted CDFs. Figure 1 confirms that: i) the median firm size is around four worker for all sectors, and ii) less than 10% of firms in these sectors are comprised of self-employed micro entrepreneurs. This is in line with Appendix Table A1, and again confirms that these are sectors where smaller and larger firms coexist, and that are not dominated by micro entrepreneurs.

Column 3 of Table 1 shows the number of firms that were then selected to participate in the full survey by random extraction from the firms in the listing with complete screening information. In line with our initial calculations, this number is close to 1,000. Column 4 shows our final sample of firms that agreed to answer the full survey. Comparing columns 4 and 3, we note that around 99% of the firms included in the final sample agreed to participate in the

small, informal establishments.

[17]All estimates from the survey sample reported in the paper are appropriately weighted to reflect this initial oversampling of larger firms.

[18]Across the 52 sub-counties, the percentage of firms in the listing that falls outside the sub-county limit is 9%.

[19]Of the 214 firms that did not complete the screening: (i) for 94 the firm owner refused to participate in the screening; (ii) for 43 the firm was identified but no one was ever around the firm to answer the screening questions during the period our enumerators were in the locality.

survey. The very high rate of compliance at both the screening and the survey stage limits concerns related to the representativeness of our final sample.

In each firm we surveyed the owner as well as all the employees working on our pre-defined core products, as discussed in more detailed below.. In total, as shown in Column 5 of Table 1, then this yielded a sample of 3,185 employees across our 2,916 firms.

2.2 Survey Design

We designed a survey to collect detailed information on output, inputs and production processes. Our objective was to zoom inside the firm, and paint a picture as complete as possible of the way these firms operate.

Our survey builds on and extends recent firm-level surveys in developing countries, such as those in De Mel et al. (2018), Hardy and McCasland (2017), Alfonsi et al. (2019), Bassi and Nansamba (2019) and Jensen and Miller (2018). Similarly to these surveys, we collect a wide range of firm-level characteristics, such as: revenues; profits; wages; total value of capital stock owned; detailed characteristics of both the owner and the employees (such as age, education, experience, and various measures of sector-specific skills including vocational training and on the job training received); management skills of the owner;[20] expectations and perceived constraints of the firm owner.

We then go beyond these related studies by collecting information on the entire production process for key products that are among the most common in these sectors. This allows us to study differences in how the *same* output is produced across firms in the *same* sector. In practice, we worked with the Uganda Industrial Research Institute to identify for each sector one core product produced by most firms in the sector. These turn out to be: two-panel doors for Carpentry; sliding windows for Metal Products, and maize flour for Grain-milling. We then dissect the production process for each of these products into a series of production steps that firms typically engage in to complete the product. For each firm in the survey we then collect information on: (i) whether they produce the pre-specified core product; (ii) whether they perform the pre-specified production steps; and (iii) the exact combination of capital and labor used in each production step.[21] That is, for each step we know: (i) which manual tools and modern electrically powered machines are used for that step; (ii) which employees work on that step; (iii) measures of efficiency relating to the time taken by the employee (or team of employees) to complete the step. We can then link this information to a detailed roster of all the employees and tools/machines used in the production of our core products, that records

[20]To measure management skills we use the same questions as in De Mel et al. (2018), and we combine them into one index following exactly the same approach as in that paper.

[21]In case the surveyed firms produced alternative production steps for the core product those were also recorded in the survey.

more information than typically available in other firm datasets.

Just to highlight a few unique features of our data that are relevant for the analysis in this paper, on the capital side we collect very detailed characteristics of each machine, such as: weekly hours used; whether it is owned or rented; purchase (or rental) cost; where the machine was purchased/where it is rented from; country of production; age; current value; expected remaining life. On the labor side, we collect information for each employee and firm owner on: machine-specific skills; cognitive and non-cognitive skills; time-diaries where we measure hour by hour the time spent doing different activities in the last work-day before the survey.

This information was collected through in-person surveys conducted by our enumerators, who spent three days at the median firm, asking questions for multiple hours each day in pre-arranged time slots when the owner and employees were available.[22] To minimize measurement error and ensure data quality, enumerators were paid primarily based on the quality of interviews rather than on the quantity of surveyed respondents.

In the next Section we use this rich data to describe production in these sectors, with a focus on how differences in usage of the capital and labor input across firms map into difference in productivity.

3 Descriptives on the Organization of Production

We now present a number of key facts on the organization of production in these sectors that emerge from our survey. The aim throughout this Section is to document the role of firm size in production and the sources of economies of scale. To fix ideas, we first clarify the characteristics of the typical firm in our context. We then quantify the amount of heterogeneity in the output these firms produce, and in their labor productivity. We then zoom inside the production process of the individual firm, and discuss the potential role of both the capital and labor inputs in explaining differences in labor productivity and in generating economies of scale. We conclude this section with a discussion on the output market where these firms oeprate, focusing on the determinants of demand and the role of competition. In presenting these descriptives, we highlight differences across our sectors, and how these contribute to our evidence on whether there are economies of scale that seem to be un(der)exploited.

3.1 Basic Firm Descriptives

Table 2 reports basic descriptive characteristics for the firms in our sample, their owners, and their employees. On firm characteristics, as highlighted already in Figure 1, Panel A of Table

[22]To minimize disruption of firm activities, enumerators were instructed to survey the owner and employees outside of regular working hours as much as possible , such as during lunch break or at the end of the work-day. Many interviews were also conducted during the weekend.

2 shows that the average firm is small in terms of number of employees, employing about 5 employees. Average monthly revenues and profits are $1515.8 and $273.0, respectively. To put these numbers into perspective, per capita GDP in Uganda was $709 in 2018. This shows that the average firm is highly profitable by Ugandan standards, and operating beyond subsistence level. The average firm age has been in business for almost 10 years and the great majority of firms have a trading license to operate from the local authority, which highlights that these firms are established entities.

Panel B reports basic owner characteristics. The average owner is 39 years old and has 10 years of education. To put these numbers into perspective, data from Barro and Lee (2013) show that, in 2010, the average prime age male in Uganda spent less than 7 years in school. Firms owners are thus more educated than the average, which is not surprising considering that we are focusing on mostly urban settings, where education attainment is usually higher (Porzio and Santangelo (2019)). Finally, Panel B shows that the average owner supplies 9.4 hours per day for the firm, so that for the majority of owners this is their primary work activity.

Panel C shows basic employee characteristics. Employees are younger and more educated than owners, consistent with cohort effects in education. Average tenure is 3.5 years, and the average employee works 9.8 hours per day for the firm. This shows that these are stable and regular jobs. Finally, the average employee makes about $71 per month. So these are well-paying jobs by Ugandan standards.

Taken together, the evidence from Table 2 shows that our sample is comprised by established and profitable firms that employ regular and well-paid workers. Our sample is representative of firms in these sectors along the entire firm size distribution. This is an important difference with most related studies that target micro enterprises by design, such as De Mel et al. (2008) and De Mel et al. (2018).[23]

3.2 Distribution of Economic Activity

We now present three key facts about the distribution of production activities: (i) the market is populated by many small firms that produce similar products using similar production processes; (i) firms are spatially concentrated in clusters; (iii) there is large heterogeneity in labor productivity across firms.

Many similar small firms We have already discussed in the context of Figure 1 and Table 2 that the average firm size is small. Figure 2 reports the distribution of the types of output produced by Carpentry firms in our sample. We note that production is concentrated around

[23]Our sample of firms is more similar to those in Alfonsi et al. (2019), Bassi and Nansamba (2019) and Hardy and McCasland (2017) who target firms also beyond micro enterprises. None of these surveys however is representative of the entire firm size distribution.

some key products produced by most firms. For instance, 70%-80% of the firms produce beds and doors. And among firms producing doors, over 70% of firms produce the 2-panel door, which is our core product for carpentry (that was pre-specified). The pattern for Metal fabrication and Grain milling reported in Appendix Figure A4 shows similar results. Figure 3 then shows that not only Carpentry firms produce similar products, but they also do so using very similar production steps. Indeed, the great majority of firms are engaged in most of the pre-specified production steps that we asked about for the core product of the two-panel door. As shown in Appendix Figure A5, this is valid also in the other two sectors. Taken together, this evidence shows that the market is composed by many small firms that are engaged in the production of similar products using similar production steps. In other words, we do not find evidence of specialization of economic activity across firms.

Spatial concentration We can use the initial firm listing to study the spatial concentration of firms in our data. This reveals that firms are concentrated in firm clusters: in carpentry and metal fabrication there are approximately six firms of each sector per square mile; the density is lower but still significant for grain milling with over two firms per square mile. Another way to see the extent of spatial concentration is to calculate the median number of firms falling within a 250 meter radius from each firm in our data. These turn out to be: 4 firms in carpentry, 2 in metal products and 1 in grain milling, again suggesting that the degree of spatial concentration is substantial, especially in carpentry and welding. The clustered nature of economic activity in these sectors can be appreciated visually in Appendix Figure A3, which maps the distribution of firms from the listing in one of our sampled sub-counties. Indeed, we see that firms tend to cluster together around major roads.

Heterogeneity in labor productivity Despite producing similar products following similar production steps, we document large differences in labor productivity across firms in the same sector. Figure 4 shows the distribution of residual profits per worker for carpentry.[24] The unconditional dispersion in profits per worker is represented by the lighter grey line. This shows a very wide dispersion. For instance, firms at the 75th percentile of the distribution are over five times more productive than firms at the 25th percentile of the distribution. Figure A6 in the Appendix shows very similar results for metal fabrication and grain milling.

[24]We focus on profits per worker as our preferred measure of labor productivity as this captures both the revenue-side and the cost-side of productivity. Results using revenues per worker or quantity of the core product sold per worker as measure of productivity are similar.

3.3 Understanding Productivity Dispersion and the Role of Scale

Since firms in this context produce similar products using similar production processes, the differences in labor productivity documented above must arise from differences in either: (i) the efficiency (or quality) of the labor and capital inputs used; (ii) the intensity with which they are combined in production; (iii) the scale of operations. We now explore these possibilities for both the capital and labor input.

3.3.1 Capital

Importance of modern machines The main productive capital in this context are machines and tools. In particular, there is a sharp contrast between "modern machines" that are electrically powered, and "hand tools" that are human powered.[25] These largely perform the same production steps, but vary in their efficiency, capacity and cost, as explained in more detail below.

For each production step we create a measure of the extent to which it is "mechanized". To do this, for each step we identify in the data the firms with the largest number of different modern machine types used in the production of that step.[26] For each firm we then compute their mechanization rate for that step defined as the number of different machine types they use, divided by the number of different machine types used by the most mechanized firms in the data. Figure 5 shows for the case of carpentry that there is substantial variation in mechanization rates across steps: while most firms are involved in all steps, they vary in the extent to which they perform such steps using modern machines as opposed to manual tools.[27]

We further document that usage of modern machines across production steps is the strongest predictor or profits per worker. Figure 4 reports how the distribution of residual profits per worker varies as we condition on different observables. We see that basic observables such as firm size and firm age, owner age and education, employee age, education and experience, do not explain much of the variation in profits per worker. More advanced owner and employee characteristics such as owners' cognitive and managerial skills, and employees' cognitive skills, vocational training and on the job training, explain a little more of the variation, but not much more. The largest share of the variation is explained instead by the extent to which the production steps are mechanized. Indeed, just controlling for mechanization and nothing else reduces the dispersion in profits per worker by 30%.[28] This confirms that modern machines are

[25]For example, in carpentry a modern machine would be a thickness planer, while a hand tool would be a hand planer.

[26]These are the firms at the 95% or above of the distribution of machine types used in the production of the step.

[27]Appendix Figure A7 shows this is also true for the other sectors, though differences in mechanization rates are lower in grain milling.

[28]Appendix Figure A6 shows similar results for the other sectors. The contribution of mechanization towards explaining productivity differences is lower in grain milling, and this is in line with Appendix Figure A7 that

the most important correlate of differences in labor productivity across firms.

Machine capacity and economies of scale We document that modern machines are expensive and have high capacity, especially in carpentry and grain milling. Figure 6 shows the percentage of firms using different types of machines across the production steps for the predefined core product. Starting from Panel A, we note that most of the machines in carpentry are expensive. For example, thickness planers are the most common type of machine, but they cost $4,280 on average – more than 30 times the median monthly profit ($125). Panel C shows that in grain milling hammer mills are among the most common machines, and they cost $2,230 on average, which is almost 20 times median monthly profits ($121). In metal fabrication instead, machines tend to be substantially less expensive: oil-cooled welding machines, that are used by about 80% of firms, cost around $300, or only two months worth of profits ($157).

In addition to being expensive, machines also tend to have a capacity that is too high for the needs of a single firm. Figure 7 reports the average hours that each machine is operated per week, conditional on usage. Panel A and B show that excess capacity is very high in both carpentry and metal fabrication: the average (median) machine is used by one single firm for about 4 (8.5) hours per week in carpentry, and for about 9 (18) hours per week in metal fabrication. In grain milling instead, capacity utilization is much higher, and machine capacity is much more aligned with the needs of individual firms: the average (median) machine is used for 48 (45) hours per week, that is, almost at full capacity.

These results on machine capacity and utilization would seem to show that there are large and unexploited economies of scale, especially in carpentry: modern machines are highly productive, but they also have a high fixed cost and a capacity that is much larger than the needs of every single firm. The potential for unexploited economies of scale is instead lower in metal fabrication and grain milling – it is lower in metal fabrication because while machines have high capacity there, they are not very expensive; it is lower in grain milling because even though machines are expensive, they are utilized heavily by each firm.[29]

Rental market for machines A natural market solution to the presence of indivisibilities related to large productive machines would be to organize a rental market for these machines. We therefore use our detailed machine-level data to study whether a rental market has emerged. Given the discussion above, we would expect this to be larger in carpentry than in the other two sectors. Figure 6 shows the break-down of the percentage of firms that use a machine between those that own the machine, and those that rent it. The Figure reveals a striking finding: in carpentry most machines are *rented* (Panel A), while the rental market is almost entirely absent in metal fabrication and grain milling (Panel B and C). For instance, Panel A

shows less variation in mechanization in grain milling.

[29]This is also consistent with the fact that grain milling firms are on average larger as shown in Table 2.

shows that while almost 60% of firms use a thickness planer, less than 7% own one. That is, we document that an active rental market has emerged in carpentry to partially mitigate the productivity cost from small firm size. Such a rental market is primarily across firms in the same sector: our data shows that in at least 60% of cases, firms report renting the machine from a nearby firm in the same sector.[30] As most of these machines are large and heavy, the rental market is operationalized by workers carrying their intermediate inputs to the firm where the machine is located, and paying the firm owner to let them perform the required production step with their machine.

Figure 8 then shows that thanks to the rental market, market-level capacity utilization is increased greatly. For each machine, we compute total hours supplied to the market using data on machines owned, and total hours demanded to the market summing up all the hours a given machine type is reported as being used by machine owners as well as renters.[31] This allows us to create a measure of market level capacity utilization. Thanks to the rental market, overall capacity utilization in carpentry (Panel A) is almost as high as capacity utilization in grain milling, which we discussed above is close to full capacity.

Finally, as expected, Figure 9 shows that the rental market is much more common for large and expensive machines.

Taken together, these findings show that: (i) there are large economies of scale in carpentry, driven by the indivisibility of large and expensive production machines; (ii) an active inter–firm rental market has emerged to alleviate the productivity costs of being small, at least partially; (iii) on the contrary, we do not document an active rental market in metal fabrication and grain milling, since the costs of being small are much less significant in those sectors.

3.3.2 Labor

Return to skills for the firm Turning to the labor input, we first examine the relationship between worker characteristics and firm profitability. As highlighted already above, Figure 4 shows that worker characteristics do not play a primary role in explaining differences in profits per worker, while usage of modern machines is the strongest predictor of profitability. We probe this further by running a regression of log profits per worker on the same (basic and

[30]In the rest of the cases, firms report to be renting the machines from intermediaries. We speculate thatin the majority of these cases the firms are renting from another business in the same sector, rather than from an intermediary specialized in machine rentals. A few reasons lead us to reach this conclusion: i) in our data, all machines are equally likely to be rented from another firm or from an intermediary, while we would expect proper intermediaries tospecialize in the more profitable machines; ii) within firm, there is no heterogeneity – i.e. either all machines are rented from an intermediary, or from another firm; iii) in practice, we have been able to find only very few workshops specialized in machine rentals in the areas covered by our survey.Overall, we conclude thatwe are likely underestimating the share of firms renting from other firms in the same sector.

[31]For these calculations we consider our entire sample as the market.

advanced) worker characteristics included in 4.[32] Our rich data allows us to control for a wide set of worker characteristics including also whether workers received any vocational training, and their cognitive ability as measured by a Raven matrices test. The results are reported in Table 3 for carpentry. Columns 1 and 2 show that there is a positive and strong relationship between average worker education and profits per worker; however, other worker characteristics do not have a significant coefficient, and if anything average tenure has a negative relationship with profits per worker. In Column 2 we add our measure of mechanization, that is the number of different machine types used in production of the core product. In line with Figure 4, we find this is a much stronger predictor of profits per worker than worker characteristics: the Adjusted R-squared more than doubles once we control for mechanization in Column 2. Columns 3 and 4 further control for sub-county fixed effects. This kills the relationship between worker education and firm profitability, while mechanization remains a very strong predictor.[33] Taken together, these results show that: (i) there is geographical sorting between highly educated workers and high profit firms, as indicated by the positive coefficient on average worker education in Columns 1 and 2; (ii) within sub-county, worker characteristics are only a weak predictor of profits per worker; (iii) mechanization is the strongest predictor of profits per worker.

Labor organization within the firm We next study the organization of labor within the firm, and in particular how this varies across the size distribution. Our rich data allows us to provide direct evidence on potential economies of scale driven by the labor input. We first document whether workers are more specialized in larger firms, as labor specialization is one potential channel leading to economies of scale in the labor input. Focusing on carpentry, the left panel of Figure 10 shows a non-parametric regression of the number of production steps that employees work on, regressed on firm size. While we do see some evidence of specialization, this is not strong: even in large firms the average employee tends to work on more than half of the production steps, that is far from the full specialization allocation. Another way in which the labor input could drive economies of scale is teamwork, that could allow a more efficient use of labor. We look for this in the middle panel of Figure 10, but again this shows very weak evidence of increasing team-work as the firm size grows: even in firms with 10-15 employees, 75% of the steps or even more are performed alone. Finally, a larger size might allow a more intense use of the labor input by reducing idle time (e.g. through better coordination of hours within the firm). The right panel in Figure 10 shows again weak evidence of this: workers spend close to 3 hours per day idle, and this does not vary much across the size distribution, except perhaps at the very top of the distribution.[34] In short, this evidence shows that any gains from

[32] We also control for firm characteristics in these regressions. The firm-level controls are: firm size, firm age, total value of capital stock owned and an index of managerial skills of the owner.

[33] Appendix Tables A2 and A3 show these results hold similarly for metal fabrication and grain milling.

[34] Figures A9 and A10 in the Appendix show similar results for metal fabrication and grain milling.

a more efficient organization of labor as firm size increases are limited, and so are unlikely to drive economies of scale.

Diseconomies of scale In fact, we argue that if anything our data is consistent with the presence of *diseconomies* of scale in the labor input. Table 4 reports the results of a Mincerian equation of worker monthly earnings in carpentry, controlling for sub-county fixed effects and clustering standard errors at the firm-level. The results in Column 1 show that worker characteristics *do* matter in important ways for worker earnings: we document a precisely estimated education gradient, as well as age and tenure profiles. Column 2 shows this is robust to controlling for hours worked. In Column 3 we add firm size as control, and the coefficient on this variable shows that larger firms pay significantly higher wages: a 1% increase in firm size is associated with a 0.2% increase in worker earnings.[35] Column 4 shows we get the same conclusion if we control for firm revenues instead of firm size, and this is robust to the inclusion of additional firm controls in Column 5.[36] Taken together, the evidence from Table 3 and 4 shows that: (i) worker skills are not a main driver of firm profits; (ii) the cost of labor is higher in larger firms as measured by either number of workers or revenues. If anything, this points to diseconomies of scale in the labor input.[37]

We further show that firms operate in a labor market with significant frictions, which further contribute to diseconomies of scale in labor. In particular, Table 5 shows that: (i) the majority of workers are recruited through referrals, which is by nature difficult to scale up as a recruitment method and symptomatic of labor market frictions; (ii) the main labor market friction is related to screening workers, rather than to lack of skilled labor *per se* of to difficulties in meeting workers;[38] (iii) in about a third of cases, the owner would be willing to raise workers' wages if they threatened to leave the firm; (iv) in line with the previous point, owners say that it would take them on average more than a month to find a replacement if their workers left; and (iv) turnover is very low in these firms despite the absence of any firing or hiring laws. In short, Table 5 shows labor market frictions are substantial in this context, and this is true across all sectors we study, thus further contributing to diseconomies of scale in the labor input.

[35]Note that all regressions in Table 4 control for sub-county fixed effects, so these results are not just capturing geographical sorting.

[36]The firm-level controls are: firm age, total value of capital stock owned and an index of managerial skills of the owner.

[37]Tables A4 and A5 show similar results for metal fabrication and grain milling.

[38]This is in line with recent experimental evidence on the importance of information frictions at recruitment in a number of African countries, including Uganda. See Abebe et al. (2018); Abel et al. (2019); Alfonsi et al. (2019); Bassi and Nansamba (2019).

3.4 Demand and Competition

As highlighted in Figure 1, while the average firm is small, there is substantial heterogeneity in firm size. In line with dispersion in firm size, we also find dispersion in total output (produced and sold). In this subsection we present descriptive evidence on the output market in which these firms operate, with an emphasis on the determinants of demand and the role of competition across firms. This informs us about the sources of differences in firm size, as well as about the structure of the output market. We then use this evidence to justify some of our modeling choices later in the paper. In short, the evidence suggests that: (i) demand is very local and highly segmented across space, and in line with this lack of demand is cited as an important constraint by firms; (ii) output price dispersion is limited, so that dispersion in revenues per worker is mostly driven by variation in quantity per worker rather than prices; (iii) price competition among firms is limited. Below, we present these key facts in more detail.

Demand is highly local In order to understand the determinants of demand, we ask firms what share of their sales in the three months preceding the interview was sold to final consumers (both domestic and foreign), subsidiaries of the firm, wholesalers/retailers, and the Government.[39] Across the three sectors, over 90% of sales were made to final consumers, and in the great majority of cases sales are made directly at the firm premises, which emphasises the local nature of demand. We further investigate the geographical sources of final consumer demand and find that the majority of customers originate from within the same parish as the firm (Figure 11a). Put differently, the empirical evidence suggests that output markets are highly segmented across space, and that firms in remote areas struggle to be profitable. In line with difficulties in finding customers, at least 50% of firm owners/managers report that the lack of demand is a relevant constraint to firm growth. This pattern is consistent across all three sectors included in the survey, and is depicted for the carpentry sector in Figure 11b.

Little price dispersion, high quantity dispersion In Figure 12 we investigate the extent of output price variation, both across firms and within firm. To do so, we focus on prices for the core product (e.g. two panel doors) produced by firms in the carpentry sector. We ask firms for the minimum (top panel), average (middle panel) and maximum prices (bottom panel) at which a unit of their core product was sold to final consumers in the last month. The unconditional price distribution for the minimum, average, and maximum sale prices are depicted on the left hand side of Figure 12, and show relatively little dispersion - the ratio of the 75th percentile to the 25th percentile of prices in each case is no larger than 1.50. The right hand panel of 12 shows the conditional minimum, average, and maximum sale prices for all main products in the

[39] Subsidiaries are defined as firms or wholesalers that have the same ownership as the interviewed firm.

top, middle and bottom panels (respectively).[40] The corrected price series constructed in this manner also report a similar degree of price dispersion. Notably, data on output prices suggests the presence of significant *within* firm price dispersion instead - with the maximum sale price reported to be 46% larger than the minimum sale price received by a firm on average. Price variation within the firm is driven mostly by bargaining with customers, that is reported as the main reason for price variation by firms.

While across-firm price variation is limited, we find substantial dispersion in revenues per worker. Figure 13 shows the distribution of monthly revenues per worker from sales of the core product (e.g. two panel doors) produced by firms in the carpentry sector. The unconditional revenue distribution from the sale of two panel doors (left hand panel) shows notable dispersion across firms - where firms at the 75th percentile earn almost five times the revenues (per worker) from two-panel door sales relative to firms at the 25th percentile. The right hand panel shows a residual revenue per worker estimate computed from revenues earned by firms for the sale of all main product types, which is then corrected for sub-county fixed effects, differences in product types, and an index for product quality. The corrected (or conditional) revenue per worker series constructed in this manner reports a lower (though still significant) dispersion across firms - where firms at the 75th percentile earn three times the revenues relative to firms at the 25th percentile.

Put together with the left and right hand panels of Figure 12 respectively, the dispersion in revenue per worker seems to be driven more by the dispersion in quantities sold by firms than by the spread in output prices. That is, some firms are able to produce and sell more of their products, while charging similar prices. This variation in quantity produced and sold is consistent with the local and segmented nature of demand discussed above.

Limited competition on prices Although the lack of demand is perceived to be an important constraint to firm growth, we do not find evidence consistent with firms engaging in intense price competition. For instance, our data shows that any engagement in marketing, advertising or price undercutting (in response to competition) remains very limited: only 9.6% of firms in the carpentry sector report strictly positive expenditures on marketing or advertising of their products, and the ones that do engage in marketing/advertising, mostly do so to increase sales rather than prices. In addition, when asked about the reasons leading to recent price cuts, less than 5% of firms report having done so as a response to competitive pressure from other firms, while the main reason (over 60% of cases) is bargaining with customers. This suggests that price competition across firms is limited.

Taken together, the evidence on the structure of the demand market and competition shows

[40]These price series are corrected for sub-county fixed effects, differences in core product types, and an index for product quality.

most of the variation in revenues is given by quantities rather than prices, as firms operate in an environment where output markets are segmented, with little competition on prices.[41]

3.5 An Efficient Sharing Economy?

We have provided direct evidence of economies of scale generated by the large capacity of modern machines. Especially in carpentry, machines are too large for the typical firm size, which could prevent small firms from adopting more advanced technology and hinder their productivity. However, we have also shown that an inter-firm rental market for machines has emerged, allowing small firms to access machines that they would otherwise find unprofitable to purchase. In other words, the rental market mitigates the risk of firms falling into poverty traps by allowing them to achieve scale *collectively*.

The data alone is, however, not enough to quantify the overall cost of small scale and how it is affected by the presence of a rental market. In fact, while the data clearly point out that the rental market mitigates the cost of small scale, it cannot be used to directly answer the key most important question, which is: "what fraction of the gains from scale are reaped collectively through the rental market?" In order to answer this question, we need to measure the costs or frictions that are associated with the inter-firm transactions that we have documented. For this purpose, in the next section we develop a model and estimate it with our data. The model will allow us to measure, through a revealed preferences approach, the transaction frictions and thus to quantify both the residual cost of small scale and the gains generated by the rental market.

4 Model

We develop a model consistent with the stylized facts documents in Section 3. We model the choice of managers that decide how much output to produce and, importantly, whether to produce it using labor or machines. The main focus of the model is to understand the role of the rental market for machines for aggregate productivity in the sector, and economies of scale. We thus build the most parsimonious model that allows us to address the question in the context of our data.

We first describe the environment of the economy and the problems solved by each agent and define a notion of competitive equilibrium in this setting. We then bring the model to the data, focusing on the estimation of the frictions in the rental and labor markets. Finally, we use the estimated model to perform counterfactuals and policy experiments.

[41] Limited competition in output markets is intuitively consistent with the presence of thick rental markets for capital inputs. In the presence of intense competition among firms, the leasing relationship (which requires coordination and cooperation among rival firms) may break down.

4.1 Economic Environment

Time is discrete, and the economy is static: we abstract implicitly from any consumption/savings decision, and from asset accumulation. This choice is driven by the nature of our data, which is made of only one cross-section. As we explain in details when we discuss our estimation strategy, some model primitives, in particular the shadow cost of capital r, capture, in a reduced form, the effect of past actions.

Agents and Individual Heterogeneity. The economy is inhabited by a mass μ of managers that differ along two dimensions i) the shadow cost of capital, r_i, which captures the fact that some individuals might have more asset for self-financing and/or might have access to better credit opportunities; ii) a demand shifter for the output their produce, ω_i, which captures differences across individuals in their managerial skills and other characteristics (such as social connections) that determine demand. To keep the notation light, we omit the i subscript throughout the description of the model.

Production Function. Production of one unit of the final good requires to fulfill a sequence of tasks $x \in [0, 1]$. Each task must be completed, or, in other words, the production functions is Leontief in the output of each individual production task. In order to complete a task x, the manager can use either only labor, or a step-specific Cobb-Douglas aggregator of labor and machine time. More specifically, the units of step x completed by a manager are given by

$$(1 - \mathbb{I}_{x\in\mathbb{M}})\, \lambda_x l_x + \mathbb{I}_{x\in\mathbb{M}} \mu_x k_x^{\alpha_x} l_x^{1-\alpha_x}$$

where $\mathbb{I}_{x\in\mathbb{M}}$ is an indicator function equal to 1 if x is in the set of tasks that the manager mechanizes – i.e. $\mathbb{M}$; l_x and k_x are labor and machine time used in step x; λ_x and μ_x are the step-specific productivities, and α_x is the step-specific capital share. We assume that λ_x, μ_x, and α_x are features of the production function which are identicial for all managers. For example, a step might require a long time if performed with only labor, while being fast if performed with machine, and requite a relatively large number of machine time relative to labor. Such a step, would have a low λ_x, and high μ_x and α_x.

Machines. Each task x has an associated machine. Machine x can be purchased at price $p_{x,b}$, where the subscript b is for buy. The purchase price $p_{x,b}$ includes all costs, both monetary and non-monetary that are associated with the purchase of a machine and that have to be paid upfront. Further, a machine x has a flow cost – equal to $\delta_x p_{x,b}$ – , which is the sum of depreciation and maintenance. Each machine x supplies 1 unit of time of production capacity,[42]

[42]In practice, in the data we observe weekly machine hours and thus we map the one unit of time into a full week worth of utilization, at 12 hours per day.

and machines are indivisible. Consistent with the empirical evidence, we allow each firm to purchase at most one machine of each type x, and we consider parametric restrictions such that this constraint never binds – i.e. μ_x is sufficiently large that even the largest firm can fulfill all demand of each step x with $k_x \leq 1$. As a result, if a manager of firm i purchase a machine x, that machine has a *within-firm excess capacity* equal to $1 - k_x \geq 0$.

Machines' Rental Market. The machine's excess capacity can be leased to other firms in a competitive market subject to two types of transaction frictions.

First, manager faces a convex cost $\chi(C_x; x, \mu)$ where C_x is the total capacity of machine x used, and μ is the mass of individuals in the market. We also let the convex cost to possibly differ across machines (hence x indexes χ). The convex cost has to be paid only if the manager decides to lease the machine. It should be interpreted as the cost of coordinating machine usage between own needs and renters time. Since the cost is to be paid only if the machine is rented and it depends on the total capacity utilization and not on the number of units lent, then some managers – consitent with evidence – might decide to not lease at all a given machine. The convex cost $\chi(C_x; x, \mu)$ is index by μ to capture the role of market size and machine indivisibility. In practice, in markets with very few individuals a manager that decides to buy one machine, might face not enough demand from renters. Since we are assuming that there is a *continuum* of individuals, this slack demand driven by machine's indivisibility is not directly captured in the model.[43] While working with a continuum of individuals provide tractability, we still like to capture – albeit in reduced form – the role of market size. We do so by having $\chi(C_x; x, \mu)$ decreasing in μ. For example, we can simply pick $\chi(C_x; x, \mu)$ such that if $\mu < \hat{\mu}_x$, then the cost of increase capacity beyond your own is infinite. As a result, in equilibrium, a rental market for machine x emerges only if $\mu \geq \hat{\mu}_x$.[44]

Second, each machine renter pays a transaction iceberg cost τ_x for each unit of machine used. τ_x captures the cost of moving inputs to the workshop or of waiting for machine usage. All costs are expressed in units of output.

The Managers' Problem. Managers maximize profits. Profit maximization entails to choose how much to produce and with which input mix. The choice of the input mix, includes several sets of decisions. For each task $x \in [0, 1]$, the manager decides whether to mechanize the task and, if the task is mechanized, how much capital and labor to use. For each mechanized task, the manager has also to choose whether to buy or rent the associated machine. $\mathbb{B} \subseteq \mathbb{M}$ and $\mathbb{R} \subseteq \mathbb{M}$ are the sets of tasks for which the manager chooses respectively to purchase or

[43] The reason is very simple. In equilibrium, there will be a small enough mass of machine's buyer, such that the rental market is non-slack. Effectively, we are not modeling the indivisibility of individuals.

[44] Yet, irrespective of μ, a manager faces the same direct cost to buy a machine, since cost of buying does not depend on market size.

rent the machine. We assume that the manager either buys or rent a given machine, which is consistent with evidence. As a result $\mathbb{B} \cup \mathbb{R} = \mathbb{M}$ and $\mathbb{B} \cap \mathbb{R} = \emptyset$. For each purchased machine $x \in \mathbb{B}$, the manager also has to decide whether to lease it to other firms and for how many hours. $\mathbb{L} \subseteq \mathbb{B}$ is the set of machines that the manager leases and $\{C_x\}_{x \in \mathbb{B}}$ is the overall capacity of each purchased machine, which must be weakly larger than the used capacity k_x. Summing up, the manager problem reads as

$$\pi(q, r) \equiv \max_{\mathbb{R}, \mathbb{B},\, \mathbb{L}, \{l_x,\, k_x\}_{x \in [0,1]}, \{C_x \geq k_x\}_{x \in \mathbb{B}}} p_y y - wL - (\bar{p}_r + \bar{\tau}) K_r - \bar{p}_b - \bar{\chi}_b + \pi_L$$

where

$$\begin{aligned}
p_y &= q y^{-\eta} P \\
y &= \min_{x \in [0,1]} \left\{ \max \left\{ \lambda_x l_x ; \mu_x k_x^{\alpha_x} l_x^{1-\alpha_x} \right\} \right\} \\
L &= \int l_x dx \\
\bar{p}_r &= \frac{\int_{\mathbb{R}} p_{x,r} k_x dx}{\int_{\mathbb{R}} k_x dx} \\
\bar{\tau} &= \frac{\int_{\mathbb{R}} \tau_x p_{x,r} k_x dx}{\int_{\mathbb{R}} k_x dx} \\
K_r &= \int_{\mathbb{R}} k_x dx \\
\bar{p}_b &= \int_{\mathbb{B}} (r + \delta^x) p_{x,b} dx \\
\pi_L &= \int_{\mathbb{L}} p_{x,r} (C_x - k_x) dx \\
\bar{\chi}_b &= \int_{\mathbb{L}} \chi_L (C_x; x, \mu) dx + \int_{\mathbb{B}} \chi_b (C_x; x, \mu) dx \\
w &= \omega L^{\frac{1}{\theta}} \\
\mathbb{L} &\subseteq \mathbb{B}
\end{aligned}$$

where p_i^y is the price of output;[45] y is total output; L is labor input; K_r is total rented capital input, and $\bar{p}_r$ and $\bar{\tau}$ are the average direct and indirect rental prices for one unit of capital; $\bar{p}_b$ is the total cost of all purchased machines, and π_L is the net profit from machine leasing,

[45]Notice that functional form for the price of output can be generate by a standard CES demand system, where we have shut down any equilibrium interaction – i.e. assuming that P is constant rather than being determined by the output choices of other firms. This assumption simplifies the computation and is consistent with the evidence in Section 3.

and $\bar{\chi}_b$ is the total capacity cost of all owner machines. The capacity cost is itself made of two components: χ_b is the (convex) capacity cost that has to be paid irrespective of whether a firm is leased or not, it should be interpreted as operatio and maintenance cost; χ_L is the additional (convex) cost to be paid if the firm leases out the machine, it should be interpreted as the cost of coordinating production time. Finally, notice that the firm faces an increasing labor supply curve, $w = \omega L^{\frac{1}{\theta}}$, where the parameter θ modulates labor market frictions, as we describe below.

The Workers' Problem. Workers supply labor to firms. We model all the workers as one aggregate family with utility function $U_w \equiv U(C, N)$ where

$$\begin{aligned} C &= \int w_j L_j dj \\ N &= \left(\int L_j^{\frac{\theta+1}{\theta}} dj \right)^{\frac{\theta}{\theta+1}}, \end{aligned}$$

j indexes all the jobs available, and we are assuming that there is no interaction between firms in our market. As a result, each firm simply faces – irrespective on the behavior of all other firms – an increasing labor supply curve – given by $w = \omega L^{\frac{1}{\theta}}$ – , where θ captures how steeply it increases.

This mathematical structure captures, in a parsimonious way, frictions in the labor market, while abstracting from any consumption inequality that they may generate. The parameter θ modulates the extent of the frictions. If $\theta \to \infty$, the labor aggregator N is simply the sum of labor supplied to all entrepreneurs, which leads in equilibrium to no wage dispersion across firms – i.e. each manager can hire as much labor as he wishes at the equilibrium wage. Instead, if θ is finite, then managers face an increasing labor supply curve, and they need to pay a higher wage in order to grow the firm size. As a result, there is wage dispersion across firms, and a size-wage premium – similarly to frictional labor models such as Burdett and Mortensen 1998. Therefore, the lower θ the stronger the degree of labor market frictions, and we can estimate θ in the data using the relationship between wage and firm size (conditional on other confounding controls). θ is going to be an important parameter, since the costlier it is for a firm to expand its labor force, the more firms will expand by mechanizing production steps.

4.2 Equilibrium

In equilibrium, managers maximize profits, and the rental market for machines clears. All the other markets are in partial equilibrium.

Machines' Rental Market Clearing. The set of machines that are supplied on the rental market is itself an equilibrium object, and it is given by $\bigcup_{i \in \Omega} \mathbb{L}_i$, where Ω is the set of managers

in the economy. For each leased machine, the price has to clear the market – i.e supply and demand of machine capacity have to be equal. Supply of machine's capacity in the rental market is given by the sum of the capacity chosen by all managers that decides to lend a given machine. Supply increases in the rental price, due to i) manager's capacity choice; ii) share of managers that, conditional on mechanizing, decide to buy rather than rent. Demand for machine's capacity in the rental market is given by the sum of all the managers that decide to mechanize the associated task, but not to purchase the machine themselves. Demand decreases in the rental price due to i) the higher the rental price the fewer managers decide to mechanize a given task; ii) the higher the rental price the fewer managers decide to access the machine through rental rather than purchase.

The equilibrium rental price, p_r^x, of each machine $x \in \bigcup_{i\in\Omega} (\mathbb{R}_i \bigcup \mathbb{L}_i)$ is such that demand and supply are equal:

$$\int_{\Omega} (C_{x,i} - k_{x,i} y_i) \, \mathbb{I}_{x\in\mathbb{L}_i(p_r^x)} di \quad = \quad \int_{\Omega} k_{x,i} y_i \mathbb{I}_{x\in\mathbb{R}_i(p_r^x)} di,$$

where $\mathbb{I}_{x\in\mathbb{L}_i(p_r^x)}$ and $\mathbb{I}_{x\in\mathbb{R}_i(p_r^x)}$ are indicator functions equal to 1 if manager i decides respectively to lease or rent machine x. As described, these sets are functions of p_r^x.

To conclude the section, we define the competitive equilibrium.

Definition of the Competitive Equilibrium. *The competitive equilibrium is given by firm-level output and total labor demand* $\{y_i, L_i\}_{i\in\Omega}$*; step-level capital and labor utilization for each firm* $\{l_{x,i}, k_{x,i}\}_{i\in\Omega, x\in[0,1]}$*; sets of machines that are mechanized, purchased, rented, and lent to other firms* $\{\mathbb{M}_i, \mathbb{B}_i, \mathbb{R}_i, \mathbb{L}_i\}_{i\in\Omega}$*; capacity utilization for each purchased machine* $\{C_{x,i}, \ \forall x \in \mathbb{B}_i\}_{i\in\Omega}$*; and rental price for each machine for which a rental market is active* $\{p_{x,r}\}_{x\in\bigcup_{i\in\Omega}(\mathbb{R}_i\bigcup\mathbb{L}_i)}$ *such that i) the rental market clears; ii) the workers' family maximizes utility; and iii) each manager* (q_i, r_i) *maximizes profits.*

4.3 Characterization and Numerical Solution

The general equilibrium of model does not entail an analytical solution. Nonetheless, we characterize, through a series of Lemmas proven in the appendix, some of its key properties. We then discuss how to solve the equilibrium and show a few numerical examples.

4.3.1 Analytical Characterization

We next describe a few key properties of the solution. We analyze the input choice within each production step and we work backward, first describing the relative input choice conditional

on mechanizing a step, and then looking at how machines are accessed and whether the firm decides to mechanize a specific step.

Lemma 1: Within Step Capital/Labor Ratio. *Consider a manager (q_i, r_i) that decides to mechanize task x – i.e. $x \in \mathbb{M}_i$. The ratio of capital to labor machine time in step x is given by*

$$\frac{k_x}{l_x} = \begin{cases} \left(\frac{w_i}{p_{x,r,i}(1+\tau_x)}\right)\left(\frac{\alpha_x}{1-\alpha_x}\right) & \text{if } x \in \mathbb{R}_i \quad \text{(rents)} \\ \left(\frac{w_i}{\chi_b'(k_x;x,\mu)}\right)\left(\frac{\alpha_x}{1-\alpha_x}\right) & \text{if } x \in \mathbb{B}_i \text{ and } x \notin \mathbb{L}_i \quad \text{(owns)} \\ \left(\frac{w_i}{p_{x,r,i}}\right)\left(\frac{\alpha_x}{1-\alpha_x}\right) & \text{if } x \in \mathbb{B}_i \text{ and } x \in \mathbb{L}_i \quad \text{(owns and leases)} \end{cases}.$$

Lemma 1 is directly implied by the fact that the within step production function is Cobb-Douglas in machine and labor time. The relative machine intensity differs across the types of machine access due to different marginal cost. In particular, the marginal cost of a renter is equal to the rental price multiplied by the transaction cost; the marginal cost of a machine owner that decides not to lease the machine is given by the marginal cost of increasing capacity utilization; and the marginal cost of a machine owner that leases the machine is given by the opportunity cost of machine time, hence by its rental price.

Lemma 2: Capacity and Leasing Choice. *Consider a manager (q_i, r_i) that decides to buy machine x – i.e. $x \in \mathbb{B}_i$. The optimal capacity is $C_{x,i} = \max\left\{k_{x,i}, \chi_r^{'-1}(p_{x,r}; x, \mu) + \chi_b^{'-1}(p_{x,r}; x, \mu)\right\}$, where $k_{x,i}$ is the machine time used by manager i, which does not depend on $p_{x,r}$, and $p_{x,r}$ is the equilibrium rental price. As a result, there is a cutoff rental price $\hat{p}_{x,r,i}$ such that manager i finds it optimal to lease some of the machine time and the leased capacity by firm i, i.e. $C_{x,i} - k_{x,i}$, is weakly increasing in $p_{x,r}$.*

The lemma shows two channels through which machine capacity supply increases in the rental cost of machine: i) the higher the rental price, the more managers would find it optimal to lease machine time; ii) the higher the rental price, the higher the capacity leased from each manager.

Lemma 3: Choice to Rent or Buy Machines. *Consider a manager (q_i, r_i) that decides to mechanize task x; i.e. $x \in \mathbb{M}_i$. There is a cost of capital cutoff $\hat{r}_i^x$ such that manager i decides to buy rather than rent machine x if and only if $r_i \leq \hat{r}^x$. The cutoff $\hat{r}_i^x$ is increasing in q_i and τ_x.*

The lemma highlights several key properties of the solution. First of all, it shows that, as expected, managers that face a cheaper cost of capital are more likely to purchase machines. Second, it clarifies the role of the transaction cost τ_x and its interaction with q_i. As long as τ_x

is positive, then the larger the quantity produced by a firm the higher the incentives to buy. The intuition is simple, the transaction cost τ_x plays the role of a variable cost.

A.1 Assumption on leasing cost (No specialized lenders) *We assume that the leasing coordination cost, χ, is sufficiently large that it is never convenient to buy a machine just to lease it on the rental market. Therefore, we assume that for all C_i^x*

$$(r_i + \delta^x)\, p_b^x \geq p_r^x C_i^x - \chi\left(C_i^x; x, \mu\right).$$

The implications of this assumption are consistent with the fact that, as we showed in Section 3, virtually no firm owns more than one machine of a given type.[46]

Lemma 4: Choice to Mechanize a Step. *Consider a manager (q_i, r_i). He decides to mechanize a task x if an only if*

$$w_i \quad \geq \quad \hat{w}_i\left(q_i, r_i, \frac{\mu_x}{\lambda_x}\right) \tag{1}$$

where $\hat{w}_i$ is decreasing in its three arguments.

Lemma 4 entails the main economic forces at play. The manager decides to mechanize a task only if machines are cheaper than labor. However, importantly, the relative cost of machine and labor is firms specific. In particular, managers that face higher demand or lower cost of purchasing capital have, in equilibrium and taking into account the optimal choice of machine access, a lower relative cost of machine inputs and thus are more prone to mechanize. The presence of the rental market implies that the relative factor prices, and thus the mechanization choice and ultimately the capital intensity depend not only on cost of capital, but on the overall market for a specific machine.

Another implication of this lemma is the presence of a machines' ladder. Even managers that face relatively low cost of labor and high cost of capital optimally decides to mechanize the tasks that are cheap to mechanize – i.e. have relatively high productivity of mechanization, $\frac{\mu_x}{\lambda_x}$ – high capital intensity firms, instead, mechanize a larger share of the overall tasks. As a result, the proper way to check the mechanization of a firm is to count the number of tasks that are mechanized, consistent with the empirical evidence.

[46]This assumption is necessary to prove some of the Lemmas below. In particular, if relax A.1 the relationship between mechanization and output would not hold since – for some parametrization – low q_i managers are more likely to mechanize than high q_i since they effectively specialize in renting out the excess capacity.

4.3.2 Numerical Solution

We solve the general equilibrium model numerically through an iterative procedure on machine rental prices.[47]

The solution entails policy functions that describe how each manager fulfills each production step. In Figure 14, we include the policy functions in the (q_i, r_i) for three parametrization which capture the features of some core machines used in carpentry. The left-panel shows the policy function for a machine that has the same characteristics of drills: inexpensive, yet useful in production. Since drills are inexpensive, only a few firms, either with very low demand, or very high cost of capital, decide to rely on labor to complete the production steps for which drills are used. Also, only few firms decide to lease out drills since their low price makes the transaction cost in the rental market relatively expensive. Instead, the majority of managers simply decide to buy and use drills. The middle-panel shows the case of machines like thickness planers. Thickness planers are expensive, have high capacity, and are difficult to be substituted with labor. For these reasons, only a few firms purchase a thickness planer, while most firms rent it. The right-panel shows the case for a step that is relatively cheap to be completed with labor. One example is wood drying: most firms dry their wood under the sun, and only very few use the machine to speed up wood drying, the electric cylinder.

4.4 Bringing the Model to the Data

We next bring the model to data. We first explain how we can use the model and data together to estimate the size of the frictions in the rental and labor markets. We then describe how we calibrate the production function. Finally, we discuss how we solve numerically and estimate the overall model.

4.4.1 Frictions in the Rental Markets

Consider the choice of a manager that decides to mechanize the production step x. The manager would choose a ratio of labor and capital input to minimize production cost. As shown in Lemma 1, the relative input ratio must satisfy the following restriction

$$\frac{\hat{p}_x k_x}{w l_x} = \frac{\alpha_x}{1-\alpha_x} \tag{2}$$

where w is the wage, and $\hat{p}_x$ is the marginal cost of one unit of capital for step x. The marginal cost of one unit of capital depends on how the manager access the capital. If the manager access machine x through the rental market, then $\hat{p}_x = (1+\tau_x)\, p_{x,r}$, where $p_{x,r}$ is the rental price and τ_x the wedge. If the manager purchases machine x, then the marginal cost is equal

[47] Details are included in Appendix **??**.

to $\hat{p}_x = p_{x,r}$ if the machine is leased and to the marginal cost of capacity, $\chi_b^{'}(k_{x,i}; x, \mu)$, if the machine is not leased.

Since we assume that all managers face an identical production technology, comparing within-step capital labor ratio of managers that rent and lease a given machine allows us to pin down the wedge τ_x. Specifically, consider a manager i that rents machine x, and a manager j that purchases and leases machine x, then the following relationship holds

$$\frac{(1+\tau_x)\, p_{x,r} k_{x,i}}{w_i l_{x,i}} = \frac{p_{x,r} k_{x,j}}{w_j l_{x,j}}.$$

Rearranging and taking logs gives the equation

$$\underbrace{\log k_{x,j} - \log k_{x,i}}_{\text{capital gap}} = \underbrace{\log(1+\tau_x)}_{\text{rental wedge}} + \underbrace{\log(w_j) - \log(w_i)}_{\text{wage gap}} + \underbrace{\log(l_{x,j}) - \log(l_{x,j})}_{\text{labor gap}}. \tag{3}$$

The gap in machine utilization between a machine owner/leaser and a machine renter depends on the size of the wedge, the difference in the marginal cost of labor (wage) and the difference in labor usage. Equation (3) motivates the empirical specification

$$\log k_{x,i} = \alpha_0 + B_x X_{x,i} + \gamma_x R_{x,i} + \varepsilon_i \tag{4}$$

where X_i is a set of controls, and R_i is a dummy equal to 1 if firm i is rents machine x. The estimate coefficient γ pins down the size of the rental wedge as follows $\tau_x = \exp(-\gamma) - 1$.

We run regression (4) separately for each step including a rich set of controls, including firm and manager characteristics, sub-county fixed effects, controls on the type and quantity of products, and machines. The results are shown in columns (1)-(7) of Table (6). For all steps but one, the estimated γ_x are negative, significant, and economically large. Since the estimated magnitudes across steps are similar, in column (8) we pool all the steps together – thus effectively assuming that the rental wedge is constant – and include a machine fixed effect. The estimated coefficient ($\hat{\gamma} = -0.558$) implies a large wedge on the rental market: the estimated wedge is equal to 75% of the direct rental price.

Ideally, we should run specification (4) including only firms that either rent or lease a machine. However, we do not machine level information on whether a given machine is leased. The concern is that we might overestimate the size of wedge, since firms that own, but do not lease, a machine have marginal cost of machine time equal to 0. We expect that the rich set of controls attenuate the concern. In fact, through the lens of our model, controlling for firm size and overall output would be sufficient to properly identify the size of the wedge. Consistent with this view, when we limit the set of firm-level controls, as we do in column (9), the estimated wedge increases. Finally, column (10) includes the most stringent specification, which includes

firm-level fixed effect, thus estimating the the rental wedge by comparing, within firm, the relative utilization of machines that are rented or owned. Even in this case, the estimated coefficient ($\hat{\gamma} = -0.33$) is sizable, and corresponds to a wedge of 40%. Overall, we conclude that while the rental market dramatically improves the overall capacity utilization of machines, it is nonetheless plagued by sizable frictions.

4.4.2 Frictions in the Labor Markets

Estimating frictions in the labor market is simple. The model generates a relationship between average firm wage and firm size which can be directly estimated in our data across firms

$$\log w_i = \log \omega + \frac{1}{\theta} \log L_i. \tag{5}$$

In practice, we estimate specification (5) with a rich set of controls to capture other possible determinants of firm wage – most importantly, workers' ability.

The results of the regression are shown in Table (4), and imply a value of θ equal to 5. For comparison, recent work by Berger et al. (2019), estimates, using United States data, a similar within market labor friction, given by 3.74.

4.4.3 Calibration of the Step-by-Step Production Function

In order to calculate the benefits of the rental market, and the cost of its frictions, we need to calibrate the production function of output. Recall that we assume the following functional form for the production function

$$y = \min_{x \in [0,1]} \left\{ \max \left\{ \lambda_x l_x; \mu_x k_x^{\alpha_x} l_x^{1-\alpha_x} \right\} \right\},$$

which is Leontief across production steps, but allowing the manager to fulfill each step either with labor only or with a combination of labor and machine time. The structure of production is motivated by the empirical evidence, and in particular by the following two observations: i) the overwhelming majority of firms complete all production steps; ii) within steps, some firms use only labor, while others use both labor and machines. Further, we assume that labor and machine time aggregate through a Cobb-Douglas with step specific capital share, given by α_x. Overall, we need to estimate, for each step, three parameters: i) the productivity of performing the step only with labor λ_x; ii) the productivity of performing the step with labor and machines μ_x; iii) the capital share α_x. As discussed in Section (3), we argue that is plausible to assume that all managers face similar $(\lambda_x, \mu_x, \alpha_x)$, while the differences in skills are mostly captured by differences in demand q_i.

The Cobb-Douglas assumptions allows us to rely on firm-level maximization to compute the

capital share α_x. As already shown in equation (2), the functional form assumption implies that step-level ratio of expenditures in capital and labor inputs directly pins down α_x. While the result relies on the properties of the Cobb-Douglas, the insight is more general: if machines are relatively important for a given step, then the manager will spend a high share of input costs for that steps for machine time. In practice, we do not directly observe the marginal cost of machine time $\hat{p}_x$. However, as discussed, our model shows that marginal cost is equal to the equilibrium rental rate for firms that own and lease machine x. In practice, for each step x, we restrict the sample to the firms that mechanize the step and that own the associated machines. We then calculate for this set of firms the ratio of capital and labor expenditures, and we use the median across firms to calculate α_x. Table (7) shows the results. The median across firms for each steps are in column (3): for most step, the median firm spends a similar amount for machine and labor input. Column (6) includes the implied α_x: for most steps, the estimated capital share is approximately 50%, which strikes us as a reasonable value for manufacturing. For comparison, column (4) includes the median capital/labor expenditure ratio for machine renters, calculated using the same marginal price of capital, $p_{x,r}$, as for firm owners. At fixed prices, the relative capital expenditures are lower for renters, consistent with the fact that their marginal cost is higher than the rental price since it includes also the rental wedge τ_x. This result highlights the importance of distinguishing between machine owners and renters. We might be concerned that firm-step level capital/labor expenditure ratios are estimated with large amount of noise. For this reason, in column (5) we first calculate the average capital expenditure across all machine owner, and then divide it by the average labor expenditure in that step. This second approach provides similar results.

Finally, we need to compute the relative productivity of performing a step with labor or with labor and capital together.

4.4.4 Estimation of the Full Model

We parametrize the joint distribution of managers over (r_i, q_i) and we estimate the model through simulated method of moments.

[Work in progress]

4.5 Counterfactuals and Policy Analysis

[Work in progress]

5 Conclusion

[TBD]

References

Abebe, Girum, Stefano Caria, Marcel Fafchamps, Paolo Falco, Simon Franklin, and Simon Quinn, "Anonymity or Distance? Job Search and Labor Market Exclusion in a Growing African City," 2018, *mimeo.*

Abel, M., R. Burger, and P. Piraino, "The Value of Reference Letters - Experimental Evidence from South Africa," *American Economic Journal: Applied*, 2019, *forthcoming.*

Acemoglu, Daron, Ufuk Akcigit, Harun Alp, Nicholas Bloom, and William Kerr, "Innovation, reallocation, and growth," *American Economic Review*, 2018, *108* (11), 3450–91.

Akcigit, Ufuk, Harun Alp, and Michael Peters, "Lack of selection and limits to delegation: firm dynamics in developing countries," Technical Report, National Bureau of Economic Research 2016.

Alfonsi, Livia, Oriana Bandiera, Vittorio Bassi, Robin Burgess, Imran Rasul, Mushi Sulaiman, and Anna Vitali, "Tackling Youth Unemployment: Evidence from a Labor Market Experiment in Uganda," 2019, *mimeo.*

Bandiera, Oriana, Robin Burgess, Narayan Das, Selim Gulesci, Imran Rasul, and Munshi Sulaiman, "Labor Markets and Poverty in Village Economies," *The Quarterly Journal of Economics*, 2017, *132* (2), 811–870.

Banerjee, Abhijit, Esther Duflo, Nathanael Goldberg, Dean Karlan, Robert Osei, William Parienté, Jeremy Shapiro, Bram Thuysbaert, and Christopher Udry, "A multifaceted program causes lasting progress for the very poor: Evidence from six countries," *Science*, 2015, *348* (6236), 1260799.

Banerjee, Abhijit V and Esther Duflo, "Do Firms Want to Borrow More? Testing Credit Constraints Using a Directed Lending Program," *The Review of Economic Studies*, 2014, *81* (2), 572–607.

Barro, Robert J and Jong Wha Lee, "A new data set of educational attainment in the world, 1950–2010," *Journal of development economics*, 2013, *104*, 184–198.

Bassi, Vittorio and Aisha Nansamba, "Screening and Signaling Non-Cognitive Skills: Experimental Evidence from Uganda," *mimeo*, 2019.

Bento, Pedro and Diego Restuccia, "Misallocation, establishment size, and productivity," *American Economic Journal: Macroeconomics*, 2017, *9* (3), 267–303.

_ and _ , "On Average Establishment Size across Sectors and Countries," Technical Report, National Bureau of Economic Research 2018.

Berger, David W, Kyle F Herkenhoff, and Simon Mongey, "Labor Market Power," Technical Report, National Bureau of Economic Research 2019.

Bloom, Nicholas, Aprajit Mahajan, David McKenzie, and John Roberts, "Why do firms in developing countries have low productivity?," *American Economic Review*, 2010, *100* (2), 619–23.

Buera, Francisco J, Joseph P Kaboski, and Yongseok Shin, "Finance and development: A tale of two sectors," *American economic review*, 2011, *101* (5), 1964–2002.

Foster, Andrew D and Mark R Rosenzweig, "Are there too many farms in the world? Labor-market transaction costs, machine capacities and optimal farm size," Technical Report, National

Bureau of Economic Research 2017.

Hardy, Morgan and Jamie McCasland, "Are Small Firms Labor Constrained? Experimental Evidence from Ghana," 2017, *mimeo.*

Jensen, Robert and Nolan H Miller, "Market Integration, Demand, and the Growth of Firms: Evidence from a Natural Experiment in India," *American Economic Review*, 2018, *108* (12), 3583–3625.

Jr, Robert E Lucas, "On the size distribution of business firms," *The Bell Journal of Economics*, 1978, pp. 508–523.

Mel, Suresh De, David McKenzie, and Christopher Woodruff, "Returns to Capital in Microenterprises: Evidence from a Field Experiment," *The Quarterly Journal of Economics*, 2008, *123*, 1329–1372.

_ , _ , and _ , "Labor Drops: Experimental Evidence on the Return to Additional Labor in Microenterprises," *American Economic Journal: Applied Economics*, 2018, *forthcoming.*

Porta, Rafael La and Andrei Shleifer, "Informality and development," *Journal of Economic Perspectives*, 2014, *28* (3), 109–26.

Porzio, Tommaso and Gabriella Santangelo, "Does Schooling Cause Structural Transformation?," 2019.

Poschke, Markus, "The firm size distribution across countries and skill-biased change in entrepreneurial technology," *American Economic Journal: Macroeconomics*, 2018, *10* (3), 1–41.

Tables

Table 1: Sample size

	N. of Firms identified in listing	N. of Firms screened for survey eligibility in listing	N. of Firms selected for survey	N. of Firms interviewed in survey	N. of Employees reported by owner/manager	N. of Employees interviewed in survey
	(1)	(2)	(3)	(4)	(5)	(6)
All sectors	2,916	2,702	1,127	1,115	3,185	2,854
Carpentry	1,487	1,381	518	516	1,340	1,196
Metal fabrication	1,171	1,092	441	433	1,259	1,112
Grain milling	258	229	168	166	586	546

Notes: The Table provides information on firm coverage and the final sample of firms and employees obtained in our survey. Column 1 describes the number of firms identified in each sector through a comprehensive listing of all firms (in carpentry, metal fabrication and grain milling) conducted in the 177 sampled parishes. Each firm identified in the listing was asked to participate in a few screening questions (e.g. firm size) to determine eligibility for the final survey. Column 2 provides the number of firms that completed the screening questions across the three sectors, which was approximately 93% of firms identified in the listing (Column 1). Column 3 shows the number of firms that were selected to participate in the survey by random extraction from the firms in the listing with complete screening information. This number is close to 1,000, which conforms to our initial calculations. Column 4 reports the number of firms that agreed to participate in the full survey, and demonstrates a very high compliance rate of around 99% among firms included in the final sample (Column 3). In each participating firm we surveyed the owner as well as all the employees working on our pre-selected core products (one for each sector). The total number of employees working on the core products, as reported by firm owners or managers, is shown in Column 5. The total number of employees that agreed to participate in the full survey are further reported in Column 6 (approximately 90% of employees reported in Column 5).

Table 2: Basic descriptives

	All sectors	Carpentry	Metal fabrication	Grain milling
	(1)	(2)	(3)	(4)
Panel A: Firm characteristics				
Number of employees	4.7	4.6	4.8	4.8
Value of capital stock owned (USD)	1981.3	1700.6	1686.2	5894.8
Average monthly revenues (USD)	1515.8	1200.7	1816.4	2154.2
Average monthly profits (USD)	273.0	219.4	347.6	239.4
Average monthly profits per worker (USD)	52.4	43.7	66.1	37.8
Firm age (years)	9.9	10.3	9.0	11.7
Firm has trading licence (%)	82.2	76.7	85.7	89.8
Panel B: Owner characteristics				
Owner age (years)	39.2	39.1	37.8	48.2
Owner years of education	9.9	9.9	10.0	9.9
Hours (usual) worked per day for the firm	9.4	9.8	9.3	7.0
Panel C: Employee characteristics				
Employee age (years)	28.0	29.0	26.3	30.5
Employee years of education	9.4	8.9	10.2	8.0
Employee tenure (years)	3.5	3.5	3.3	3.8
Hours (usual) worked per day for the firm	9.8	9.7	10.0	9.8
Employee monthly wage (USD)	70.9	73.2	71.3	50.0

Notes: The Table provides basic descriptive statistics across the three sectors regarding a range of firm, owner and employee characteristics in Panels A, B and C respectively. The statistics reported are calculated for the average firm. Figures reported in US dollars are in nominal terms, and were converted from Ugandan shillings (UGX) to US dollars (USD) using an exchange rate of 3,800 UGX/USD.

Table 3: Relationship between worker characteristics and profitability in carpentry

Characteristics of Av. Employee	(1) Log Profit pw	(2) Log Profit pw	(3) Log Profit pw	(4) Log Profit pw
Years of Schooling	0.062***	0.052**	-0.007	-0.004
	(0.023)	(0.021)	(0.020)	(0.019)
Age	-0.010*	-0.003	-0.001	-0.000
	(0.005)	(0.004)	(0.005)	(0.004)
Years of Experience at the Firm	-0.043**	-0.050***	-0.023*	-0.031**
	(0.017)	(0.015)	(0.014)	(0.014)
Has received vocational training	0.037	0.009	0.134	0.124
	(0.166)	(0.143)	(0.142)	(0.130)
Cognitive Score	0.059	0.057	0.033	0.050
	(0.047)	(0.040)	(0.041)	(0.037)
No. of Machine Types Used		0.139***		0.087***
		(0.011)		(0.011)
Observations	512	512	511	511
Adjusted R^2	0.141	0.319	0.512	0.564
Subcounty FE	No	No	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
F-test on worker traits: pvalue	0.000	0.000	0.408	0.000
F-test on firm controls: pvalue	0.000	0.000	0.000	0.000

Notes: OLS regression coefficients. Robust standard errors are reported in parenthesis. *** (**) (*) denotes significance at the 1% (5%) (10%) level. OLS regressions of log profits per worker on select covariates corresponding to the average employee in a firm are reported in Columns 1 and 3. Column 3 allows for sub-county fixed effects, whereas Column 1 does not. A measure of mechanization, i.e. the number of different machine types used in the production of the core product, is included in the regression specifications presented in Column 2 (with no sub-county FE) and Column 4 (which includes sub-county FE). All four regressions consist a set of firm controls including firm size, firm age, total value of capital stock owned and an index of managerial skills of the owner. P-values from F-tests on worker characteristics (for the average employee) and firm controls are presented in the second last and last row of the table.

Table 4: Mincerian earnings regression in carpentry

Employee Characteristics	(1) Log Earnings	(2) Log Earnings	(3) Log Earnings	(4) Log Earnings	(5) Log Earnings
Years of Schooling	0.024***	0.024***	0.021***	0.021***	0.020***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
Age	0.036***	0.048***	0.048***	0.047***	0.044***
	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)
Age Squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure at the Firm	0.020***	0.013**	0.012**	0.011**	0.015**
	(0.006)	(0.006)	(0.006)	(0.005)	(0.007)
Vocational Training	0.007	0.035	0.039	-0.029	-0.019
	(0.066)	(0.066)	(0.065)	(0.062)	(0.061)
Cognitive Score	0.022	0.025	0.031	0.030	0.035*
	(0.023)	(0.022)	(0.021)	(0.020)	(0.019)
Usual Hours Worked		0.365***	0.324***	0.265**	0.243**
		(0.121)	(0.121)	(0.109)	(0.119)
Log Firm Size			0.198***		
			(0.069)		
Log Firm Revenues				0.258***	0.217***
				(0.040)	(0.045)
Observations	1,050	1,050	1,050	1,050	1,050
Adjusted R^2	0.209	0.213	0.224	0.278	0.288
Subcounty FE	Yes	Yes	Yes	Yes	Yes
Other Firm Controls	No	No	No	No	Yes

Notes: OLS regression coefficients. Standard errors are clustered at the firm level, and are reported in parentheses. *** (**) (*) denotes significance at the 1% (5%) (10%) level. The Table reports results of a Mincerian equation of worker monthly earnings (on a log scale). Column 1 focuses on the contribution of employee traits to earning levels, and Column 2 shows that this effect is robust to controlling for hours worked. Column 3 includes an additional control for firm size, and shows that larger firms pay significantly higher wages (a 1% increase in firm size is associated with a 0.2% increase in worker earnings). Column 4 further demonstrates we get the same results by controlling instead for firm revenues, and that this is robust to the inclusion of additional firm controls in Column 5. Each of the five columns includes controls for sub-county fixed effects. Hours workers, firm size, and monthly firm revenues are in log scale. Tenure is in years, and vocational training is an indicator variable

Table 5: Labor market frictions

	Carpentry (1)	Metal fabrication (2)	Grain milling (3)
Lack of employees with right skills is a serious problem	28%	25%	29%
Finding workers with right skills is a serious problem	32%	27%	31%
Screening workers at recruitment is a serious problem	35%	37%	36%
Number of employees who left in the last six months	0.57	0.62	0.68
Share of firms with no workers leaving in last six months	76%	72 %	76%
Share of workers hired through referrals	54%	59%	46%
Would offer wage rise to keep current workers from leaving	36%	33%	28%
Number of days taken to replace a worker if he leaves	42	44	27

Notes: The Table provides a few summary statistics to suggest sizable frictions in the labor markets for our three sectors. Each row corresponds to a different question asked to firm owners. Rows 1-5 report averages across firms. Rows 6-9, instead, reports averages across all employees, since the manager answer the question separately for each employee in the firm.

Table 6: Estimates of Wedges in Rental Market for Machines in Carpentry

Dependent variable: Log Monthly Machine Hours										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Step 3	Step 4	Step 5	Step 6	Step 7	Step 8	Step 9	Pooled	Pooled	Pooled Firm FE
Machine is Rented (Yes = 1)	-0.635***	-0.880***	-0.587*	-0.709***	-0.724**	-0.491**	0.203	-0.558***	-0.757***	-0.333***
	(0.171)	(0.219)	(0.315)	(0.166)	(0.295)	(0.195)	(0.230)	(0.110)	(0.114)	(0.083)
Observations	472	309	251	485	125	361	183	1,728	1,728	1,728
Adjusted R^2	0.260	0.430	0.345	0.324	0.440	0.336	0.287	0.347	0.263	0.728
Machine FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No	No	No	No	Yes
Subcounty FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Log Wage Bill Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Firm and Manager Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Product Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Machine Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weighted	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No

Notes: OLS regression coefficients with Standard errors clustered by firm in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. OLS regression coefficients. Regressions are at the machine-level, and include all machines in the data used in steps 3-9 of the production process for doors. The dependent variable throughout is the log of total monthly machine hours used in a given production step. Columns 1 to 7 break the sample of machines by the step in which they are used. In Columns 8-10 instead we use the full sample of machines. The main independent variable of interest is a dummy equal to one if the machine is rented, and zero otherwise. Firm and Manager controls include an index of managerial quality; we also control for the log of total monthly wage bill used in the production step, where this is calculated using information on total monthly labor hours used in a given production step together with information on the hourly wages of employees assigned to a given step. Product controls include: Log quantity of doors produced in the last month; total number of products produced in the last month; a dummy for whether the main product of the firm is two-panel doors, our pre-defined core product; an index of output quality. Machine level controls include: Number of machines of a given type usd in the production step; log current value of the machine; age of the machine in years; expected remaining life of the machine in years; a dummy for whether the machine was manufactured abroad. Columns 1-7 are weighted by the intensity of machine usage in a given step, so that machines that are more common in a given step get higher weight for that step.

Table 7: Step-Level Capital Intensity in Carpentry

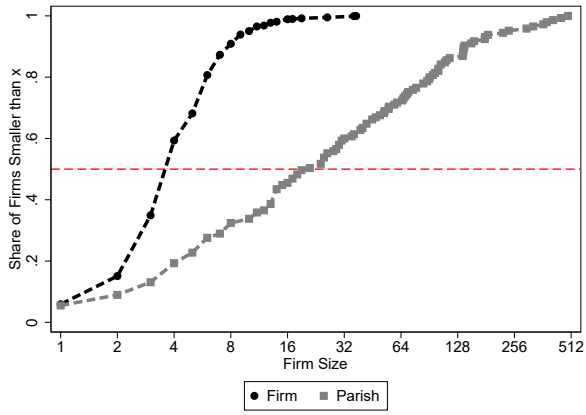
	Share of Firms performing step with modern machines	Share of Firms performing step with modern machines that are owned	Median Capital Labor Ratio for Owners	Median Capital Labor Ratio for Renters	Ratio of across-firm Average Capital to across-firm Average Labor for owners	α	λ	μ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Step 3 - Cutting	57%	17%	1.31	0.91	1.73	0.57		
Step 4 - Plaining	57%	11%	1.25	0.60	1.19	0.55		
Step 5 - Thicknessing	53%	9%	0.60	0.67	1.08	0.37		
Step 6 - Edging	55%	15%	0.73	0.68	1.28	0.42		
Step 7 - Sanding	23%	10%	3.11	1.14	4.24	0.74		
Step 8 - Mortising	50%	16%	0.93	0.56	1.11	0.48		
Step 9 - Finishing	37%	21%	0.88	0.59	0.98	0.47		

Notes: For the statistics in column 2, we consider a firm as owning the modern machines used in a given step if they own all the machines used in that step. For the statistics in column 3 we first compute the capital labor ratio within each firm for a given step, and then take the median of this ratio across firms. To compute the capital labor ratio we proceed as follows. For the numerator, we first calculate for each firm the total hours of modern machine time used in a given step per month. We price this at the average hourly machine rental rate, where average rental rates are computed using information on all machines rented in our data. Hourly machine rental rates are calculated at the machine level and so vary machine by machine. For the denominator, we use the total monthly labor hours used by the firm in the production of a given step. These also are priced at the average hourly wage as calculated using information on all employees in our sample. We take the ratio of monthly capital expenditure to monthly labor expenditure for each step, and report the median value. In column 3 we do this only for firms that own all the machines used in the production of a given step. In column 4 we do this only for those firms that are renting at least part of the machines used in the production of a given step. The way we price labor and capital in column 3 and 4 is the same. Column 5 is similar to column 3 but there instead we first compute the average of the numerator across firms, and the average of the denominator across firms, and then compute their ratio. Column 6 reports the implied median values of α, as calculated from column 3.

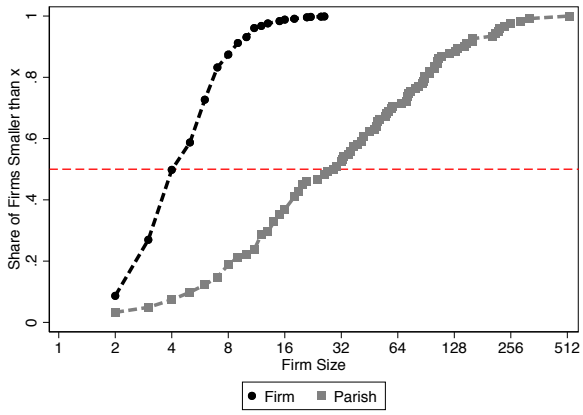
Figures

Figure 1: Firm size distribution in initial listing

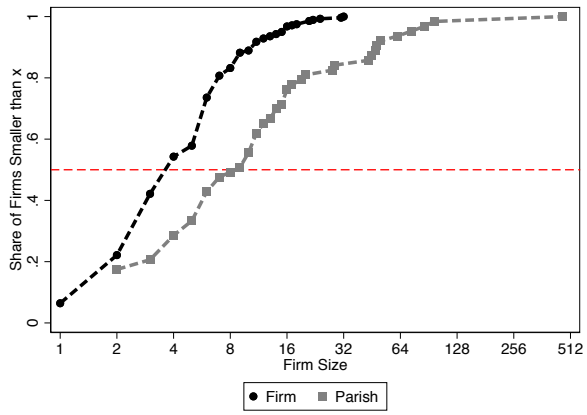
(a) Carpentry



(b) Metal Fabrication



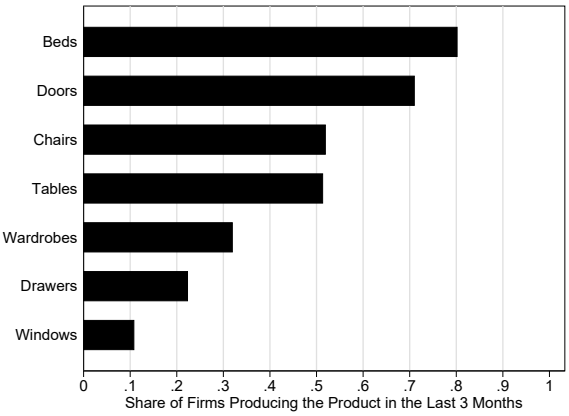
(c) Grain Milling



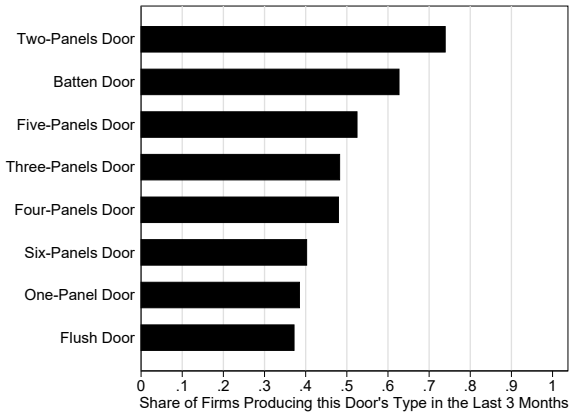
Notes: The Figure reports the CDF of firm size in the three sectors covered by our survey. The sample includes all firms identified in the initial firm listing. The black line is the CDF of individual firm size, where size is the total number of employees, plus the firm owner. The gray line is the CDF of firm size at the parish level, that is, by summing the firm sizes on all the firms operating in the same sector and in the same parish. The horizontal red line is drawn at the 50th percentile. The x-axis is in log-scale.

Figure 2: Share of firms in carpentry producing a given product

(a) Types of products

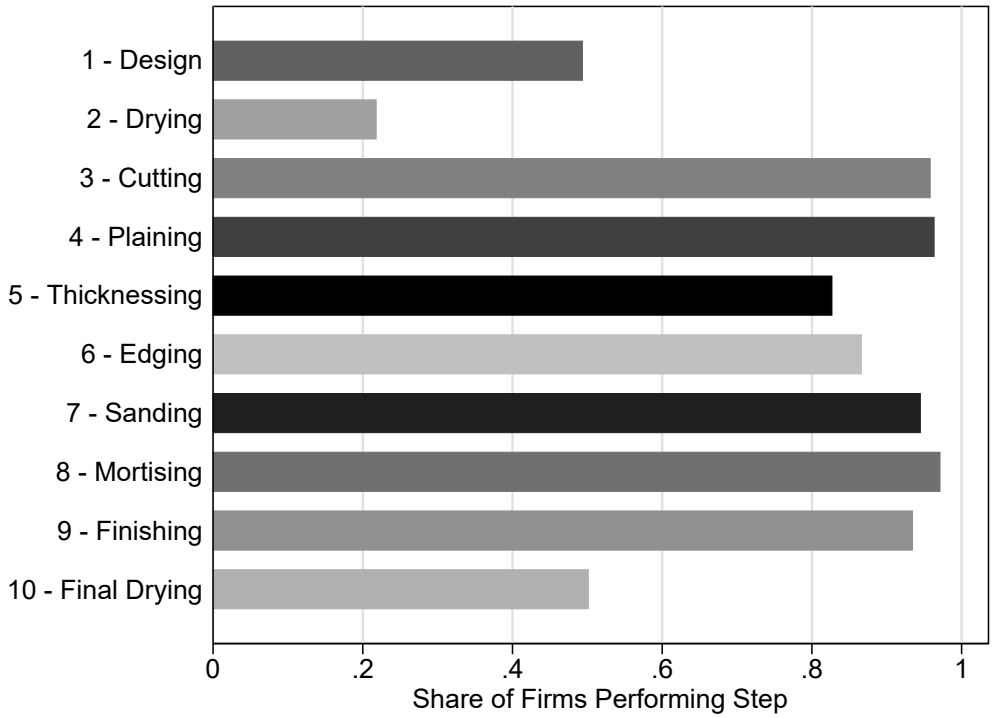


(b) Types of doors



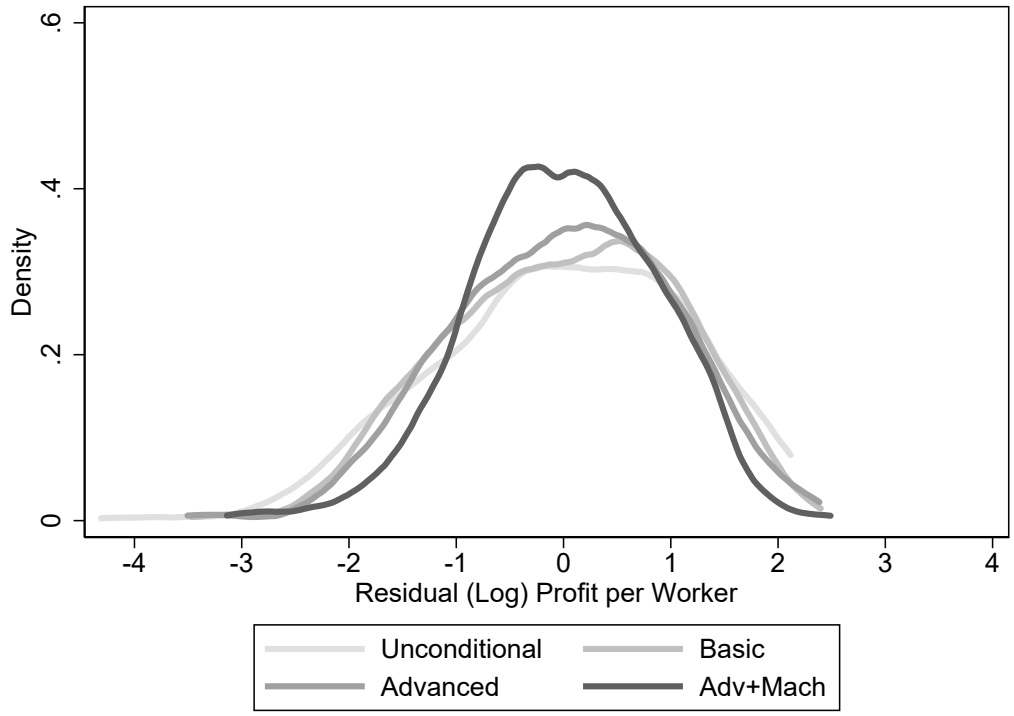
Notes: The figures reports the share of firms surveyed in the carpentry sector which produced various types of standard products (listed on the y-axis) in the 3 months preceding the survey. The left figure (2a) shows that firms within the sector typically produce similar products. The right figure (2b) shows that two panel doors, which is our main product for the carpentry sector, is produced by the majority of door-producing carpentry firms. The product was selected ex-ante.

Figure 3: Share of firms in carpentry performing a given step for the production of 2-panel doors



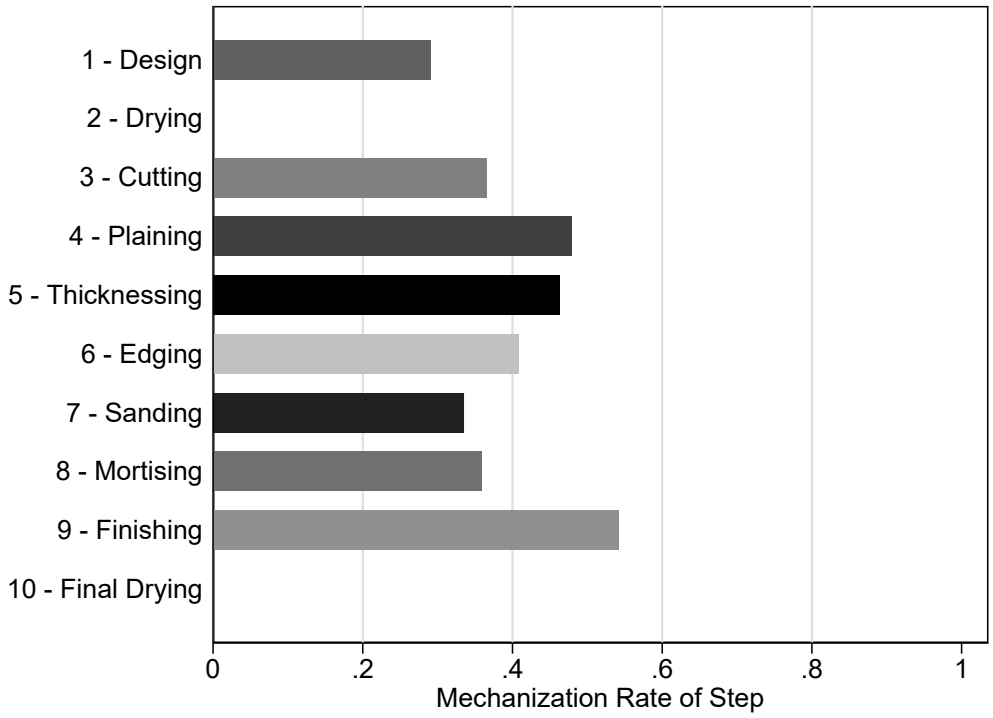
Notes: For each of 3 sectors covered in the survey (i.e. carpentry, welding and maize milling) we selected one core product (ex-ante) and categorized its production process into a series of steps. The steps were compiled prior to the roll-out of the survey. The main product identified in the carpentry sector was two-panel doors which is produced by the majority of door-producing carpentry firms. The Figure displays the share of carpentry firms (on the x-axis) that perform the identified steps (enumerated on the y-axis) in the production of two-panel doors. It shows that most firms producing the same product employ very similar production steps.

Figure 4: PDF of residual profits per worker in carpentry



Notes: The Figure shows the Probability Density Function (PDF), or distribution, of residual (log) profits per worker in the carpentry sector. The unconditional distribution of profits per worker (lighter grey line) shows a very wide dispersion - firms at the 75th percentile are over five times more productive than firms at the 25th percentile. Much of the variation in profits per worker is unexplained by controlling for basic firm, owner and employee observable characteristics (light grey line) such as firm size and age, owner age and education, and employee age, education and experience. The inclusion of more advanced controls (dark grey line) such as owners' cognitive and managerial skills, and employees' cognitive skills, vocational training and on the job training account for some of the variation, though not much more. The largest portion of observed variation in profits per worker is explained by the extent to which the production steps are mechanized. The darker grey line represents the distribution of profits per worker when controlled for advanced characteristics and mechanization.

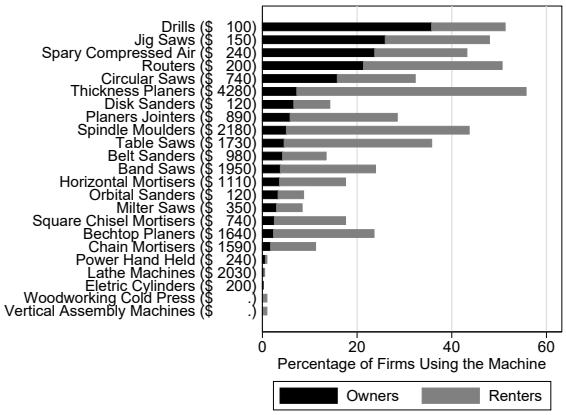
Figure 5: Mechanization rate of production steps in carpentry



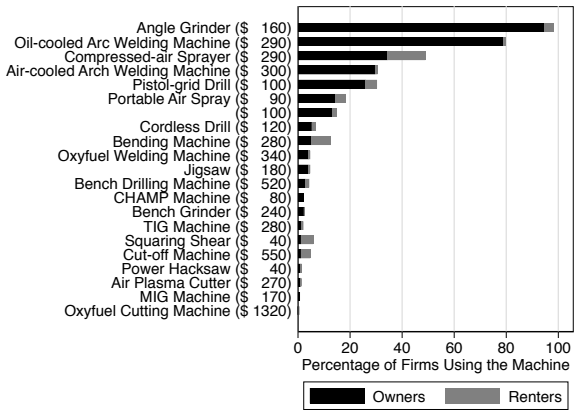
Notes: The Figure shows the rate of mechanization (x-axis) of each production step (y-axis) identified for the core product in the carpentry sector (i.e. two-panel doors). The rate of mechanization of a production step is defined as the number of different machine types employed by a firm divided by the number of different machine types used for that step by the most mechanized firms (top 5%) observed in the data. The data suggests that there is substantial variation in the mechanization rates across steps: while most firms are involved in all production steps, they vary in the extent to which they perform such steps using modern machines.

Figure 6: Usage of modern machines by ownership vs rentals

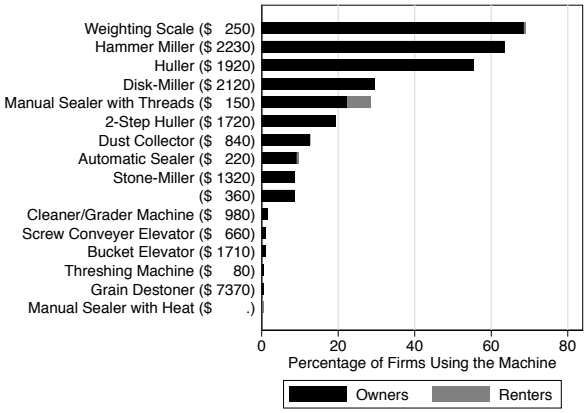
(a) Carpentry



(b) Metal Fabrication



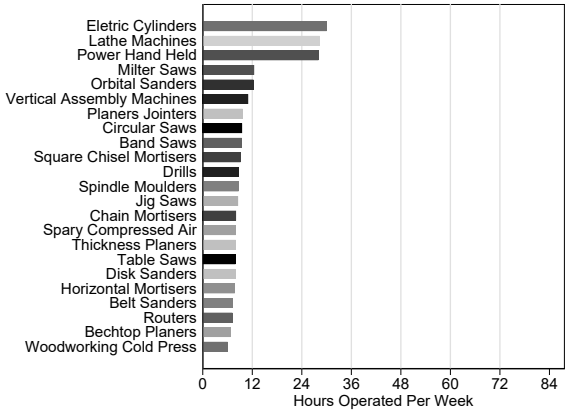
(c) Grain Milling



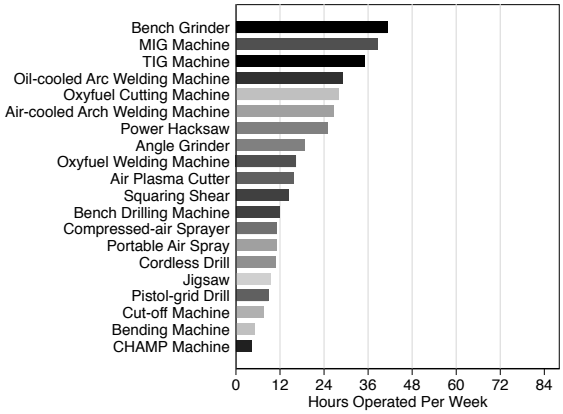
Notes: The Figure decomposes the percentage of firms that use a machine in the carpentry (Sub-Figure 6a), metal fabrication (Sub-Figure 6b) and grain milling (Sub Figure 6c) sectors among those firms that own the machine (black) and those that rent it (grey). Machines used in the production of the core products in the various sectors (e.g. two-panel doors in the case of carpentry) are listed on the y-axis, whereas the percentage of firms using these machines is displayed on the x-axis. The top-most graph shows that in carpentry there is clear evidence of an active rental market for machines, whereas in metal fabrication (middle) and grain milling (bottom) the rental market is either very thin or non-existent.

Figure 7: Hours firm uses the machine per week, conditional on usage

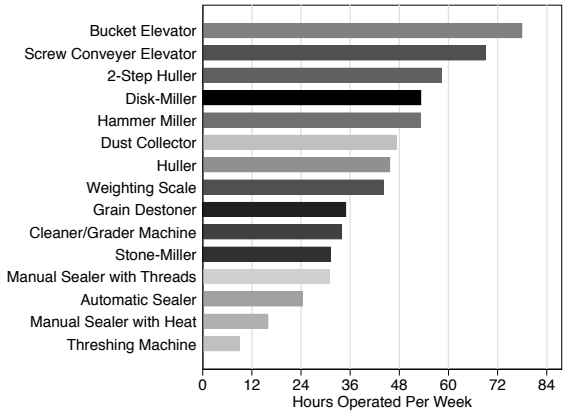
(a) Carpentry



(b) Metal Fabrication



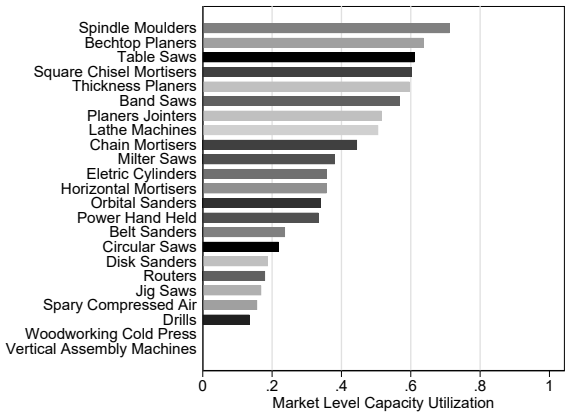
(c) Grain Milling



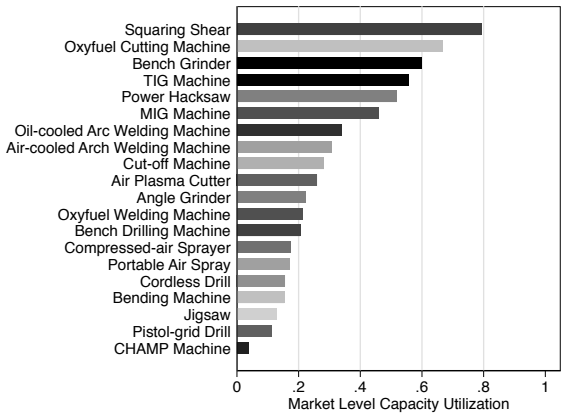
Notes: The Figure reports the average hours that machines are operated per week (conditional on usage) for the production of core products across the three sectors. Machine types are listed on the y-axis, and the hours of operation per week are shown on the x-axis. Sub-Figure 7a (top panel) and Sub-Figure 7b (middle panel) suggest that excess capacity is very high in carpentry and metal fabrication: the average (median) machine is used by a firm for about 4 (8.5) hours per week in carpentry, and for about 9 (18) hours per week in metal fabrication. Capacity utilization is much higher in grain milling (Sub Figure 7c, bottom panel), where the average (median) machine is used for 48 (45) hours per week (at almost full capacity).

Figure 8: Market level capacity utilization of machines

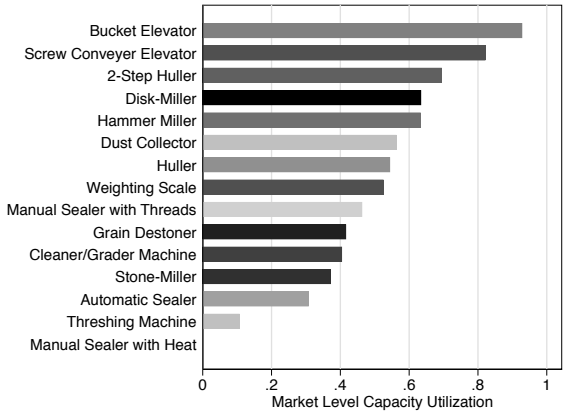
(a) Carpentry



(b) Metal Fabrication

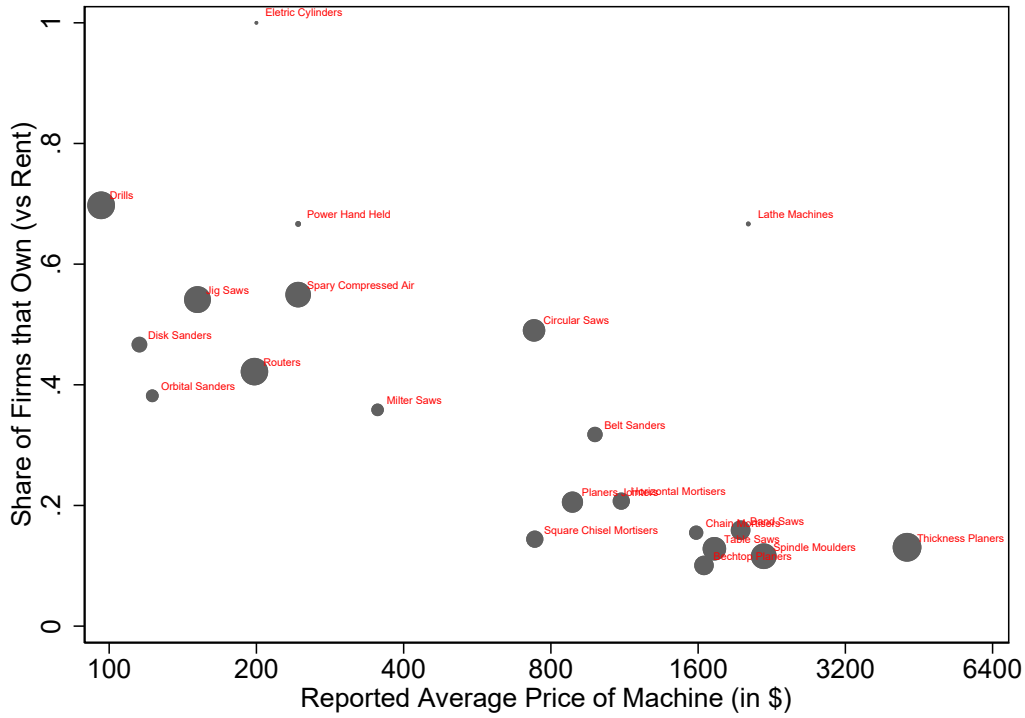


(c) Grain Milling



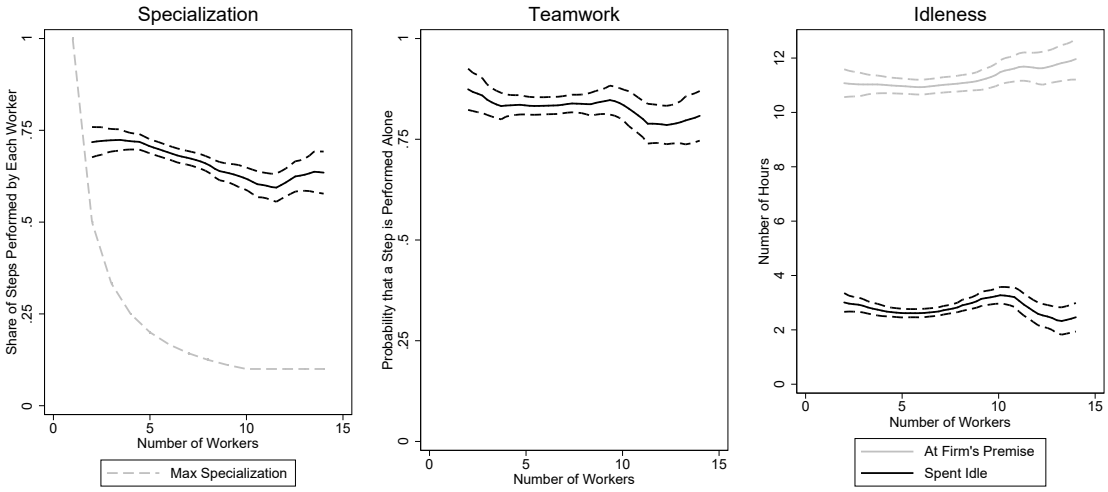
Notes: This Figure displays the market level capacity utilization of machines used in the production of core products in carpentry (Sub-Figure 8a), metal fabrication (Sub-Figure 8b) and grain milling (Sub-Figure 8c). The three sector panels demonstrate the role of the machine rental market (see Figure 6) in increasing the capacity utilization of machines (see Figure 7) at the market level. For a given machine, market-level capacity utilization (depicted on the x-axis) is calculated using data on total hours supplied to the market relative to total hours demanded by the market. Hours supplied is computed from data on machine ownership, whereas hours demanded is a summation of machine usage (in hours) reported by firms that either own or rent machines. Notably, the presence of a thick rental market in the carpentry sector (Figure 6) contributes to comparable market-level machine capacity utilization levels in the carpentry (top panel) and grain milling (bottom panel) sectors, even though the firm-level machien capacity utilization is much lower in carpentry.

Figure 9: Share of firms in carpentry that rent vs own as a function of machine price



Notes: This Figure shows that rentals are most common for more expensive machines in the carpentry sector. It depicts a strong negative correlation between the share of firms that own (vs. rent) machines (shown on the y-axis), and the reported average price of machines in US dollars (shown on the x-axis). Data points for the various machine types are scaled in proportion to their usage by carpentry firms in the production of two-panel doors (see: Sub-Figure 6a).

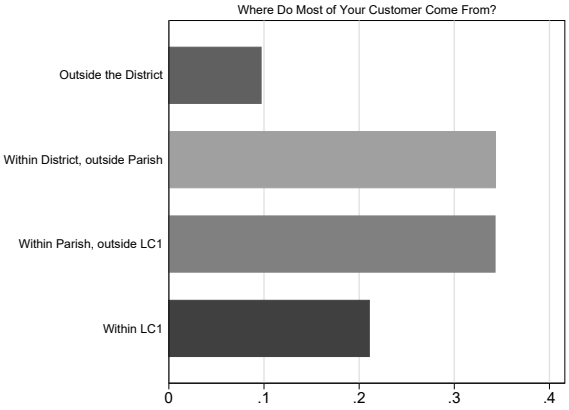
Figure 10: Organization of labor across the size distribution in carpentry



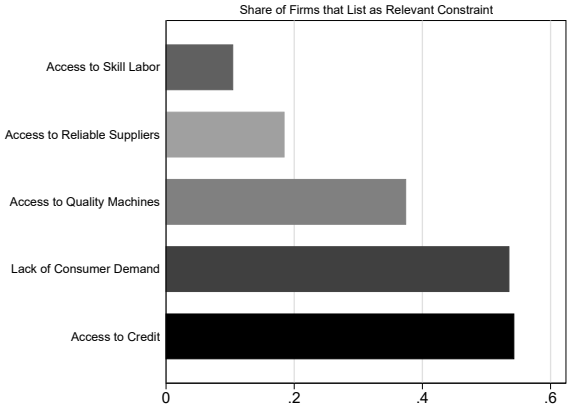
Notes: The Figure shows how the organization of labour varies with firm size in the carpentry sector. The black curve in Panel A (on the left-hand side) shows the mean share of production steps performed by each worker conditional on firm size. The conditional mean function was obtained through a non-parametric regression, and the 95% confidence interval is depicted using the black dotted line (here firm size is measured by the number of workers employed). The grey dotted curve shows the the minimum share of steps that each worker has to complete given the total number of steps (10) and the firm size on the x-axis. It serves to highlight a large gap between observed patterns of labour organization and full specialization - even among the largest firms. Panel B (in the middle) explores the possible contribution of teamwork in driving economies of scale. The graph plots the probability that a production step is performed alone (on the y-axis) against the number of workers (x-axis). It shows that even in firms with 10-15 employees, at least 75% of the steps are performed alone. Panel C (right-hand side) further investigates whether larger firm size is associated with a more intensive use of labour inputs, as measured by lower idle time among workers. The solid grey curve represents the average number of hours spent by workers at a firm's premises, and the solid black curve represents the average number of hours spent idle by workers employed (both mean functions are conditional on firm size). The graph shows that workers spend close to 3 hours/day idle, and this does not vary much across the size distribution, except at the very top. The dotted lines represent 95% confidence intervals in both cases.

Figure 11: Role of Demand in Carpentry

(a) Sources of Final Consumer Demand

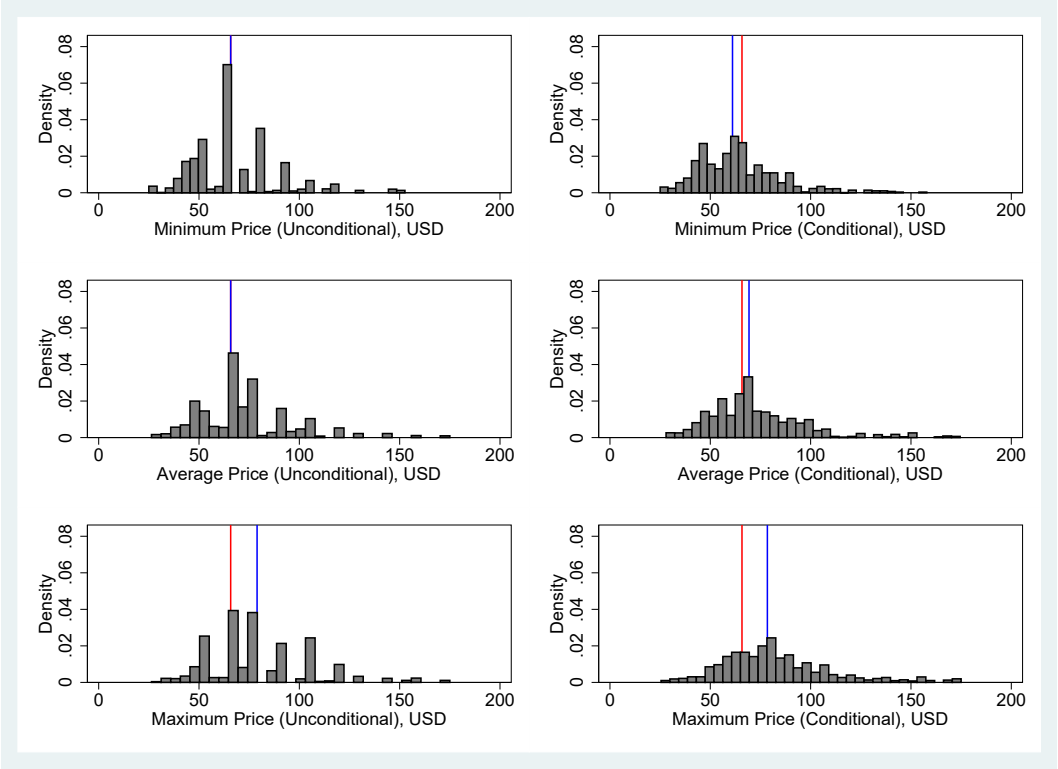


(b) Perceived Constraints to Firm Growth



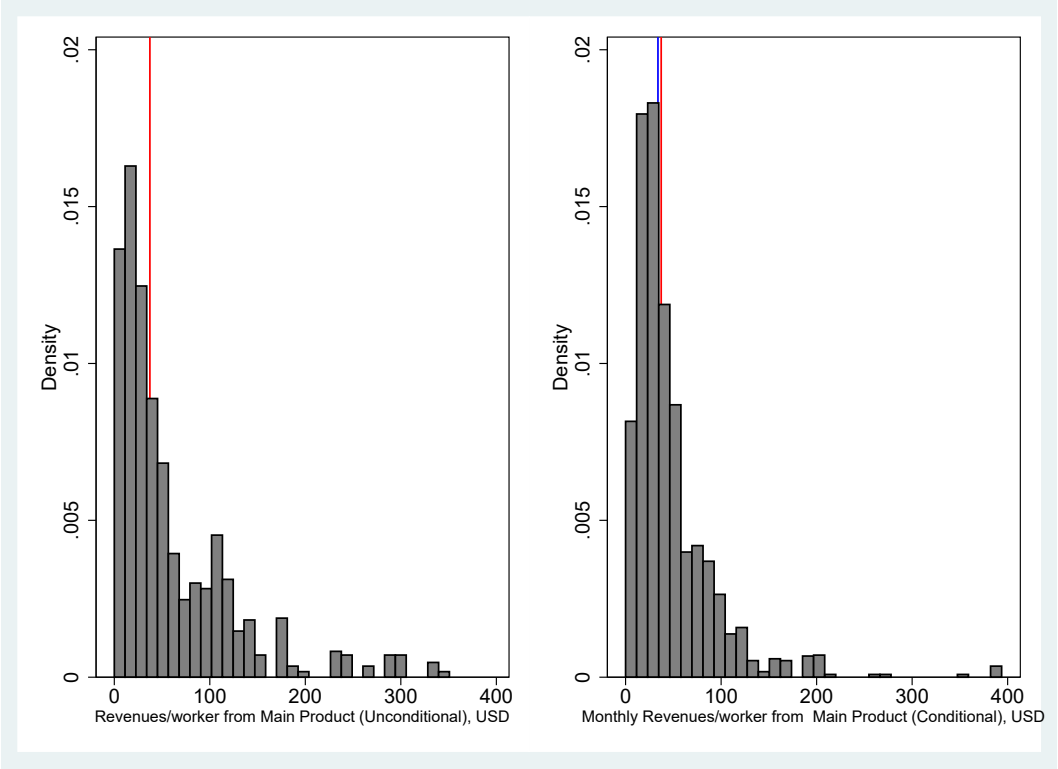
Notes: Figure 11a represents the geographical sources of final consumer demand. The share of final consumers (shown on the x-axis) originating from outside the district or within the same district as the firm (shown on the y-axis) is depicted in the bar chart. A district is sub-divided into administrative units known as parishes, which are further split up into Local Councils (LC 1). The figure decomposes the sources of final consumer demand among these four mutually exclusive categories, and shows that the majority of customers originate from within the same district as the firm (i.e. the summation of the bottom three categories). Figure 11b reports the share of firms (on the x-axis) in the carpentry sector which list various factors (listed on the y-axis) as relevant constraints to increasing the profitability of their business. Firms report the top three challenges faced by them in this regard. The graph shows that at least fifty percent of the firms list the lack of consumer demand as a significant challenge.

Figure 12: Distribution of Minimum, Average and Maximum Output Prices (Main Product, Carpentry Sector)



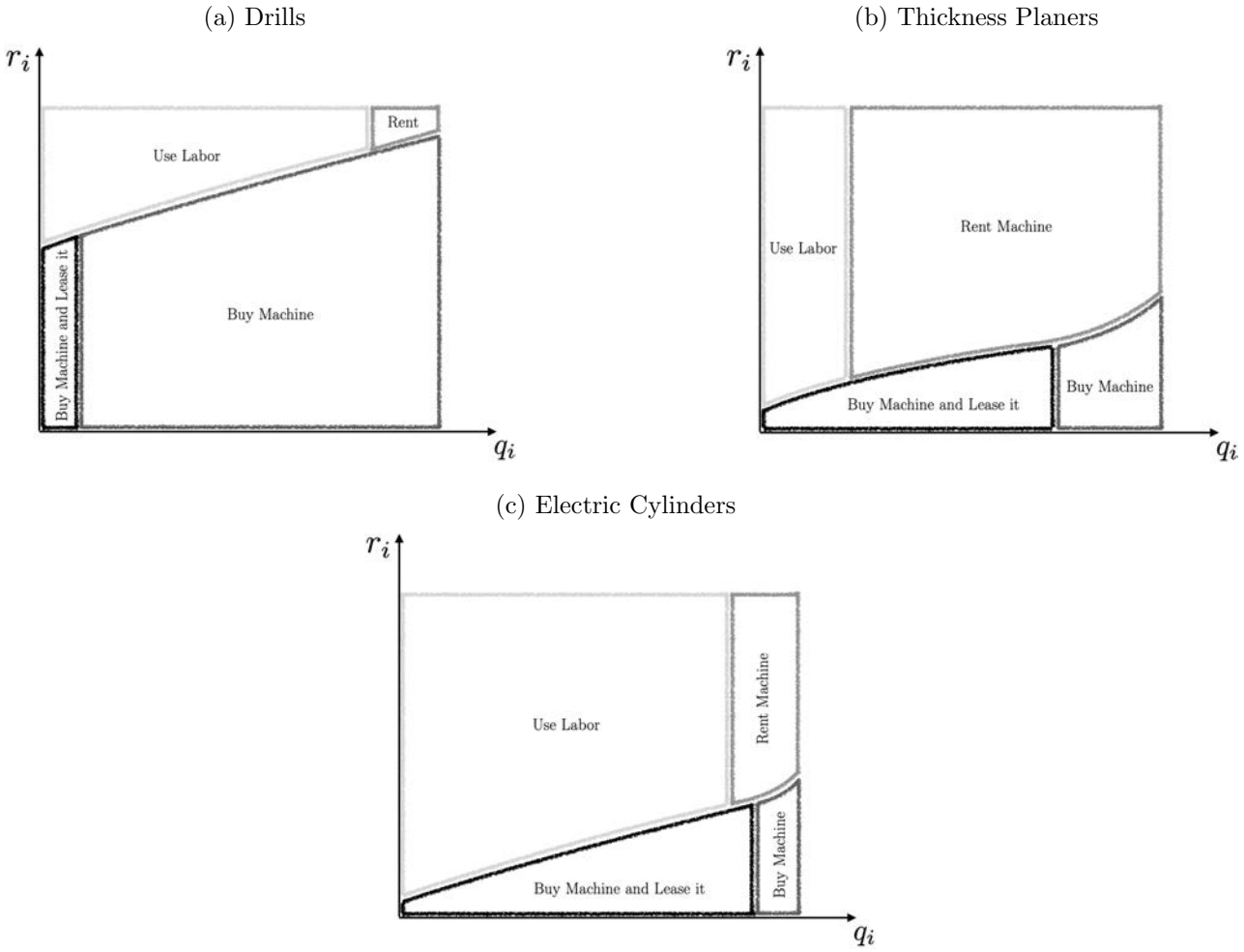
Notes: The figure demonstrates the distribution of output prices for the core product (e.g. two panel doors) produced by firms in the carpentry sector. We ask firms for the minimum (top panel), average (middle panel) and maximum prices (bottom panel) at which a unit of their core product was sold to final consumers. The red vertical line corresponds to the median unconditonal average price for two panel doors across all six panels, whereas the blue vertical line depicts the median corresponding to each series (captioned under the x-axis in each case). In the case(s) where these two medians coincide, only the blue vertical line is visible. The unconditional price distribution for the minimum, average, and maximum sale prices of two panel doors are depicted on the left hand side of the figure, and shows some (though limited) dispersion across firms - the ratio of the 75th percentile to the 25th percentile in each case is no larger than 1.50. The right hand panel shows the minimum, average, and maximum sale prices for all main products in the top, middle and bottom panels (respectively). These price series are corrected for sub-county fixed effects, differences in product types, and an index for product quality. The corrected (or conditional) price series constructed in this manner also reports price dispersion of a similar order of magnitude (the 75th/25th percentile ratios for each of these series is also approximately 1.50). For purposes of this graph, each of these price series has been winsorized at 25 USD below and 175 USD above to correct for outliers.

Figure 13: Distribution of Revenue per Worker (Main Product, Carpentry Sector)



Notes: The figure demonstrates the distribution of monthly revenues per worker earned from sales of the core product (e.g. two panel doors) produced by firms in the carpentry sector. The red vertical line corresponds to the median unconditional revenues earned from the sale of two panel doors across both panels (in per worker terms and US dollars), whereas the blue vertical line depicts the median corresponding to the conditional revenue estimate and is shown only in the right hand panel. The unconditional revenue distribution from the sale of two panel doors (left hand panel) shows notable dispersion across firms - where firms at the 75th percentile earn almost five times the revenues (per worker) from two-panel door sales relative to firms at the 25th percentile. The right hand panel shows a residual revenue per worker estimate computed from revenues earned by firms for the sale of all main product types, which is then corrected for sub-county fixed effects, differences in product types, and an index for product quality. The corrected (or conditional) revenue per worker series constructed in this manner reports a lower (though still significant) dispersion across firms - where firms at the 75th percentile earn three times the revenues relative to firms at the 25th percentile. Put together with the left and right hand panels of Figure 12 respectively, the dispersion in revenue per worker seems to be driven (weakly) more by the dispersion in quantities sold by firms than the spread in output prices.

Figure 14: Policy Functions for Three Machines



Notes: The Figure shows the policy functions in the (r_i, q_i) space for three production steps whose associated machines that have primitive characteristics, in the model, that capture the key features of drills; thickness planers; and electric cylinders. The policy functions divide the (r_i, q_i) space – r_i is the cost of capital and q_i is the firm demand – into four regions, which describe how the step is completed by different managers. The managers in the "Use Labor" region, rely only on labor to fulfill the step. The ones in the "Rent Machine" region, use a modern machine, and access it through the rental market. The ones in the "Buy Machine and Lease it" region, purchase a modern machine, use it for production, and lease out the excess capacity. Finally, the ones in the "Buy Machine" region purchase the modern machine, but do not lease it out to other firms.

A Details about Sampling Strategy

[Work in Progress]

B Appendix Tables and Figures

Table A1: List of ISIC sectors by share of employment in firms of size 5+

ISIC (1)	Activity (2)	# Firms (3)	# Firms (5+) (4)	Avg Size (5+) (5)	Empl share (5+) (6)
2511	Manufacture of structural metal products	3172	832	12.11	0.023
1072	Manufacture of sugar	9	7	1276.14	0.021
3100	Manufacture of furniture	5470	952	8.78	0.019
114	Processing and preserving of fruit and vegetables	2178	915	8.05	0.017
1061	Manufacture of grain mill products	2609	524	13.17	0.016
1077	Tea Processing	27	25	265.08	0.015
1071	Manufacture of bakery products	2317	257	22.43	0.013
3290	Other manufacturing n.e.c	162	113	32.21	0.008
1410	Manufacture of wearing apparel, except fur apparel	13281	324	8.94	0.007

Notes: This Table includes the list of manufacturing sectors with the highest overall employment share in establishments with 5 or more employees. The statistics are calculated using the Census of Business Establishments, conducted by the Ugandan Bureau of Statistics (UBOS). Sectors with ISIC codes 2511, 3100, and 1061 are the three sectors that we selected. They are the sectors with the highest employment share, once we exclude Manufacture of sugar, for which we had very few firms, and Processing and preserving of fruit and vegetables, that we found included many farms, rather than manufacturing establishments.

Table A2: Relationship between worker characteristics and profitability in metal products

Av. Employee's Characteristics	(1) Log Profit PW	(2) Log Profit PW	(3) Log Profit PW	(4) Log Profit PW
Years of Schooling	0.057**	0.033	0.006	-0.001
	(0.028)	(0.026)	(0.025)	(0.024)
Age	-0.010	-0.012*	-0.013	-0.013*
	(0.010)	(0.007)	(0.008)	(0.007)
Experience at the Firm (in Yrs.)	0.008	0.011	0.036	0.022
	(0.035)	(0.031)	(0.031)	(0.030)
Has received vocational training	-0.407	-0.355	-0.118	-0.147
	(0.257)	(0.248)	(0.206)	(0.204)
Cognitive Score	0.198***	0.211***	0.116**	0.127***
	(0.059)	(0.053)	(0.047)	(0.047)
No. of Machines Types Used		0.338***		0.194***
		(0.031)		(0.038)
Observations	422	422	422	422
Adjusted R^2	0.075	0.297	0.421	0.470
Subcounty FE	No	No	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
F-test on worker traits: pvalue	0.001	0.001	0.076	0.000
F-test on firm controls: pvalue	0.060	0.000	0.000	0.000

Notes: See Table 3 in the main text, which shows the same regressions for carpentry.

Table A3: Relationship between worker characteristics and profitability in grain milling

Av. Employee's Characteristics	(1) Log Profit PW	(2) Log Profit PW	(3) Log Profit PW	(4) Log Profit PW
Years of Schooling	0.033	0.022	-0.035	-0.032
	(0.039)	(0.039)	(0.034)	(0.034)
Age	0.011	0.016	0.010	0.011
	(0.013)	(0.012)	(0.012)	(0.012)
Experience at the Firm (in Yrs.)	0.030	0.038	0.011	0.016
	(0.041)	(0.040)	(0.037)	(0.037)
Has received vocational training	-0.366	-0.677	-0.057	-0.201
	(0.667)	(0.683)	(0.650)	(0.640)
Cognitive Score	0.194**	0.114	0.104	0.062
	(0.095)	(0.097)	(0.083)	(0.086)
No. of Machines Types Used		0.305***		0.167
		(0.085)		(0.114)
Observations	157	157	156	156
Adjusted R^2	0.109	0.169	0.377	0.386
Subcounty FE	No	No	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
F-test on worker traits: pvalue	0.184	0.392	0.325	0.957
F-test on firm controls: pvalue	0.004	0.000	0.980	0.145

Notes: See Table 3 in the main text, which shows the same regressions for carpentry.

Table A4: Mincerian earnings regression in metal fabrication

	(1) Log Earnings	(2) Log Earnings	(3) Log Earnings	(4) Log Earnings	(5) Log Earnings
Years of Schooling	0.012	0.013*	0.013*	0.012	0.009
	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)
Age	0.041***	0.041***	0.042***	0.046***	0.047***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Age Squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure at the Firm	0.039***	0.038***	0.034***	0.030***	0.029***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Vocational Training	0.115	0.108	0.107	0.089	0.061
	(0.075)	(0.076)	(0.076)	(0.076)	(0.077)
Cognitive Score	0.006	0.007	0.011	-0.001	0.002
	(0.020)	(0.020)	(0.021)	(0.020)	(0.019)
Usual Hours Worked		0.222	0.224	0.192	0.165
		(0.144)	(0.140)	(0.132)	(0.135)
Log Firm Size			0.140**		
			(0.069)		
Log Firm Revenues				0.141***	0.096***
				(0.033)	(0.035)
Observations	925	925	925	925	925
Adjusted R^2	0.349	0.350	0.357	0.380	0.390
Subcounty FE	Yes	Yes	Yes	Yes	Yes
Other Firm Controls	No	No	No	No	Yes

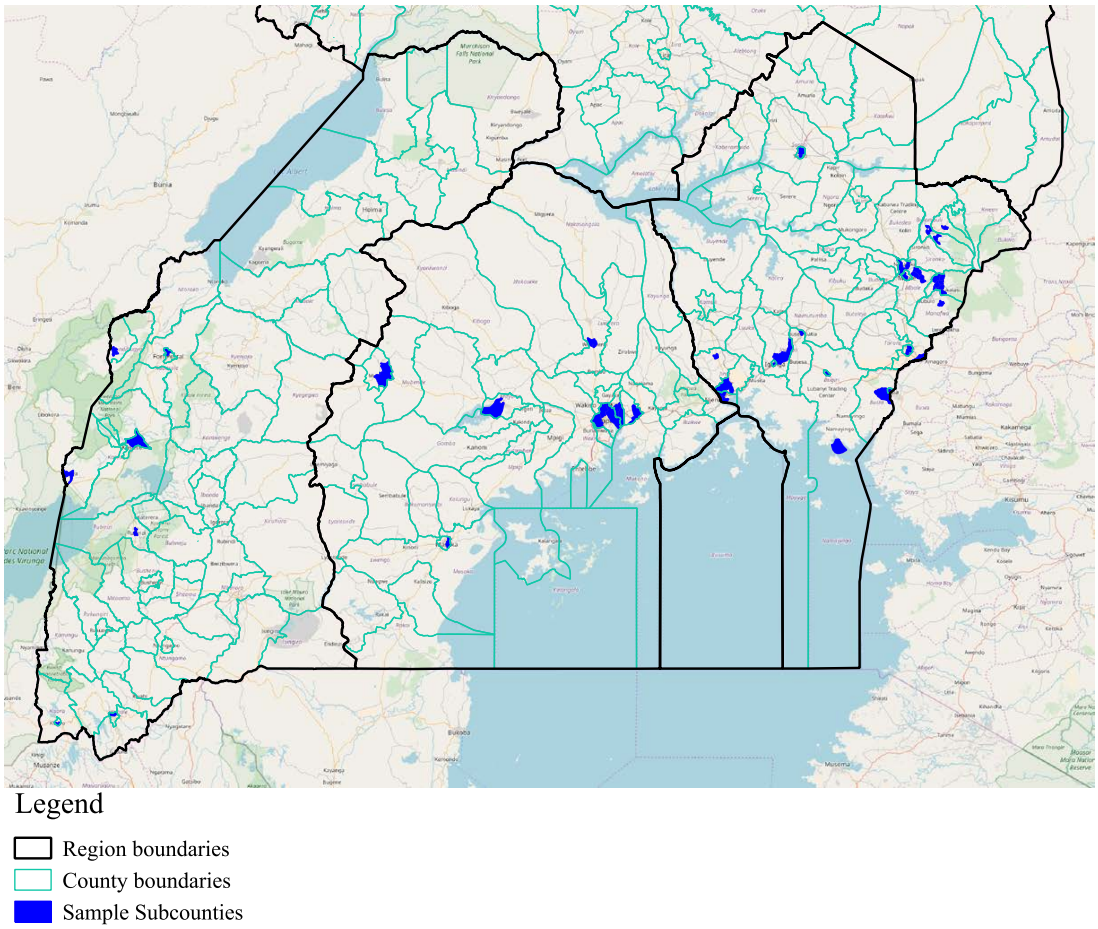
Notes: See Table 4 in the main text, which shows the same regressions for carpentry.

Table A5: Mincerian earnings regression in grain milling

	(1) Log Earnings	(2) Log Earnings	(3) Log Earnings	(4) Log Earnings	(5) Log Earnings
Years of Schooling	0.022**	0.020*	0.019**	0.021**	0.020**
	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)
Age	0.006	0.004	0.002	0.007	0.000
	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)
Age Squared	-0.000	-0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure at the Firm	0.014	0.011	0.008	0.008	0.010
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Vocational Training	0.104	0.101	0.039	-0.002	-0.007
	(0.110)	(0.112)	(0.104)	(0.104)	(0.103)
Cognitive Score	0.097**	0.088**	0.063*	0.047	0.034
	(0.039)	(0.038)	(0.036)	(0.032)	(0.032)
Usual Hours Worked		0.493***	0.454***	0.327**	0.356***
		(0.153)	(0.145)	(0.135)	(0.128)
Log Firm Size			0.323***		
			(0.074)		
Log Firm Revenues				0.172***	0.128***
				(0.036)	(0.039)
Observations	516	516	516	516	516
Adjusted R^2	0.302	0.327	0.375	0.433	0.450
Subcounty FE	Yes	Yes	Yes	Yes	Yes
Other Firm Controls	No	No	No	No	Yes

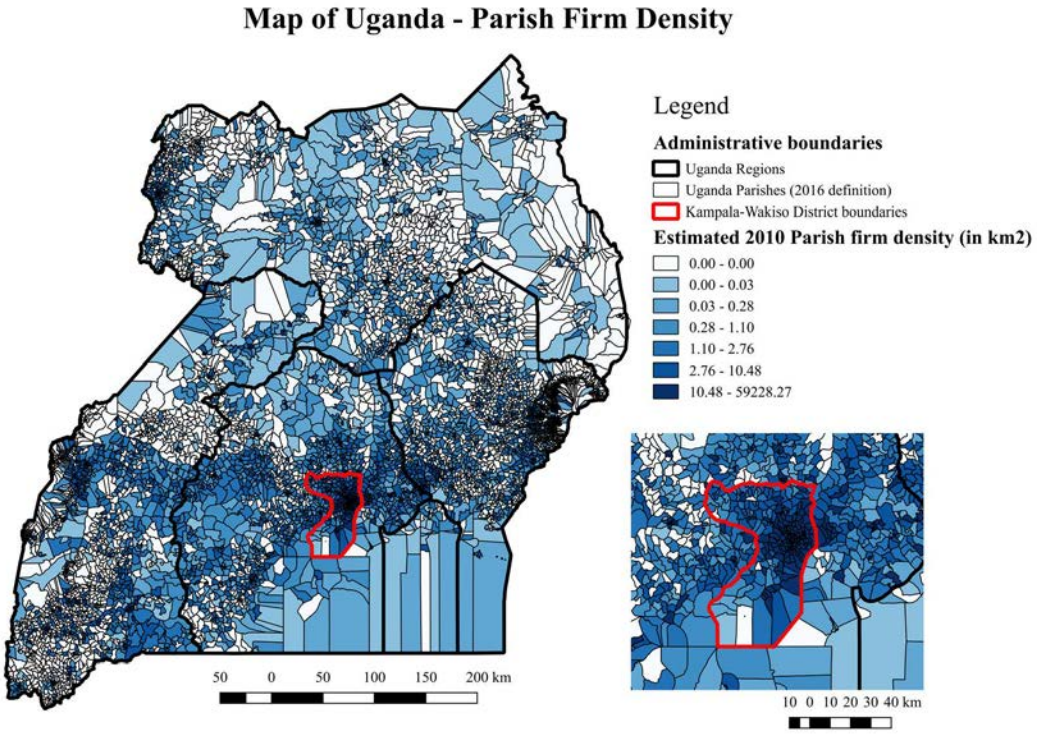
Notes: See Table 4 in the main text, which shows the same regressions for carpentry.

Figure A1: Geographical scope of the survey



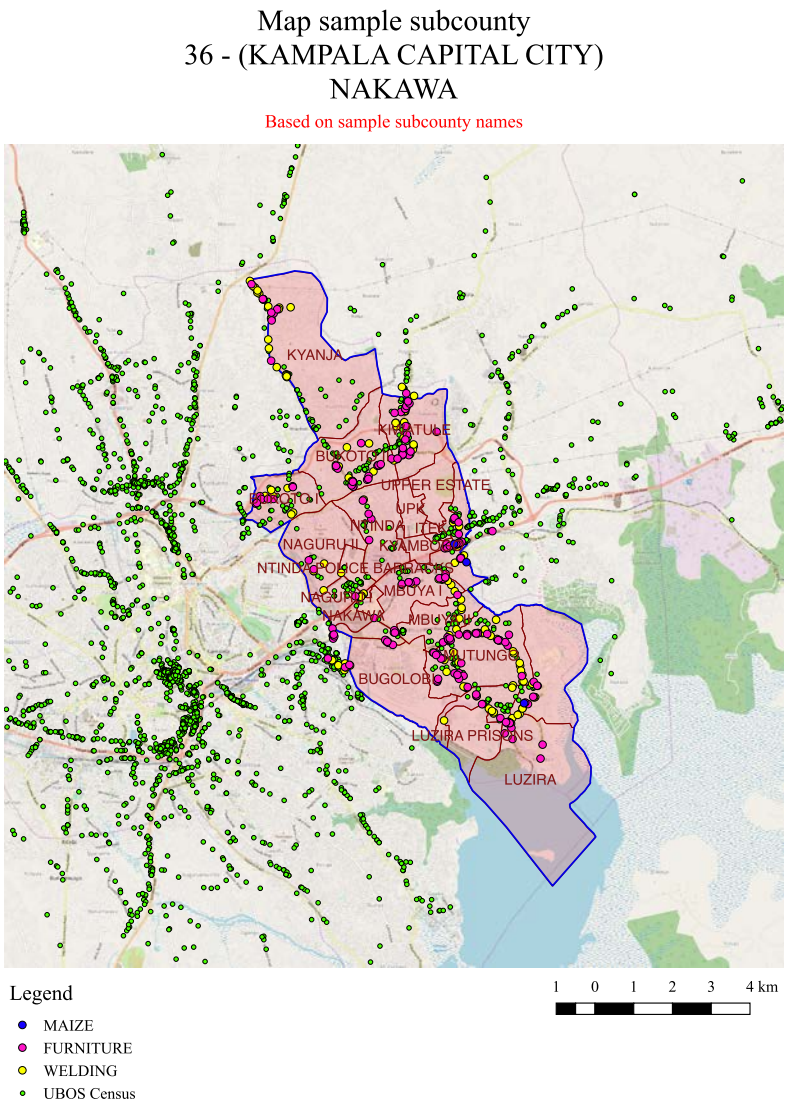
Notes: The Figure shows in dark blue the subcounties in our sample. The figure highlights that our sample region is scattered across the country.

Figure A2: Firm Density by Parish



Notes: The Figure shows the map of firm density, which we have used to predict the number of expected firms in each subcounty. We computed firm density using the number of firms from the Census of Business Establishments conducted by the Ugandan Bureau of Statistics (UBOS).

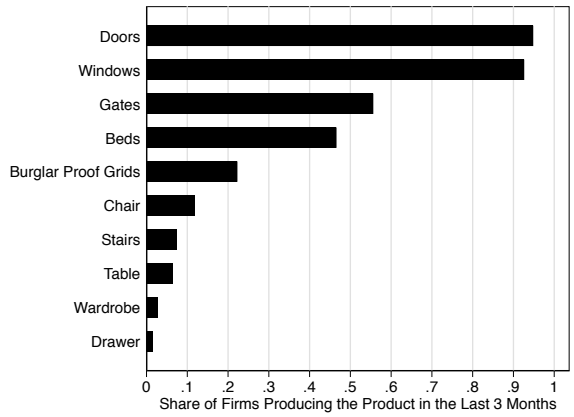
Figure A3: Example of listing exercise in one sampled sub-county



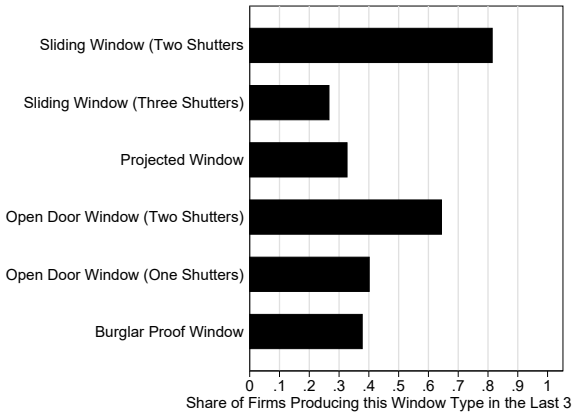
Notes: The Figure shows the Nakawa sub-county in the capital city of Kampala. The shaded pink area represents the sample region, where we listed every single firm. In the map we plot four types of firms: i) blue dots are the firms in the maize sector; ii) pink dots are the firms in the carpentry sector; iii) yellow dots are the firms in the welding sector; iv) green dots are all the firms (of all sectors) from the 2010 census of manufacturing. The map shows that firms are clustered near each other. We selected this sub-county for illustration reasons, and all the other maps are available upon requests.

Figure A4: Share of firms in metal fabrication and grain milling producing a given product

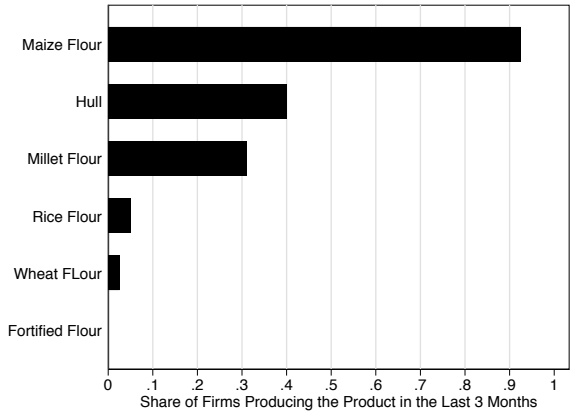
(a) Types of products - Metal fabrication



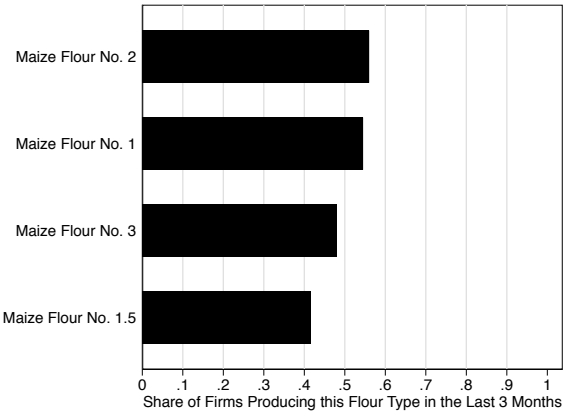
(b) Types of windows - Metal fabrication



(c) Types of products - Grain milling



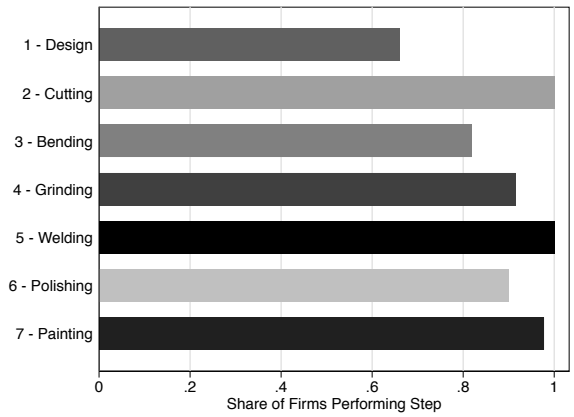
(d) Types of flour - Grain milling



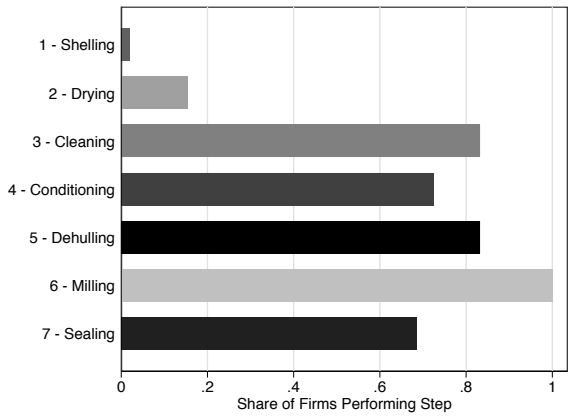
Notes: See the Figure 2 in the main text, which shows the same data for carpentry.

Figure A5: Share of firms in metal fabrication and grain milling performing a given step for the production of core product

(a) Metal fabrication



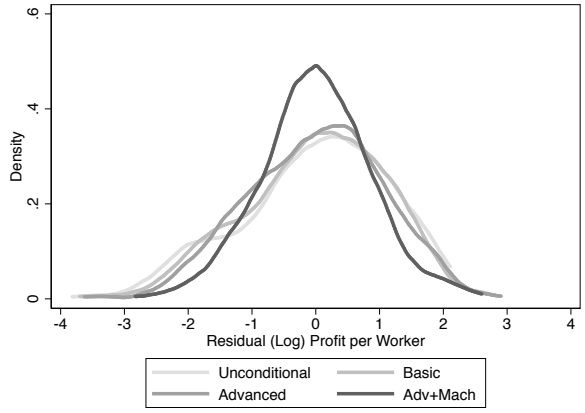
(b) Grain milling



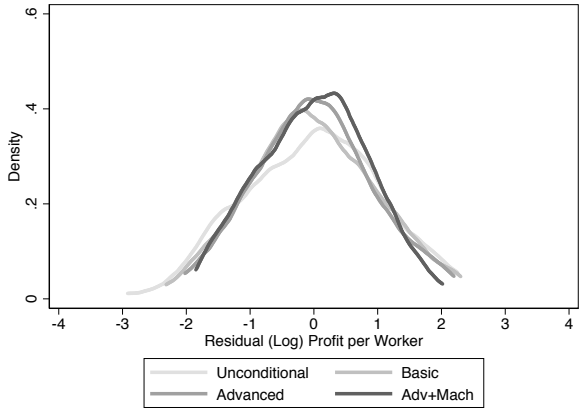
Notes: See the Figure 3 in the main text, which shows the same data for carpentry.

Figure A6: PDF of residual profits per worker in metal fabrication and grain milling

(a) Metal fabrication

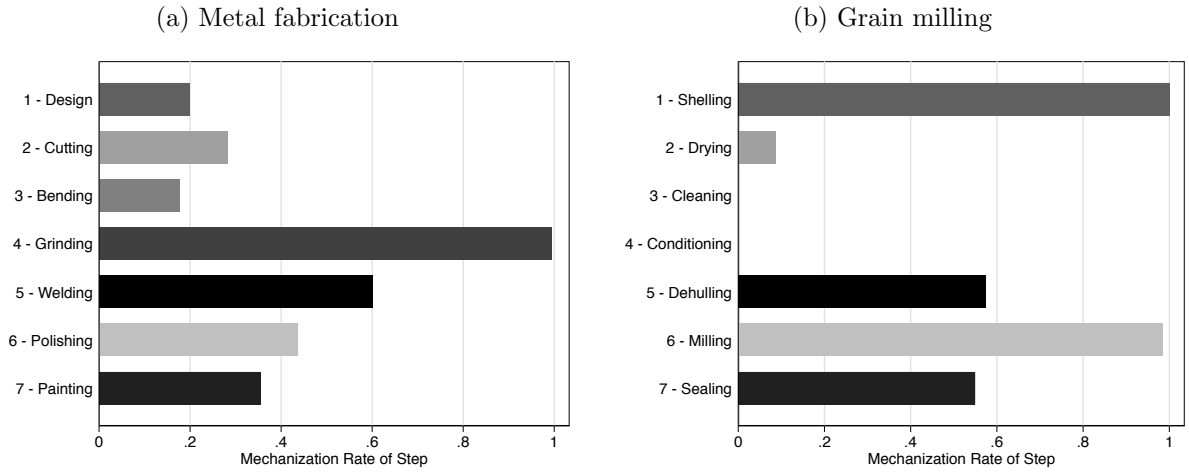


(b) Grain milling



Notes: See the Figure 4 in the main text, which shows the same data for carpentry.

Figure A7: Mechanization rate of production steps in metal fabrication and grain milling

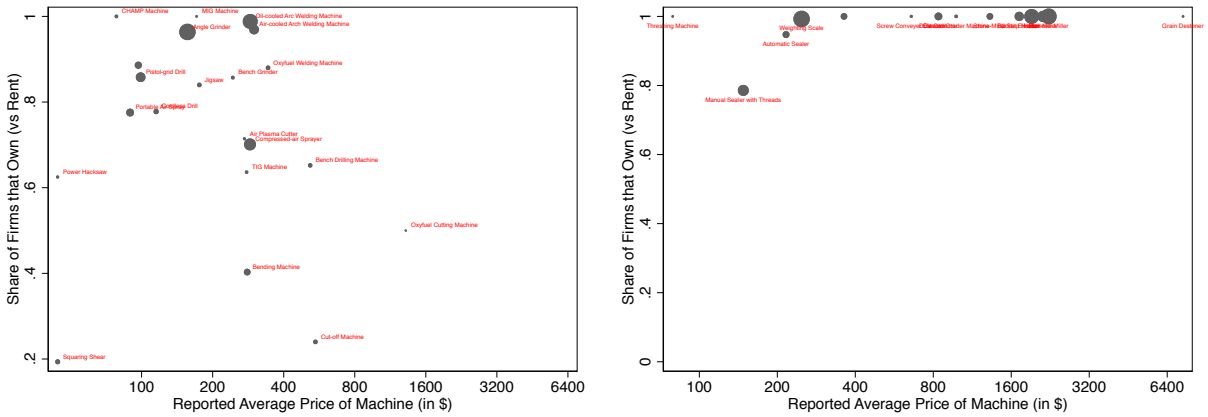


Notes: See the Figure 5 in the main text, which shows the same data for carpentry.

Figure A8: Share of firms in metal fabrication and grain milling that rent vs own as a function of machine price

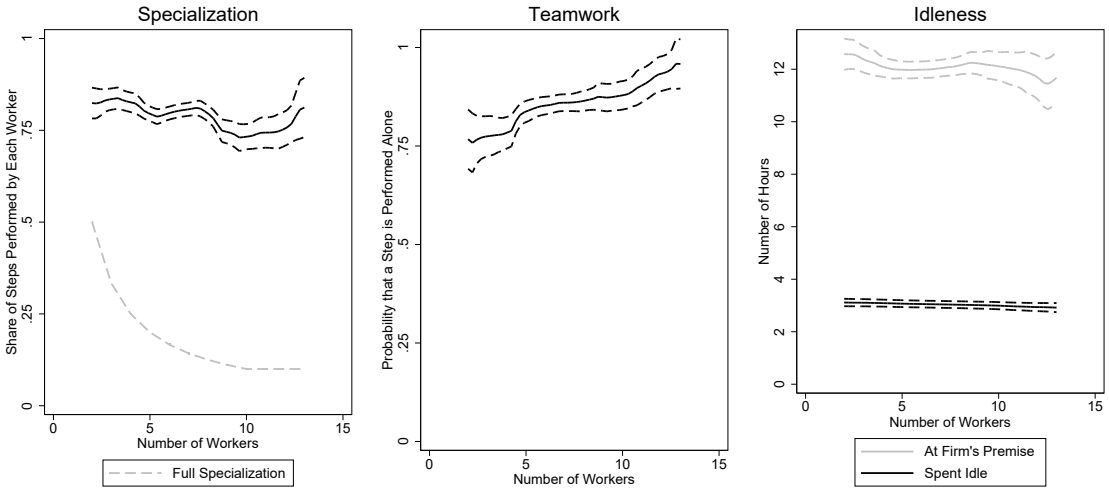
(a) Metal fabrication

(b) Grain milling



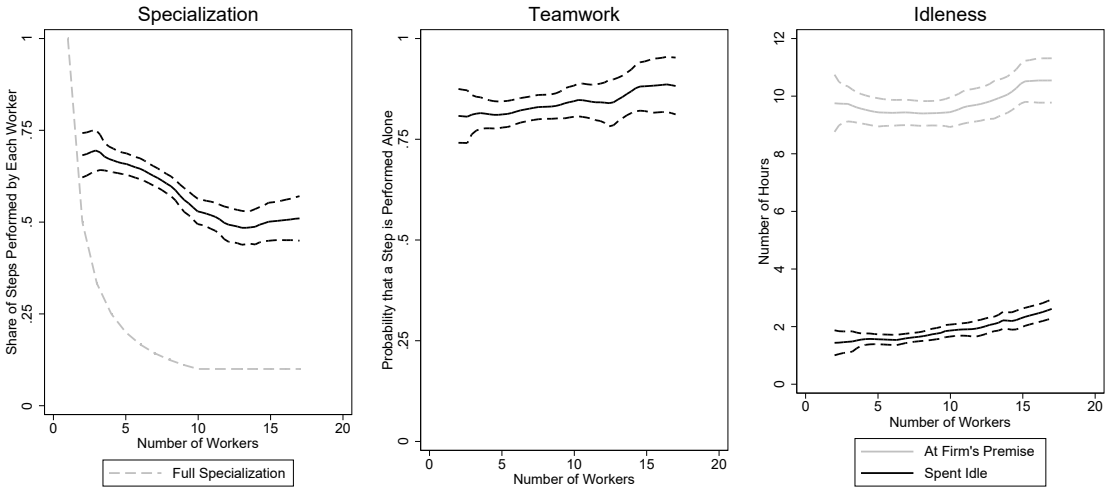
Notes: See the Figure 9 in the main text, which shows the same data for carpentry.

Figure A9: Organization of labor across the size distribution in metal fabrication



Notes: See the Figure 10 in the main text, which shows the same data for carpentry.

Figure A10: Organization of labor across the size distribution in grain milling



Notes: See the Figure 10 in the main text, which shows the same data for carpentry.