

The Labor Market between Firms: Labor Sharing in Urban Uganda

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Abstract

In low-income countries, firms face persistent challenges in hiring, such as costly skill verification and volatile demand. I document an informal solution in which firms in manufacturing clusters lend verified skilled workers to one another, a system I call “*labor sharing*”. Using novel surveys of over 500 firms and 1,000 workers in two manufacturing sectors in Uganda, I find nearly 80% of surveyed firms participate, and that labor sharing provides state-contingent labor, allowing firms to flexibly meet demand shocks. Stated choice experiments show that firms value labor sharing at a 25% premium over other hiring channels, while workers value it similarly to other referrals. In an estimated hiring model with demand uncertainty and hidden worker skill, labor sharing increases total welfare by 7% relative to an economy without sharing, benefiting both firms and workers, and supports more, smaller firms. Sharing improves allocation within firms over time by smoothing demand shocks, but shifts permanent jobs to lower-productivity lending firms. In counterfactual policy experiments, I show that labor sharing shapes the impact of skill policies. Certification further concentrates skilled workers at lending firms, while training benefits higher-productivity borrowing firms and enables them to expand their permanent workforce.

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1 Introduction

Maintaining an appropriate workforce is a persistent challenge facing small firms in low- and middle-income countries (LMICs) (Breza & Kaur, 2025). In skilled trades, this is particularly difficult for two reasons.¹ First, vetting new hires is costly, as quality can only be verified by observing the worker on the job (Alfonsi et al., 2020; Bassi & Nansamba, 2022). Second, demand is highly volatile, so the number of workers a firm needs fluctuates over time. Together, these force firms to either screen repeatedly to meet each peak in demand, or carry slack labor in idle periods, both of which can suppress firm growth (Hardy & McCasland, 2023; Walker et al., 2024). In high-income countries, temporary staffing agencies resolve both of these issues by providing firms with on-demand, verified workers. In LMICs, common adaptations only solve one of these problems. Referrals deliver workers of known quality, but not reliably on short-notice, and usually on permanent arrangements which the firm maintains in slow periods (Beaman & Magruder, 2012; Pallais & Sands, 2016). Day laborers from spot markets or other short-term hiring lets firms expand quickly, but without verified quality (Barker et al., 2025).

In dense clusters of small firms, owners solve both problems by lending each other skilled workers, in an informal system of labor subcontracting that I term *labor sharing*. This practice has been noted in studies of manufacturing clusters in LMICs in Africa and Asia, but none directly measure it or analyze its impact on the broader market.² Despite producing similar products to their competitors, firms face largely firm-specific demand fluctuations. So, firms with slack lend verified workers to separately owned firms facing high demand, often without direct compensation in reciprocal arrangements. Labor sharing thus extends the hiring manager’s reach beyond the firm’s boundary, allowing firms to collectively place workers where they are needed most and flexibly adjust their workforces. But by offering skilled workers without full hiring costs, labor sharing may substitute for permanent hiring and keep some firms afloat. These effects matter because governments spend heavily on active labor market policies (ALMPs), such as training and certification, that increase the supply of or reveal skilled labor, aiming to ease the process of firms finding the right workers.³ Such programs are typically designed as if firms only hire from walk-ins, referrals, or spot markets, yet labor sharing already performs similar functions by certifying a pool of on-call workers. The effects of these policies thus pass through labor sharing, altering how firms hire and who benefits.

In this paper, I ask how labor sharing enables firms to respond to screening frictions and demand volatility, how firms and workers value it, and how its presence shapes the effects of training and certification policies. Answering these questions requires new data. Labor sharing operates as a

¹Small, informal firms employ the majority of sub-Saharan Africa’s workers (International Labour Office, 2018). In Uganda where this study takes place, manufacturing is the third most-common non-agricultural sector among small firms (*National Small Business Survey of Uganda*, 2015).

²Similar practices have been qualitatively documented among carpenters in Arusha, Tanzania (Megumi Muto et al., 2011) and Central Java, Indonesia (Birgi, 2024), and among metalworking firms in Katwe, Kampala (Yamazaki, 2019).

³Job training is among the most common labor market policies in developing countries (Carranza & McKenzie, 2024); from 2002 to 2012, the World Bank and client governments invested nearly \$9 billion in 93 skills training projects (Blattman & Ralston, 2015). In Uganda, the National Development Plan commits to assessing and certifying the competencies of apprentices and trainees (“Fourth National Development Plan (NDP-IV)”, 2025).

common informal replacement for temporary staffing agencies or coordinated spot markets, which are not present in the sectors I study. It is used by four in five firms in my setting, and appears in manufacturing clusters in other LMICs. Despite this, standard labor market data often overlook it because it relies on unpriced and undocumented obligations between firms. Even detailed hiring data collapse different types of connections into a single broad category of referrals, which obscures the distinct role of labor sharing.

I overcome these data limitations by surveying over 500 firms and 1,000 of their workers in the carpentry and metal fabrication industries in and around Uganda’s capital, Kampala. The main innovation of my surveys is to measure firm-to-firm hiring directly with modules focused on inter-firm relationships, along with detailed measurement of worker job history and referral types. To the best of my knowledge, these data are unique in an LMIC context. With these data, the paper proceeds in three parts. First, I document five facts about the prevalence, structure, and functions of labor sharing, as well as costs incurred by firms such as worker or customer loss, or supervision of borrowed workers. Second, I embed a series of stated choice experiments into both firm and worker surveys to document how each side of the labor market trades off hiring channels and contract attributes, allowing me to measure what borrowing firms will pay for a shared worker and what lending firms require to send one out. Third, I combine data on realized hiring flows, wages, and output with choice experiment parameters to estimate an equilibrium model of the local labor market. The model quantifies how labor sharing affects worker wages and employment, firm profits, entry and exit, and how it shapes the effects of training and certification.

In the first part of the paper, I document that labor sharing is a common practice and has a distinctive structure. Over 80% of firms in the target sectors report ever participating, and it is the most active hiring channel in this labor market. The average firm hired from other firms more than twice as often as through any other single channel, and the average sharing firm borrows or lends a worker once every 10 days. It also widely impacts workers, with over half reporting being hired through labor sharing at some point in their careers. Labor sharing ties are reciprocal and locally concentrated, meaning firms often send workers to and receive workers from the same firms, which are often located within walking distance. Owners arrange the transfers but do not directly compensate with cash or in-kind payment. Firm-network foundations and lack of contract and compensation distinguish labor sharing from spot hiring and formal subcontracting, respectively. Further, shared workers are primarily hired on a temporary basis, and are far less likely to stay on permanently than social network referrals.

Labor sharing persists because, unlike other available hiring channels, it jointly solves screening and demand adjustment problems firms often face simultaneously. First, sharing delivers workers whose quality is already known, so firms can bypass the screening that other channels require. Elicited beliefs show that owners view shared workers as more skilled and less demanding of supervision than other hires. These beliefs align with observed patterns in the labor force, as shared workers have more industry experience. Labor sharing thus offers a clear quality signal not always found in referrals. Second, labor sharing reallocates skilled workers to firms with high labor demand.

Firms face highly variable output demand, with busy months bringing in five times the revenue of slow months. These demand fluctuations appear to be firm-specific, so a busy firm generally has an idle neighbor.⁴ Consistent with this, firms facing more volatile demand adjust by relying on existing labor sharing relationships more heavily. Because shared workers are returned after the shock passes, labor sharing lets firms meet demand shocks without carrying excess slack or delaying delivery.

The last piece of descriptive evidence uncovers costs for involved firms and workers that are unpriced yet govern labor sharing flows. Firms frequently (79%) report an appropriation-related concern when lending workers, such as losing workers or customers, and a majority report that workers they lend return later than expected. Borrowing firms bear costs such as supervision and risk of theft or damages, while also taking on an obligation to lend out their own workers at an unknown point in the future. In labor sharing, these costs load on inter-firm relationships rather than being compensated in a transfer fee. Few firms consider consolidating to reduce these transaction costs; only 10% have ever considered merging with a sharing partner, mainly due to trust and financial concerns. Nor are formal intermediaries likely to help, as firms cite high costs and low trust as reasons they don't already exist. Separately, workers incur hassle costs since they are frequently asked to relocate on little notice. Shared workers report significantly more difficulty planning transport, self-employment work, and family events compared to those who are not shared. Labor sharing may also stand in for investments in skills, as any worker skills, knowledge, or designs will likely be partially captured by competitors. Consistent with this, shared workers report fewer days receiving training than unshared workers.⁵

In the second part of the paper, I conduct a series of stated choice experiments to estimate the value of individual labor sharing exchanges for borrowing firms, lending firms, and workers. For firms, I field three experiments that allow me to recover willingness to pay for attributes of a hire in a hypothetical scenario, each targeting a different aspect of firm hiring decisions (Maestas et al., 2023; Mas & Pallais, 2017). The first experiment estimates the borrowing firm's premium for a shared worker net of other sources by randomly varying attributes and hiring channels. I find that firms are willing to pay a premium equivalent to 25% of the median wage for shared labor over other hires. The second experiment investigates what drives this premium by varying contract features of labor sharing arrangements from the borrowing firm's perspective. I show that firms value repeated relationships over one-shot transactions. In the third and final firm experiment, I estimate the compensation lending firms require to send out workers, testing whether a wedge exists between lending and borrowing firms. I do this by varying compensation offered and characteristics of peer firms requesting workers. I estimate that firms' willingness to lend is less than half of the premium borrowing firms are willing to pay for shared workers. This gap is consistent with the costs reported

⁴Defining markets as parish $\times$ industry, 72% of the variation demand variation is firm-specific; the size of swings is more common across firms in a market (31%).

⁵Shared workers report receiving training for 2.4 days in the prior month compared to 3.2 for all other workers ($p = 0.036$). Though correlational evidence as shared workers are more experienced, this aligns with evidence from Cefala et al. (2024), who show that uncertainty over retention reduces training provision by agricultural employers in Burundi.

by lenders, and suggests lending risk suppresses the supply of shared workers in the market.

To understand the worker perspective and valuation of labor sharing, I embed in the worker survey a parallel choice experiment where respondents choose between hypothetical offers that randomly vary in wage, the worker’s connection to the hiring firm, and other amenities. This structure allows for the estimation of the elasticity of labor supply to a firm, a key model input. I find that workers have approximately the same willingness to accept for labor sharing arrangements as other types of referrals, but all types of connections are valued over an unreferral walk-in vacancy. Yet, they value being lent out when their firm is slack, shown by a small, but significant willingness to *pay* of 5% of their wage for a job where this can happen. Over 90% of workers are paid piece rate and earn little in idle weeks, so being lent out helps smooth earnings across firms. The model therefore places the transaction costs of sharing on firms and incorporates workers’ values of being lent out as a firm-specific amenity.

Motivated by this evidence, the third part of the paper builds an equilibrium model of hiring. Where choice experiments price a single exchange, the model values labor sharing access in its entirety, taking into account how firms adjust hiring when anticipating worker exchanges with other firms in the market. I then use it to quantify labor sharing’s impacts on firm entry, profits, wages, and employment, and ask how sharing shapes who gains from training and certification, since these policies target similar market frictions. The worker side of the model is closest to Card et al. (2018), where workers choose employers by wages and amenities, and wages carry a firm-specific premium (Lamadon et al., 2022). Owners choose whether to operate by comparing expected profits with an outside option, and then post vacancies in an external market under two uncertainties. They do not know the quality of the workers they hire (Caldwell et al., 2026; Kline, 2025), and they do not know the demand they will face when production begins (Garin & Silvério, 2024). Once demand is realized, they can borrow or lend skilled workers whose quality is already verified by the lending firm, at fixed prices recovered in the firm choice experiments. Labor sharing gives firms a second chance to hire after demand is known, a separate mechanism from wage and vacancy adjustments available in standard models.

In the model equilibrium, firms participate in labor sharing depending on the productivity gap between high and low demand states, and the transaction costs of borrowing and lending workers. The choice experiments pin down the implicit fee paid to the lender, additional borrowing transaction costs, and the elasticity of labor supply to the wage at individual firms. I estimate the remaining parameters, which govern production, hiring and separation rates, and the distribution of demand shocks, by simulated method of moments (SMM), targeting observed labor flows and wages from both surveys. I validate the model against a series of untargeted moments regarding manager skill, stated reservation wages, sharing participation, and fill rates.

I estimate that, compared to an economy where firms hire only through walk-ins and referrals, the economy with labor sharing produces 7.0% higher total surplus. Gains accrue to both firms and workers. Owner surplus rises by 4.5%, primarily driven by increased output in busy states. Workers gain 12.3% in surplus through a higher portion of skilled worker periods employed at

busy firms. Less-skilled workers, who are not shared, see average wages fall by 12% as they move toward lower-paying firms. Sharing has important allocative consequences. By placing workers at high-demand firms, it nearly eliminates misallocation within-firms across time. But it also shifts which firms operate and who holds permanent workers. The sharing economy supports 4.7% more firms which are smaller in size. It also shifts permanent jobs to lower-productivity firms that tend to lend out workers, while more productive firms borrow rather than growing through permanent hiring. This leads to an increase in misallocation across firms, and labor sharing only closes about a third of the gap to a frictionless market benchmark. Because sharing exchanges carry knowledge of a worker’s skill, sharing outperforms a simulated spot market, commonly found in other contexts.

Using the estimated model, I evaluate certification and training, two common ALMPs which target hiring frictions in LMICs. I find that without sharing the effects of each policy are similar across firms, but with sharing, the policies have strong, opposing allocative effects. Certification improves firms’ ability to identify skilled workers before hiring, a role lending firms already play by vouching for the workers who are shared between firms. Its aggregate effect is slightly negative, pushing less-skilled workers who cannot certify out of the market, and distributing much of the gains to skilled and certified workers who command higher wages. Certification concentrates skilled workers, and therefore gains, among lower productivity firms which lend labor, which hold them as slack and lend them out to borrowing firms at higher volume. Labor sharing provides a pre-existing source of skill signals, certification may add less, as found in Carranza et al. (2022). As in Bassi and Nansamba (2022), I find certification reallocates workers across firms without raising aggregate employment. Training, by contrast, raises total surplus by 17% because it expands the supply of skilled workers, who are relatively scarce. Its gains concentrate among high-productivity firms who can now afford to hire skilled labor permanently rather than borrow it. This aligns with what firm owners say would help most during busy periods, as 65% of surveyed owners opt for support for training workers or retaining skilled workers.

Related literature and contributions This paper makes three main contributions.

First, I provide, to my knowledge, the first detailed data documenting labor sharing as an informal, reciprocal hiring system based on networks between independent firms, record its functions and structure, measure its usage across firms, and estimate its equilibrium effects.⁶ Labor sharing differs from other hiring strategies because it addresses each of two problems common in hiring: screening frictions and demand volatility. Other documented hiring strategies only address one of these challenges. Firms often rely on referrals from managers or employees (Beaman & Magruder, 2012; Brown et al., 2016; Burks et al., 2015; Dustmann et al., 2016; Pallais & Sands, 2016), because worker quality is difficult to observe in LMICs (Abel et al., 2020; Bassi & Nansamba, 2022; Carranza et al., 2022; Hardy & McCasland, 2023). In my setting, referred hires stay permanently, which can

⁶Inter-firm worker transfers elsewhere operate through common ownership or through statutory vehicles. Examples include business groups (Brunello, 1988; Cestone et al., 2024) or worker sharing in European employer organizations (Mandl et al., 2015). Reciprocal, uncompensated labor exchange is well documented among farm households (Krishnan & Sciubba, 2009; Takasaki et al., 2014), where exchanging parties supply their own labor rather than lending employees.

leave firms carrying slack (Walker et al., 2024) or unable to meet demand shocks. Firms also rely on short-term contracts when facing variable demand but expect lower performance or lower-quality work from them (Barker et al., 2025). Using novel data on firm-worker matches, I show that labor sharing delivers verified workers for temporary stints. The most closely related work is that of Hardy et al. (2024), who find latent demand for labor reallocation among small garment manufacturers in Ghana. I show that firms in dense clusters already do this reallocation on their own.

Second, I analyze the impact of an understudied way in which firms coordinate across firm boundaries without fully consolidating. Firms are known to heavily interact with one another via capital rental markets (Bassi et al., 2022) or sharing business information (Cai & Szeidl, 2018). In addition to these channels, I show that competitors also directly share labor with one another when co-located in dense clusters, creating a decentralized system which is similar to departments within larger firms (Adhvaryu et al., 2024). I use stated choice experiments (Maestas et al., 2023; Mas & Pallais, 2017) to show that firms highly value this flexible capacity. Labor sharing provides access to skilled labor without incurring full hiring costs, replacing the function of formal labor intermediaries (Bertrand et al., 2025; Segal & Sullivan, 1997) and keeping more firms in the market who would otherwise exit. This coordination improves allocation of skilled labor within firms over time, but shifts permanent employment towards lower-productivity firms, increasing misallocation across firms (Hsieh & Klenow, 2009). This system provides a potential micro-foundation in LMICs of pooled labor agglomeration externalities suggested in high-income countries (Ellison et al., 2010; Greenstone et al., 2010).

The third contribution is to show how labor sharing shapes the effects of ALMPs, which are usually evaluated as if firms had no such alternative. Training, search assistance, and certification programs show mixed and often modest effects (Carranza & McKenzie, 2024). Training can raise earnings (Alfonsi et al., 2020), and certification can change how workers sort across firms (Bassi & Nansamba, 2022). Few studies, however, consider how these policies interact with informal institutions that already verify workers and move them across firms. I show that such an institution shapes both a policy’s aggregate effect and which firms gain from it. Certification makes skill visible to employers, a role labor sharing already plays for workers who are shared, so it mainly redistributes surplus, benefiting skilled workers who can certify and lower-productivity firms which lend workers heavily. These muted effects are consistent with Carranza et al. (2022), who note that certification effects are limited where other information sources exist. Training, by contrast, expands the supply of skill that sharing can only reallocate, and benefits primarily higher-productivity borrowing firms who can now more easily expand.

2 Hiring and Labor Sharing in Ugandan Manufacturing

Uganda has no systematic administrative data that capture high-frequency hiring patterns of small firms, making labor sharing difficult to measure. Surveys that are designed to measure informal

and short-term work record these job stints, but not how workers were connected to the firm.⁷ To address these gaps, I conducted matched surveys of firms and workers in informal manufacturing sectors in April and May 2026.

Small firms face two substantial hiring problems: worker quality is hard to verify before hiring and demand is volatile from month to month. After describing the data collection, I organize my survey data into five broad facts that show how firms use labor sharing to respond to these problems. Labor sharing is a common hiring strategy that runs through reciprocal, uncompensated ties between nearby firms. It helps firms screen workers and flexibly expand and contract in response to demand swings, but also imposes costs on both firms and workers. I use these five facts to motivate and inform the model structure in Section 5.

2.1 Setting and Surveys

I survey small- and medium-sized firms in the carpentry and metalworking, which account for roughly one in five manufacturing jobs in Kampala.⁸ Like many small-scale manufacturers in LMICs, these firms are owner-operated with a small workforce in clusters of similar firms, where workers learn skills on the job.⁹ They are also frequent targets of training and up-skilling programs.

Sampling Procedure Surveys were conducted at firms selected by a two-stage sampling protocol. First, I selected a total of 30 parishes across Kampala and bordering areas of Wakiso District.¹⁰ Parishes were ranked by total reported number of eligible firms, defined as carpentry and metalworking firms with 2–25 workers, according to the 2019/20 CoBE. Firms are highly concentrated by industry (Vitali, 2023), so this approach allows coverage of areas which hold 62% of eligible firms in the Kampala metro area. Second, within each parish, enumeration teams began at randomly drawn starting firms from the CoBE-listed establishments in selected parishes. Enumerators followed a snowball sampling strategy based on reported firm-firm ties. If no linked firm could be reached, enumerators followed a random-walk protocol, approaching every third firm until an eligible firm was identified. This intentionally over-samples network-connected firms to gain power and precision when analyzing hiring practices along firm ties.

The final sample contains 515 firms and 1,001 of their workers, approximately 38% of the eligible firm population. Up to two eligible workers were randomly selected from a worker listing conducted during the firm survey. Despite the deliberate oversampling of connected firms, the resulting sample closely resembles the eligible population, as shown in Appendix Table A1.¹¹

⁷For example, the 2016 Uganda National Manpower Survey asks about workers hired for as little as one hour, but does not ask how these workers were found or hired.

⁸According to the 2019/20 Ugandan Census of Business Establishments (CoBE), these sectors together account for 28% of manufacturing jobs in Uganda, and 27% of revenues among Kampala manufacturing SMEs.

⁹Such traits are exhibited in tailoring, auto-repair, and construction firms in LMICs.

¹⁰A parish is a Local Council II (LC2) unit, the administrative level above a village and roughly a neighborhood in urban areas. There are 107 parishes in Kampala and Wakiso with eligible firms.

¹¹Oversampling connected firms does not appear to inflate measured sharing. In a November 2025 pilot of 45 randomly selected firms, sharing was at least as prevalent as in the main sample. Sharing rates are also higher, not lower, in parishes where a larger share of the frame was surveyed, the opposite of what snowball inflation would

Firms in this setting are small and operate with highly flexible workforces paid on piece-rate contracts. The average firm has 3.3 workers present on the day of the survey, excluding the owner, but employed 5.9 unique workers over the prior month (Panel A of Table 1). At the time of survey 20% of listed workers were on temporary arrangements, which provides firms with this ability to expand. The workers in the sample are nearly all male, young, and trained on the job. The average worker is 27 years old with ten years of schooling and five years of industry experience. Over 90% are paid by piece-rate. Additional worker characteristics are reported in Table 2.

Firm Survey The firm survey, administered to the owner or manager of each firm, does three main things. First, it measures labor sharing through two independent sources. In a worker listing, I record, for each worker present on the day of the survey, how the worker was hired, their contract structure and pay, and whether they are currently being borrowed from another firm. An inter-firm relationships module asks firms to name the firms they receive workers from and send workers to. For each relationship, I record terms of exchange, reciprocity expectations, flows of workers over the past three months, encountered issues, and other types of exchange such as equipment sharing. These two sources complement each other, as the listing captures only workers physically present, and thus does not rely on recall, while the relationships module captures exchanges involving workers who have since returned.

Second, the survey documents the screening frictions and demand volatility which firms face. For each hiring channel, I measure beliefs about worker quality, retention, and theft risk as expected frequencies over ten hypothetical workers, following the methods of Delavande et al. (2011), along with the time required to assess a worker’s skill and the supervision they require. I also measure attempts and successes in hiring through each channel, which captures firm search effort and efficiency. To measure demand, I adapt an approach from Barker et al. (2025) to ask firm owners to recount production details, such as orders and product outputs, of busy, normal, and slow months at their business. I then ask them to distribute the months of the past year into each demand state. I also elicit output and revenues in each state following De Mel et al. (2009).

Third, I run three stated choice experiments to estimate willingness to pay (WTP) for worker attributes, informal contract features, and hiring sources. These estimate the premia firms are willing to pay for shared workers, measure firm preferences for sharing agreement features, and estimate the compensation firms require to lend. These are discussed further in Section 3.

Worker Survey The worker survey was administered to two randomly selected employees from the worker listing and has two parts. The first part is a work history module. For each worker, I capture up to the three most recent job stints from the past 12 months. For each job, I record the firm name, owner name, and location, allowing me to link the worker to firms in the dataset beyond their current employer. The survey also records how the worker was hired into each job, with particular focus on whether the match was coordinated between the owners or managers of two produce.

firms, thus identifying a labor sharing link at the work-stint level. The job documentation concludes by recording the tasks performed and non-wage benefits such as training and self-employment options at the firm.

The second part of the survey captures workers’ outside options and the volatility of their employment. I elicit reservation wages with two approaches: the payment card elicitation of Feld et al., 2022 and an adaptation of the reservation raise design of Mui and Schoefer, 2025. I elicit workers’ beliefs about their chances of finding work through each hiring channel. To document volatility of employment, the survey records idle work days and extended spells without paid work, alongside a one-week retrospective time-use diary (Arthi et al., 2018). Workers are also asked about perceived costs and benefits of working and moving across multiple firms. Because these modules document the conditions workers face but not how workers value them, the survey concludes with a choice experiment over hypothetical job offers, which recovers valuations of non-wage attributes and labor supply elasticities, detailed in Section 4.

2.2 Fact 1: Labor sharing is a commonly used hiring source

Labor sharing is the most common way firms in this market hire. Firms use four main channels of hiring to meet their labor demand: walk-ins, who have no prior connection to the firm, referrals through the owner’s network of friends and family, referrals through employees, and, finally, directly from other firms through labor sharing. While short-term work is common, this is fulfilled through these four channels, not through a coordinated spot market, as is common in other industries (Breza & Kaur, 2025). In the past 12 months, I find more firms hired through labor sharing than through any other source (Table 3). Over four in five firms (83%) have hired a worker through labor sharing, and nearly half were actively borrowing a worker from another firm or had one out on loan at the time of survey.¹²

Labor sharing is a common way firms are initially matched with workers, but does not lead to widespread poaching. Of workers listed at survey firms, I find 18% of workers were first hired directly from another firm, on par with employee referrals (Panel B, Table 3). However, workers initially hired directly from other firms are far less likely to be considered permanent at their new firm compared to those hired via other channels.¹³ At most 3% of workers fit a poaching pattern where they were initially hired from another firm, later converted to a permanent position, and never subsequently lent out.

Labor sharing is a common feature of workers’ careers in these markets. I estimate that 55% of workers have ever been shared. I identify shared workers from either the workers own report of being sent between firms by their owners, or by the employing firm’s report that a worker is currently borrowed or has been lent out.¹⁴ Consistent with this fact, shared workers are more mobile between firms. Table A6 reports that shared workers have worked for one more firm over the past year than

¹²Both measures combine the worker listing and the relationships module (Section 2).

¹³In this context, owners and workers refer to a “permanent” arrangement as one where the worker is expected to be physically present at the same firm on a fixed, regular schedule.

¹⁴Appendix A.2 details the classification rule and reports concordance between worker- and firm-side reports.

those who have never been shared.

2.3 Fact 2: Labor sharing relationships have common structure

Firms maintain multiple labor sharing relationships and use them actively. The average sharing firm exchanges workers with 2.1 other firms, and borrows or lends a worker every ten days. These relationships share four main structural characteristics: they are reciprocal, uncompensated, locally concentrated, and coordinated by owners and managers.

First, labor sharing relationships are bidirectional and reciprocal. In 75% of documented labor sharing relationships, the firm reports that workers flow in both directions along the link.¹⁵ Among bidirectional ties, over three in five carry an expectation of lending in the future. Sharing ties reflect a more broad level of integration with their neighbors, as firms engaging in labor sharing often share equipment and machines with the same partners (64%). Figure A1 displays examples of sharing networks formed by these ties, with arrows indicating the reported flows of workers between firms.

Second, labor sharing is overwhelmingly uncompensated. In 83% of documented relationships, the firm reports that nothing, in cash or in kind, is given directly in exchange for the worker. The worker is simply reallocated, with the borrowing firm paying the worker’s wages for the duration of the stint.¹⁶ Costs for borrowers are future obligations, as most uncompensated ties carry an obligation to lend or assist the sharing partner in the future. Because these exchanges carry no observed price, the value of access to a shared worker cannot be read directly from the data.

Third, labor sharing is locally concentrated. Over 79% of sharing ties are between firms in the same parish. Among matched pairs for which both firm owners were interviewed, the median pair spans just 77 meters.¹⁷ This proximity means that sharing firms are competing for the same customers, but also allows firms to more easily observe firm quality and enforce informal agreements.

Finally, labor sharing exchanges are coordinated by firm owners and management. In 89% of ties, transfers are arranged or approved by each firm’s owner or manager. Labor sharing is a firm-driven phenomenon and not a product of worker on-the-job search, so the model of Section 5 treats the firm owner as the decision maker over worker reallocation.

2.4 Fact 3: Labor sharing helps screen workers

Labor sharing provides access to workers who have already been screened by other sharing firms. This is particularly valuable in this market due to a lack of durable and credible signals of quality for workers, a defining feature of low-income labor markets (Bassi & Nansamba, 2022; Carranza et al., 2022; Hardy & McCasland, 2023). What certification does exist comes from technical institutions,

¹⁵One possible type of bilateral relationship that could have been captured in the data are instances of contrasting one-way ties. That is, Firm A reports borrowing workers from Firm B, while Firm B reports borrowing workers from Firm A, but neither reports sending workers to the other. There are no such instances in the data.

¹⁶This norm of uncompensated transfer does not appear to reflect binding liquidity constraints, as three in four firms report having cash on hand to cover a roughly \$80 same-day purchase, an amount over twice the prevailing weekly wage.

¹⁷Matched pairs require both firms to appear in the sample, and matching is corroborated partly on location, so this subsample may over-represent local ties. The survey-reported distance categories cover all documented relationships.

which are not well attended and do not carry a strong signal for owners. The share of a firm’s workers with completed technical training is uncorrelated with the share of workers the owner believes to be skilled ($r = -0.03$).¹⁸ Screening therefore must happen on the job, and it is a slow process, requiring over four days to assess a walk-in hire, and nearly as long for referrals (Figure 2, Panel B). It is also unreliable. Among firms that tried to hire walk-ins over the past three months, only 56% of attempts produced a worker who made sellable products. This problem is not unique to these industries, as small firm owners across Uganda report inability to screen workers as a constraint on growth (Alfonsi et al., 2020).

Owners hold better beliefs about shared workers than about workers from other hiring sources. The firm survey elicits these beliefs through a brief series of vignettes about hypothetical new workers from each of the four common hiring channels. Skill is measured using production-relevant standard: owners were asked how many of ten newly hired workers could produce a core industry product at a quality fit for sale, with no further training.¹⁹ Labor sharing dominates on this front; the average owner expects 6.3 of 10 shared workers to meet this standard, higher than every other hiring channel ($p < 0.001$ for each pairwise comparison; Figure 2, panel A). This translates to lower costs for firms. Owners report fewer days needed to screen shared workers (1.9) and less supervision (2.8 hours/day). Realized hiring reflects these beliefs. For the average firm, attempts to hire through labor sharing succeed 81% of the time.

Firms attribute this advantage directly to quality verification. When asked the advantages of labor sharing, 58 percent of sharing firms report that they know shared workers are skilled, and a quarter report they require no assessment at all. The structure documented in Section 2.3 explains how these beliefs are sustained. Because sharing partners are typically a short walk away, firms observe each other’s output and can infer worker quality from finished products. And because ties are reciprocal and extend beyond labor, sending a low-quality worker puts substantial relational capital at risk. The advantage is specific to verification rather than trust. Owners rate shared workers safer than walk-ins on theft risk (4.5 versus 6.6 of 10) but riskier than friend or family referrals (3.7), consistent with the enforcement role of referrals (Heath, 2018).

Firms that see a bigger advantage in shared workers are more likely to share and share with more partners, but do not move more workers. To show this, I construct a “belief advantage” as the firm’s quality belief for workers from other firms minus its average belief across the three other hiring channels, standardized. I then regress measures of labor sharing on this advantage, reported in Table 4a. A one-standard-deviation belief advantage is associated with a 3.6 percentage point higher probability of any sharing ($p = 0.046$) and an additional 0.19 sharing partners ($p < 0.001$). However, I do not find a significant relationship with measure of how often workers are shared.²⁰

¹⁸Firm owner beliefs over worker skill were elicited by asking owners how many of the workers present could produce the firm’s core product to a sellable standard without additional training or supervision.

¹⁹Following Bassi et al. (2022), the core products are a four-panel door in carpentry and a two-part sliding window in metalworking.

²⁰I interpret these estimates as equilibrium correlations rather than causal effects, as firms plausibly learn about shared workers through sharing itself. Still, firms with no sharing experience rate shared workers well above other hires (5.7 versus 3.8 of 10; $n = 61$), so these beliefs are not only learned through sharing.

2.5 Fact 4: Firms use labor sharing as a demand response

Labor sharing lets firms expand their productive capacity quickly to respond to large swings in demand. On average, owners split the year roughly in three, with busy months (3.5/year) occurring about as often as slow months (3.7/year). These are large swings in demand, with busy month revenue averaging approximately \$3,200 compared to just under \$600 in slow months. One way firms respond is adjusting the utilization of their existing workers. Workers surveyed at firms in slow states report spending 66.9% of their time at the firm on productive tasks compared to 73.7% at firms in normal or busy states ($p < 0.001$).²¹

Demand variation is largely firm-specific, so each busy firm likely has a neighbor with slack labor. If instead firms faced highly correlated shocks, firms would be unable to find nearby counterparties with whom to share. A variance decomposition of log monthly revenue across firms shows that about half reflects permanent differences across firms, and half reflects month-to-month fluctuations within firms (Appendix Table A8). Of the within firm fluctuations, 72% are firm-specific, and only 5% are shared with firms in the same market. The remaining 23% is common to all firms in a given month. Consistent with this, nearly every market with three or more surveyed firms contains firms reporting different demand states at the time of the survey, even though same-market firms were interviewed within days of each other.

Labor sharing offers a way for firms to adjust headcount up or down in response to demand shocks. In addition to increasing hours, 78% of firms report they would bring in additional workers during a surprisingly busy month, and when asked where they would first look for those workers, 73% name other workshops. The deployment speed of shared workers is a first-order concern for firms: 60% of sharing firms cite quick access to workers when needed as an advantage of labor sharing. When faced with slow periods, nearly as many firms respond by sending workers out to other firms (32%) as would cut back temporary hiring (39%).

Firms with more volatile demand share more workers, but do not form more sharing ties. I first construct each firm’s coefficient of variation (CV) of monthly output, weighting each state’s reported output by share of the previous year spent in each state. I then regress measures of labor sharing participation and usage on the CV, and report results in Table 4b. A unit increase in CV is associated with an increase of 2.2 workers shared over the previous three months ($p = 0.014$), with significant relationships for both workers borrowed and lent.²² In contrast with results analyzing firm beliefs, demand volatility is unrelated to whether a firm shares at all or how many sharing relationships are formed. Beliefs shape if a firm shares and who they share with, while demand dictates how heavily firms use those ties.

²¹Notably, 85% of firms increase worked hours during busy periods, but only 26% cut worked hours during slow periods, meaning that there is often slack labor held at firms driven by this variation, consistent with the findings in Walker et al. (2024).

²²The CV reflects a full year of variation, while sharing flows cover the past three months to limit recall error, so realized flows depend partly on a firm’s recent demand state. Coefficients are stable when adding current-state indicators, using a continuous cycle-position measure, or restricting to firms in the normal state.

2.6 Fact 5: Labor sharing places costs on borrowers and lenders

I document three main costs that firms incur through labor sharing, which fall differently on borrowing and lending firms. First, lending firms report appropriation risk as a major disadvantage of labor sharing. Owners report fear of losing lent workers (44%), losing customers (41%), or leaking of unique designs or production information (24%). Over half report that lent workers return later than expected. Second, borrowing firms bear the costs of hosting another firm’s workers: theft or damages (42%), and supervision.²³ Third, in line with the reciprocity expectations mentioned in Section 2.3, borrowers take on a future obligation to lend. 20% report they are expected to lend when they do not want to.²⁴

Labor sharing offers a way for owners and managers to reach across firm boundaries when consolidation is costly or infeasible. Only 10% of sharing firms have ever considered acquisition of or consolidation with their most active sharing partner. Those who have state lack of access to financing or inability to buy shared space as a key barrier (64%).²⁵ More cooperative mergers face a variety of trust and contracting issues which are difficult to overcome. The majority of firms cite at least one trust-related concern, including financial decisions or fear of losing their customer base. As a result, firms engage in labor sharing and other resource sharing, much like capital rentals in Bassi et al. (2022), but are reluctant to coordinate on financial or managerial margins. These patterns may help explain why firms in low-income countries stay small (Hsieh & Olken, 2014).

Workers involved in labor sharing bear two main costs through moving between firms on short notice and receiving less training. First, moves are not planned far in advance: 63% of workers who work for multiple firms have been asked to work elsewhere with less than one day’s notice, and 28% of these workers report that this brings difficulty planning self-employment work, family activities, or transport. Each move also carries an adjustment. Workers report a median of one full workday before they can work at full speed at a new firm, a large portion of the median shared stint of just three days. Under piece-rate contracts, this directly impacts take-home earnings. Second, labor sharing may disincentivize firms to supply general training since other firms can gain from their investment. Workers who are shared spent an average of 2.4 days training over the previous month compared to 3.2 days for those not shared ($p = 0.036$).²⁶

3 Understanding Firm Hiring Choices

Modeling the trade-offs firms face in hiring requires estimation of two wedges: what borrowing firms give up to obtain a shared worker, and what lending firms bear to supply one, neither of

²³Firm owners rate borrowed workers as lower theft and supervision risks than walk-in hires (Section 2.4), but this risk is not fully eliminated for a marginal hire.

²⁴Despite the salience of these costs for firm owners, few firms identify contract enforcement or third-party dispute resolution (8.5% and 4.7%, respectively) as a helpful policy change for adjusting during busy periods.

²⁵In randomly sampled pilot data, only 25% of firm owners had ever used a bank loan ($N = 104$).

²⁶This is consistent with experimental evidence in Burundi agricultural markets by Cefala et al. (2024) who show that guaranteeing worker return increases employer provision of training by over 50 percentage points. My data do not provide causal evidence along these lines, due to the composition differences between shared and unshared workers.

which is priced in practice. Estimating willingness-to-pay (WTP) for worker and contract attributes is challenging because observed hiring practices are endogenous to the very valuations I want to measure. Realized hiring through a channel reflects both how the firm values that channel and the availability of workers through it in the local market. Further, workers vary systematically across hiring channels, as documented in Section 2.4. I rely on three stated choice experiments embedded in the firm survey to price both sides of the exchange directly.

I design the stated choice experiments around a common vignette centered on a localized demand shock typical of the industry: an unexpected large order for a core product. In the first two experiments, the firm owner faces the shock at their own firm and must consider hiring to fulfill the order. In the third, the shock instead hits peer firms, who approach the respondent with offers to borrow a worker. Each experiment identifies a different facet of firm preferences and valuation; the first experiment varies hiring sources to estimate WTP for shared labor, the second estimates WTP for sharing-specific borrowing contract features such as reciprocity, and the third estimates the compensation lending firms require to supply a worker.

In every choice task, firms compare two offers and may decline both. The offers are hypothetical, with attribute levels set to cover the realistic range of wages and contract terms in these sectors, combined into choice tasks by a Bayesian D-efficient design that uses pilot estimates as priors, then assigns tasks at random. This follows recent work eliciting employer preferences from constructed candidate profiles (Kessler et al., 2019), including in settings where incentivized elicitation is infeasible (Barker et al., 2025). Where stated and incentivized valuations can be compared directly, they align closely: Mas and Pallais (2017) find vignette-based willingness to pay closely tracks their field-experimental estimates for most arrangements.

For each experiment, respondents are shown a series of six tasks. Responses across owners ($N = 515$) are pooled ($N \approx 3,000$ choices per experiment) and population-level attribute coefficients are estimated via multinomial logit. To identify WTP from these experiments, I assume that each respondent i derives utility:

$$U_{ijt} = x'_{ijt}\beta + \nu_{ijt}, \quad j \in \{A, B, \text{reject}\}, \quad t \in 1, \dots, 6, \quad (1)$$

where $\nu_{ijt} \sim \text{T1EV}$ and is i.i.d. across choices. The attributes which comprise x_{ijt} vary across experiments and are reported in Table 5. Full estimation details can be found in Appendix Section C.

3.1 Choice Experiment 1: Hiring Across Sources

The first choice experiment estimates the premium firms place on shared workers relative to other hiring channels. Owners choose between two worker profiles that vary in hiring source and worker characteristics. The prompt for the experiment reads:

You receive an order for 10 [*industry core product*] which need to be produced very quickly. In addition to your usual workers, which of these workers would you prefer to

hire?

Note that you can choose to not hire either worker, but this may result in delays or difficulties.

Worker profiles vary in asking wage, hiring source, industry experience, supervision required, and certification, to disentangle margins at the center of the screening problem documented in Section 2.4. The attribute space is presented in Table 5, Panel A.²⁷ To convert coefficient estimates to WTP valuations, I take the negative of the ratio of the coefficient for the target attribute to the marginal utility of the wage, evaluated at a reference weekly wage of UGX150,000.²⁸ I report WTP estimates for all attributes in Figure 3a.

Experiment Results I estimate that firms are willing to pay a substantial premium of 53 thousand UGX ($p < 0.001$) per worker-week to hire directly from other firms over a similar walk-in worker, the highest such premium among all hiring channels and 44% of the median worker-reported wage. It is substantially higher than the WTP for a referral from an existing employee ($\Delta = 23.9$ thousand UGX, $p = 0.012$). The difference between shared workers and friend referrals is positive but imprecise ($\Delta = 15.2$ thousand UGX, $p = 0.16$). Other worker attributes are priced sensibly: firms positively value additional years of industry experience and negatively value required supervision. Firms do not show any detectable preference for technical certificates, consistent with evidence that certification does not solve screening problems in this context.

The valuation of labor sharing over other sources is a price firms are willing to pay for the verified worker quality and immediate availability outlined in Section 2. The relevant counterfactual for hiring under a demand shock is therefore not walk-ins but rather the prevailing distribution of hires across all non-shared sources. I compute a composite valuation of a non-shared hire as an average weighted by each channel’s share of hires over the prior twelve months, and find that the net premium is 29.4 thousand UGX per worker-week, or approximately 25% of the median worker-reported wage (95% CI: [10.0, 50.3]). The experiment prices a hiring choice between sharing and all other channels. The model of Section 5 reads this channel premium as the borrowing firm wedge, the per-week cost a firm bears to obtain a worker through sharing, which includes transaction costs, denoted $c_s + \tau$.

3.2 Choice Experiment 2 – Labor Sharing Borrowing Experiment

The second choice experiment fixes the hiring channel to labor sharing and asks which features of labor sharing are valued by borrowing firms and drive the labor sharing premium. The vignette and prompt follow the first experiment, adding a simple reminder that “Both workers come from other firms nearby” for the sake of salience. Worker profiles vary in asking wage, industry experience, supervision required, and certification, just as in the first experiment. They additionally vary in the

²⁷An example of how the choices were displayed to the respondent is shown in Figure A2.

²⁸This reference wage is representative of both the average of wage asks in the choice experiment and the mean of worker-reported wages.

reciprocity expectation implicit in the exchange. This reciprocity attribute has three levels: the baseline level of no reciprocity expectation, a one-time obligation to lend workers in return, and an ongoing reciprocal relationship in which the respondent will expect to both lend and borrow with this same firm in the future. The attribute space is presented in Table 5, Panel B. Willingness-to-pay estimates are reported in Figure 3b.

Experiment Results I estimate that firms highly value ongoing relationships, with an estimated WTP of approximately 43,000 UGX/week, or 36% of the median wage. Importantly, this premium is significantly higher than either a one-time obligation to lend in return or an exchange with no reciprocity expectation (both $p < 0.001$). Thus, firms are willing to invest in relationships they see as more durable. Other attributes are priced similarly to the first experiment, with a positive and significant estimate for years of experience, negative and significant estimate for supervision required, and no detectable effects for technical certificates. Because respondents in the first experiment evaluated the shared-worker channel with its typical relationship terms in mind, this relationship value is already embedded in the channel premium. Despite the fact that firms report high costs, as documented in Section 2.6, they are willing to invest substantially in relationships that secure ongoing access to shared labor.

3.3 Choice Experiment 3 – Labor Sharing Lending Experiment

The final firm choice experiment asks firms to consider the lending side of labor sharing arrangements. For each choice, owners were presented with the following prompt:

Two workshop owners approach you about an order they have received and ask to borrow one of your skilled workers temporarily for a period of ONE WEEK. Imagine it is currently [demand state] for your firm. The borrowing workshop will pay all wages while the worker is there. If you can only send up to one worker, which workshop would you send to?

Note that you can keep your worker and not send to either workshop.

When lending a worker, a firm owner must consider the terms of the agreement, the relationship with the other firm, and also the conditions at their own firm. To capture this, I vary an offered fee, the right to recall the worker, reciprocity terms, the location of the partner firm, and the prompted demand state of the respondent’s firm.²⁹ I include the same reciprocity attribute levels from the second experiment but from the lender’s perspective, allowing for comparison of reciprocity norms from both sides of the exchange. The attribute space is presented in Table 5, Panel C. All estimates use the slow-state fee slope, which is the model-relevant state since lending firms are slack. Willingness-to-accept estimates are reported in Figure 3c.

²⁹Following the demand elicitation method in Section 2, I ask owners to consider scenarios in which it is a busy, normal, or slow period at their own firm.

Experiment Results Similar to findings from the second experiment, firm owners value an ongoing reciprocal relationship highly and are willing to accept around 13,900 UGX less in compensation in order to lend a worker to a firm with whom they have an ongoing relationship compared to unknown partners. Importantly, this is not simply detecting the valuation of a future borrowing option: the ongoing relationship is valued significantly higher than a one-time borrowing guarantee ($\Delta \approx 12,000$, $p < 0.001$), which has no detectable valuation. The ability to recall the lent worker is highly valued with an estimated WTA of 35,000 UGX ($p < 0.001$). The recall guarantee sharply reduces appropriation risk, as it allows firm owners to quickly regain their workers if they receive a subsequent demand shock. In reality, this attribute is not a universal feature of sharing relationships: the median firm reports a 50% probability of immediately recalling workers who are lent out. Thus, this attribute likely signals a very tight firm-firm relationship. Lastly, distant partnerships are penalized: firms must be compensated more to lend a worker to other firms outside of their immediate cluster or neighborhood, possibly for reasons of oversight.

Estimating Transaction Costs The lending experiment splits the borrowing firm’s cost into direct compensation received by the lending firm, and a transaction cost which is lost. I estimate the willingness to accept for a baseline one-week lending agreement, which is to lend a worker to a nearby firm, with an ongoing relationship but no right to recall. The WTA for this bundle is 13.9 thousand UGX (95% CI: [11.0, 16.8]), which implies a transaction cost of $\tau \approx 15.4$ thousand UGX. Measured compensation covers less than half of the borrowing firm’s perceived costs. Because the lending design likely understates the WTA, this figure is best read as an upper bound on τ (Appendix C).

4 Worker Job Search and Preferences

Survey data paint a picture of workers supplementing steady employment at a usual employer with temporary employment at other firms and self-employment, while also experiencing periods of slack. Most randomly-selected workers (82%) were surveyed at their usual firm, where they most frequently come to expecting to work. The median worker works 6 days per week at their usual firm and has a tenure of approximately 3 years. However, this consistency does not imply exclusivity. In the month prior to survey, 35% of workers reported days working at another firm and over half spent at least one day self-employed. Workers employ this patchwork approach because almost all employment (91% of listed workers) is through piece-rate contracts, and thus slack periods provide, at best, subsistence pay.

Labor sharing offers another way for workers to reduce slack. However, workers must trade-off improved utilization with adjustment costs, transport, and self-employment opportunities when agreeing to move between firms. To understand how workers trade off wages and amenities, including their valuation of sharing arrangements, I employ another stated choice experiment where workers compare hypothetical job offers, with a similar structure to the experiments of Section 3. From this

experiment, I recover labor supply elasticities and willingness to pay estimates for common contract features. Full estimation details can be found in Appendix C.

4.1 Job Offer Choice Experiment Design

The job offer choice experiment estimates the premium workers place on the connection through which a job is offered. Workers choose between two hypothetical jobs that vary in firm-worker connection, along with other contract details such as duration and self-employment options. Each worker completes six choice tasks, each offering two jobs and the option to decline both. The prompt for the experiment reads:

Consider a situation where you are not employed. You are offered the following jobs at different firms in this industry. Which of the following would you accept?

Note that you can say no to both if you believe you could find a better job elsewhere or would rather remain unemployed.

Job offers vary in offered wage, firm-worker connection, location relative to the worker’s current firm, guaranteed job duration, self-employment option, and whether the worker may be asked to move between firms. Offered wages range from 40,000 to 250,000 UGX per week, offering substantial variation above and below the median observed weekly wage of 120,000. The firm-worker connection attribute has four levels which correspond to the four main types of hiring captured in Section 2.3. Here, I frame the connection as who the worker knows at the hiring firm: nobody (corresponding to a walk-in), a worker (employee referral), the owner (family/friend referral), or whether they were sent there by another firm’s owner (labor sharing). The split-time attribute captures a willingness to pay for “stability,” that is, whether the uncertainty and potential movement associated with labor sharing incurs substantial hassle costs on the worker, or may be valued as an insurance against under-utilization. The attribute space is presented in Panel (d) of Table 5.³⁰

4.2 Experiment Results

I estimate willingness-to-pay for each attribute using a mixed logit specification evaluated at the mean offered wage in the experiment.³¹ All estimates are reported in Figure 4. Contrasting with the firm experiments, workers do not appear to value labor sharing connections over other types of connections. Rather, workers display a near uniform WTP for *any* type of connection above walking into a firm with no connection. Willingness-to-pay for connections ranges from 11,500–12,600 UGX/week, or approximately 10% of the median weekly wage (all individual $p < 0.05$, joint-equality Wald test $p = 0.95$). Thus, the labor sharing premium is strictly a firm-side object.

The remaining attributes suggest that workers prefer nearby job opportunities with options which provide flexibility. Workers require a substantial wage increase to move outside of their

³⁰An example of how the choices were displayed to the respondent is shown in Figure A2, Panel B.

³¹This requires the same distributional assumptions for worker utility as those applied to firm owners discussed in Section 3.

current cluster. I estimate a WTA of 18,400 UGX (15% of median weekly wage) to accept a job outside of their current cluster but within the parish, and 33,900 UGX (28% of median weekly wage) to accept a job outside of the same parish. Workers do not value long duration arrangements, with an extra week of guaranteed work duration carrying a negative and significant estimated WTP, consistent with the commonplace nature of working across multiple firms in this setting.

By far the most valued single attribute is the self-employment option, which in this setting takes the form of being able to take and work on one’s own orders from the firm’s space. Workers are willing to pay 29% of the median wage for this option. Self-employment is common in this setting, with over half of workers reporting some self-employment income over the previous month, allowing workers to supplement their income during idle periods. Workers also *positively* value the expectation of being sent to other firms ($WTP \approx 4.5\%$, $p = 0.02$). Because the dominant payment mode is piece-rate, a worker would only be reallocated in the case where there is opportunity elsewhere, thus movement is valued as access or exposure to more work opportunities.

Taking these results in comparison to the firm side results, workers do not require compensation to participate in labor sharing. Workers generally value mobility and flexibility, and value the connection similarly to other referrals, valuing self-employment above all else. Thus, the frictions associated with labor sharing will fall on firms in the model of Section 5.

4.3 Estimating Labor Supply Elasticities

In addition to pricing amenity valuations, this experiment also allows estimation of labor supply elasticities using the wage coefficients. I compute the elasticity of the acceptance probability with respect to the offered wage at the mean offered wage of 148,000 UGX, which is close to the mean current wage in the job history data (154,000 UGX). Using this method, I estimate an aggregate elasticity of $\varepsilon = 1.28$ (95% CI: [1.166, 1.394]). Respondents declined both offers in only 9% of tasks, so this elasticity mostly reflects switching between employers rather than leaving work. Elasticity estimates are similar for skilled workers ($\varepsilon_H = 1.27$) and less-skilled workers ($\varepsilon_L = 1.35$), and are not statistically significantly different ($p = 0.52$). Though clustered same-sector firms in theory offer plenty of outside options for workers and thus more wage sensitivity, relationship-driven hiring and costly verification push in the opposite direction, yielding more modest elasticity estimates.

This estimate lies within the range found by other studies in low- and middle-income settings, but lower than typical estimates in more formalized settings. For example, Amodio and De Roux (2024) estimate a labor supply elasticity of around 2.5 in formal Colombian manufacturing. In a meta-analysis including 59 estimates across five LMICs, Sokolova and Sorensen (2021) report a median labor supply elasticity of 1.16, more comparable to my estimates.

The worker survey directly elicited reservation wages from all workers.³² This question asks about working versus not working, so it measures a different margin from the experiment. The

³²The direct elicitation of reservation wages is from a question phrased “If you were not working, what is the lowest weekly wage you would accept for a one-week job doing your normal work?” Workers were shown a menu of wage bins spanning the range observed in the pilot surveys. Reservation wages are calculated using bin midpoints.

share of workers whose reservation wage lies below a given wage rises with that wage at an elasticity of about 0.94 for skilled workers and 1.01 for less-skilled workers.³³ A second check asks whether workers would take the same work at a new employer for 80% or 60% of their current wage. Its format follows the reservation raise of Mui and Schoefer (2025). It implies an elasticity of 1.18, close to the experiment.

Taken together, the experiment and the wage-cut ladder measure how readily workers move between employers, implying a firm-level labor supply elasticity of about 1.2 to 1.3. Stated reservation wages measure how readily workers enter or leave work, implying a participation elasticity of about 1.0. The model uses both to capture how workers substitute between firms, and between employment and unemployment.

5 Model

The discrete choice experiments in Sections 3 and 4 estimate the price a borrower pays, the compensation a lender receives, and how strongly workers respond to wages in borrowing, lending, and hiring scenarios. However, they only price one-off exchanges. They do not capture how firms trade off shared workers in equilibrium with other types of hiring, how firms’ aggregate decisions impact a labor market with sharing, or how worker outcomes at the market level are shaped by labor sharing.

Ideally, I would compare similar clusters with and without sharing systems. Because sharing is nearly universal, I develop a model to construct that comparison and use it to answer three questions about how labor sharing impacts the broader market. First, I ask how labor sharing overall shapes the set of firms that operate, how it changes firm hiring and their resulting profits, and how it impacts worker earnings and employment relative to an economy without sharing. Second, I ask whether a simpler institution, such as a day-labor market, could do the same job or better. Lastly, I ask how sharing changes the returns to training and certification policies, which are commonly funded to aid firms in finding skilled workers.

I first build a baseline economy in which firms hire only permanent workers through an “external” market, which stands in for walk-in and referral hires. This baseline builds on Card et al. (2018) in which workers choose among firms based on wages and amenities. In this adaptation, firms grow by posting costly vacancies, and wages follow a rent-sharing rule which matches patterns found in reported wages. The firm side is similar to Bassi et al. (2022), where managers who differ in ability face an entry decision and have access to rental markets for capital inputs. In my model, firms have the ability to borrow and lend workers, rather than to rent capital. I add two key frictions to this baseline model. First, firms do not observe skill until hire, reflecting the screening problems faced by firms in walk-in or referral hiring (Section 2.4). Second, they face individual demand shocks, reflecting the firm-specific volatility reported by firms (Section 2.5).

³³I estimate the slope of the empirical distribution of the ratio of reservation wage to current wage between 0.7 and 1. Estimates range from 0.86 to 1.12 across wage definitions. About 28% of workers report a reservation wage above their current wage.

The central feature of the model is a second chance to hire through labor sharing, allowing firms to adjust their workforce after learning their demand state. When only given access to slow and uncertain hiring through walk-ins and referrals, firms staff according to expected demand, leaving them short-staffed in busy periods and carrying slack in slow periods. With sharing, firms in any demand state can adjust their workforce by borrowing or lending skilled workers, provided other firms in the market have the opposite need. A shared worker arrives with known skill, as their ability has already been vetted by the lending firm. Sharing thus separates the firm paying the hiring and screening costs of a worker from the firm that uses them. Firms anticipate labor sharing exchanges, and adjust their external hiring accordingly. Finally, because labor sharing requires a counterparty, each firm's ability to borrow and lend depends on how other firms hire, so I solve for the market equilibrium.

I start by setting out agents and production, build labor supply from workers' job choices, and state the firm's problem and discuss how wages are set. Last, I add labor sharing as a way to adjust after demand is known, and characterize the full equilibrium.

5.1 Setup

The economy is populated with managers and workers. Time is discrete with common discount factor β . I assume output sells at a fixed price, and measure it in revenue.

Agents Workers are indexed by i , are risk-neutral, and supply their labor to manager-run firms. Each worker is either skilled (type $\omega = H$) or less-skilled (type $\omega = L$). A skilled worker's productivity is normalized to one, $a_H \equiv 1$, and a less-skilled worker produces a fraction $a_L \in (0, 1)$ of a skilled worker's output. Workers differ in their reservation wage r_{ij} . Workers know their own type, but it is only revealed to a manager upon hiring.

Each firm j is run by one manager, who owns it. Firm productivity has two sources. The first is managerial ability z_j , which I take directly from the observed distribution of management practices. Second, each draws a permanent idiosyncratic productivity u_j , independent of z_j , both of which are known to the manager. Together, they determine the firm's productivity. Firms also differ in their offered amenities to workers.

Production Function and Demand Firm j produces output from effective labor alone, with decreasing returns to scale. Effective labor counts each less-skilled worker as a fraction a_L of a skilled one,

$$L_j = N_{H,j} + a_L N_{L,j}, \quad (2)$$

where $N_{H,j}$ and $N_{L,j}$ are the skilled and less-skilled workers present at the firm when it produces. As noted in Section 2.5, demand is order-driven and volatile. I carry this into the model in reduced form, as a productivity term θ_d that depends on the firm's demand state d . Output in state d is

$$Y_{d,j} = \theta_d A_j L_j^\kappa, \quad \kappa \in (0, 1), \quad A_j = \exp(\lambda_z z_j + u_j) \quad (3)$$

where A_j is the firm's permanent productivity, increasing in managerial ability z_j and in the draw u_j . The model has no capital input. Productivity differences across firms, including any from unmeasured capital, enter through A_j .

Demand takes two states, busy and slow, $d \in \{b, s\}$. In the data, demand states are mostly firm-specific. Realized states in the same market (parish $\times$ industry) are only weakly correlated, and most markets hold a mix of busy and slow firms (Section 2.5, Table A8). I therefore treat each firm's state as an independent draw, across firms and across periods. A firm is busy with probability q , and productivity in a slow period is a common fraction ρ of productivity in a busy period,

$$\theta_d = \begin{cases} \theta_b & \text{with probability } q, \\ \theta_s \equiv \rho \theta_b & \text{with probability } 1 - q, \end{cases} \quad \rho \in (0, 1). \quad (4)$$

The size of the swing, governed by ρ , is what makes a firm want different headcounts in different periods. Because states are independent, there is no aggregate state, and the shares of busy and slow firms are constant across periods.³⁴

Timing and Information Firms face two uncertainties. The first is the type of each permanent hire, reflecting the screening problems of walk-in and referral hiring documented in Section 2.4. The second is the demand state, which is volatile and uncertain, as documented in Section 2.5. The order in which they are resolved gives labor sharing its role. Vacancies are posted before the demand state is known, and workers are borrowed or lent after.

The manager decides whether to operate a firm. Manager level attributes are fixed in time, so this reduces to a one-time decision of participation. Firms exit only through an exogenous hazard. Within a period, events unfold as follows:

1. Firms post vacancies in the external market. A firm does not observe the type of any individual hire. It knows only the share of skilled workers it will attract in the external market.
2. Matches form. A worker accepts if the firm's wage for their type is at least their reservation wage r_{ij} . New hires join the firm for the period, and the firm learns each worker's type.
3. Each firm's demand state θ_d is realized.
4. Knowing its state, each firm asks to borrow or offers to lend skilled workers.
5. Exchanges settle at fixed prices. A borrowing firm pays each borrowed worker the wage it pays its own skilled workers, and bears a cost of $c_s + \tau$ per worker. A lending firm receives c_s and does not pay that worker's wage for the period.
6. Firms produce with their adjusted workforces.
7. Some workers receive an outside offer and leave if it pays more than their current wage.

³⁴The survey records busy, normal and slow months. I map busy to b , and normal and slow to s (Section 6).

Figure A3 displays the sequence as a timeline, with firm decisions above the line and worker decisions below it.

5.2 Labor Supply

In the model, workers make a series of three choices. They decide whether to participate in the market, which firm to join if they enter, and whether to stay at their firm once hired. Each choice reduces to comparing a wage with a threshold. Outside offers arrive at the same rate whether or not a worker takes the job, so no choice carries an option value.

Participation First, a worker decides to enter the market if their type’s going wage exceeds their reservation relative to not working: $\exp(\mu_\omega) \geq r_i^0$. Thus, at the market level, there are N_ω^m type ω workers willing to work in the market:

$$N_\omega^m = M_\omega \cdot F_\omega^0(\exp(\mu_\omega)) \quad (5)$$

where F_ω^0 is the CDF of the distribution of reservation wages, measured in the worker survey. The local elasticity of Equation (5) with respect to the going wage is the participation elasticity ε_m . It governs how many workers the market gains when all firms pay a type more. The worker survey measures r_i^0 directly, which pins down ε_m (Section 6).

Recruitment Workers in the market then choose a firm. Workers value a job by its wage, the firm’s amenities, and their own taste for it. Worker i of type ω values a job at firm j at

$$U_{ij} = \varepsilon \ln w_{\omega,j} + a_j + e_{ij}, \quad (6)$$

where a_j is firm j ’s amenity value, as in Card et al. (2018). Amenities include a firm’s location and working conditions, and whether it lends out workers when slack, which workers value positively in the job offer choice experiment. Taste shocks e_{ij} are i.i.d. draws from a type I extreme value distribution. A worker’s reservation wage for job j , r_{ij} , is the wage at which the job’s value equals that of their best alternative.

I assume each firm is small relative to its market, a parish $\times$ industry cell. A firm paying wage $w_{\omega,j}$ then can recruit $R_{\omega,j}$ workers of type ω per period, where

$$\ln R_{\omega,j} = \Lambda_\omega + a_j + \varepsilon \ln w_{\omega,j}. \quad (7)$$

As in Card et al. (2018), amenities shift a firm’s recruitment curve rather than its wage, so at any wage, a firm whose workers can be lent out attracts more recruits. Firms hire from this flow by posting vacancies, which I assume to be the limiting side of the market. The term Λ_ω is a market-level scale that every firm takes as given. It rises with the number of type- ω job seekers and falls with the value of their alternatives. The parameter ε is the worker’s wage coefficient, or the

elasticity of the firm's recruits to its offered wage, which the worker choice experiment measures directly (Section 4).³⁵ It exceeds ε_m because workers substitute between firms more readily than between work and not working.

Finally, I assume wages are type-neutral at the firm:

$$\ln w_{\omega,j} = \mu_{\omega} + \psi_j, \quad (8)$$

where μ_{ω} is a market wage level for type ω and ψ_j is a firm component common to both types. A firm's wage depends on the worker's type, and not their reservation wage. Section 5.4 justifies this form.

Lemma 1 (Separability). *Suppose each firm is small in its market, both types share the wage coefficient ε and the amenity a_j in Equation (6), and wages are type-neutral as in Equation (8). Then the skilled share of every firm's recruits is*

$$\alpha \equiv \frac{R_{H,j}}{R_{H,j} + R_{L,j}} = \frac{e^{\Lambda_H + \varepsilon \mu_H}}{e^{\Lambda_H + \varepsilon \mu_H} + e^{\Lambda_L + \varepsilon \mu_L}}, \quad (9)$$

which is the same at every firm and does not depend on the firm's wage.

Posting a higher wage brings a firm more willing recruits, but does not allow it to tilt the mix between types. The skilled share α is therefore a property of the market, which managers know. In the terms of Kline (2025), the screening elasticity of wages is zero. A firm therefore values each hire by its expected output across states.

Two features of the setting support the lemma's assumptions. First, owners pay nearly all workers per piece (Section 2.3). A firm sets one rate per piece, so it cannot raise one type's wage without raising the other's. This matches the near-additive wage structure found in matched employer-employee data (Bonhomme et al., 2019; Card et al., 2013; Lamadon et al., 2022).³⁶ Second, the worker choice experiment cannot reject equal wage elasticities for the two types (Section 4).³⁷

Separations In addition to attracting more recruits, higher-paying firms retain workers longer. At the end of each period, a worker receives an outside offer with a type-specific probability. An offer's wage is drawn from a Pareto distribution, indexed by separation elasticity ε_s . A worker leaves their firm if the received offer exceeds their current wage.

$$\delta_{\omega,j} = \delta_{0,\omega} \left[\frac{w_{\omega,j}}{W_{\omega}} \right]^{-\varepsilon_s} \quad (10)$$

³⁵With extreme-value tastes, the exact elasticity is $\varepsilon(1 - p_j)$, where p_j is the job's choice share. For a small firm, it is ε . The experiment measures the elasticity at observed wages.

³⁶Groups can still share firm premiums unequally: Card et al. (2016) find that women receive a smaller share than men. In my data, firm-by-type wage interactions are not significant, but the tests have little power.

³⁷The experiment tests equality near observed wages, so the lemma should be read as holding near those wages. If the two types valued a firm's amenities differently, each firm would have its own skilled share α_j , which still would not depend on its wage. Estimation uses the common- α case.

where W_ω is a market reference wage for the type and $\delta_{0,\omega}$ is the separation rate of a worker paid that wage. The base rate absorbs both the offer probability and the scale of the offer distribution. Outside offers and recruits are drawn from different distributions, so the separation elasticity ε_s and hiring elasticity ε are distinct, as in Manning (2013). Types share ε_s and differ in their base separation rates $\delta_{0,\omega}$. Because wages are type-neutral, the ratio $\delta_{L,j}/\delta_{H,j}$ is the same at every firm. Firms do not dismiss workers, so every separation is a quit.

Stocks and Market Clearing A firm's hires and quits determine the stock it uses in production. Firms post m_j vacancies, which fill at rate λ_e . A share α of the resulting $h_j = \lambda_e m_j$ hires is skilled (Lemma 1). In steady state, each type's stock is its hires divided by its separation rate, $N_{\omega,j} = \alpha_\omega h_j / \delta_{\omega,j}$, with $\alpha_H = \alpha$ and $\alpha_L = 1 - \alpha$.³⁸ Summing over types, a firm's stock is its hires times their expected tenure,

$$N_j = h_j \bar{T}_j, \quad \bar{T}_j = \frac{\alpha}{\delta_{H,j}} + \frac{1 - \alpha}{\delta_{L,j}}. \quad (11)$$

The skilled share of the stock, $\alpha^N = (\alpha / \delta_{H,j}) / \bar{T}_j$, is the same at every firm. It differs from α because the two types quit at different rates.

Aggregate labor supply sums participation over types, $N^m = N_H^m + N_L^m$. Near observed wages, Equation (5) takes the form

$$N_\omega^m = \Gamma_\omega M_\omega e^{\varepsilon_m \mu_\omega}, \quad (12)$$

where Γ_ω is the scale of the reservation-wage distribution, which Section 6 pins from observed employment. The type wage levels μ_ω adjust so that each type's market clears, with the workers firms employ equal to the workers who participate:

$$\sum_j \alpha_\omega^N N_j = N_\omega^m, \quad (13)$$

where $\alpha_H^N = \alpha^N$ and $\alpha_L^N = 1 - \alpha^N$. Each firm is small, so it takes μ_ω as given.

5.3 The Firm without Labor Sharing

I first describe the problem facing the manager who can only hire on the external market. In this baseline, the manager makes two decisions. The first is whether to operate. The second, made each period, is how many vacancies to post before the demand state is known. The owner knows their firm-specific wage component ψ_j , but takes the market type wage-level μ_ω as given, thus takes wages as given. The profit of firm j in demand state d with stock of workers N_H, N_L is

$$\pi_{d,j}^0(N_{H,j}, N_{L,j}) = \theta_d A_j (N_{H,j} + a_L N_{L,j})^\kappa - w_{H,j} N_{H,j} - w_{L,j} N_{L,j}. \quad (14)$$

³⁸Hires face separation in the period they join, so the exact stock is $(1 - \delta_{\omega,j}) \alpha_\omega h_j / \delta_{\omega,j}$. The difference is small when separation rates are small.

Every firm's stock has skilled share α^N , so profit depends only on its total stock N_j . Effective labor is $\bar{a}N_j$, with $\bar{a} = \alpha^N + (1 - \alpha^N)a_L$, and the wage bill is $\bar{w}_jN_j$, with $\bar{w}_j = \alpha^N w_{H,j} + (1 - \alpha^N)w_{L,j}$.

Vacancies and Hiring An operating firm in this setup can only grow by posting vacancies in the external market. At the beginning of each period, it posts m vacancies at convex cost $C(m)$, which fill at rate λ_e . In expectation, a share of these hires α is skilled (Lemma 1), and hires join and produce the same period. Taking wages as given, the firm solves:

$$V_j(N_H, N_L) = \max_{m \geq 0} \left\{ \mathbb{E}_d[\pi_{d,j}^0(N_H + \alpha\lambda_e m, N_L + (1 - \alpha)\lambda_e m)] - C(m) + \beta V_j(N'_H, N'_L) \right\}, \quad (15)$$

$$N'_\omega = (1 - \delta_{\omega,j})(N_\omega + \alpha_\omega \lambda_e m), \quad \omega \in \{H, L\},$$

where $\pi_{d,j}^0$ is profit from Equation (14), $\alpha_H = \alpha$, and $\alpha_L = 1 - \alpha$. Incumbents and new hires survive to next week with probability $1 - \delta_{\omega,j}$, the firm's separation rate from Equation (10). Because quits fall with the wage, a higher-paying firm keeps more of the workers it hires.

Firms post vacancies weighing the expected marginal benefit of an additional worker, discounted by their expected tenure, against increasing marginal costs of vacancies. In steady state, this condition is:

$$C'(m_j)/\lambda_e = \sum_{\omega} \frac{\alpha_{\omega}}{1 - \beta(1 - \delta_{\omega,j})} [MB_{\omega,j} - w_{\omega,j}]. \quad (16)$$

where $MB_{\omega,j} = a_{\omega} \mathbb{E}_d [\kappa \theta_d A_j L_j^{\kappa-1}]$ is the expected marginal revenue product of a type- ω worker. Firms are kept small through increasing marginal hiring costs, which in this setup are entirely vacancy posting costs, not rising wages with each marginal hire (Manning, 2006). In effect, this is a model of a frictional labor market where firms take wages as given and hire through costly recruitment (Hall, 2005; Pissarides, 2000).

Ownership A manager must decide whether to operate a firm or work for a wage. A manager has an outside option w_j^o , the wage they would earn as a worker and a taste for ownership ζ_j . Firms exit at an exogenous rate δ_x each period, after which the manager earns w_j^o . The manager operates if

$$\bar{\pi}_j - c_0 + \zeta_j \geq w_j^o, \quad (17)$$

where $\bar{\pi}_j = \mathbb{E}_d [\pi_{d,j}^0 - C(m_j)]$ is the firm's expected profit per period in steady state, net of vacancy costs, from the problem in Equation (15). The term c_0 represents a fixed entry cost. The manager's characteristics are fixed, so the decision is made once.

5.4 Wage Setting

With matching frictions, any wage between a worker's reservation wage and their value to the firm is an equilibrium outcome. A wage norm can select from this bargaining set (Hall, 2005).

I build the wage rule to match three descriptive facts about wages and to align with the main

components of the production function. First, there exists a skilled worker premium, where skilled workers get paid 27% more than less-skilled workers. Second, there is substantial across-firm wage dispersion. Lastly, there is a small, but statistically significant, pass-through elasticity of wages with respect to revenue per worker of about 0.10.³⁹

Standard surplus sharing or a fixed markdown of marginal product would pass revenue through far more strongly, so I use a log-additive rule with rent sharing:

$$\ln w_{\omega,j} = \underbrace{\mu_{\omega}}_{\text{type component}} + \underbrace{\xi_j}_{\text{firm component}} + \underbrace{\beta_{\text{pt}} \ln(\bar{y}_j)}_{\text{pass-through}} \quad (18)$$

where μ_{ω} is the market wage level for type ω , set by Equation (13), and $\bar{y}_j$ is firm j 's expected revenue per worker. The firm premium ξ_j is in part tied to productivity (Card et al., 2018; Lamadon et al., 2022). The parameter β_{pt} is the elasticity of wages with respect to revenue per worker.⁴⁰ Together, the last two terms form the firm component of Equation (8), $\psi_j = \xi_j + \beta_{\text{pt}} \ln \bar{y}_j$.

Each term follows a part of production in Equation (3). The type term prices the two kinds of labor. The firm premium moves with productivity A_j through its rent component. The pass-through term moves with productivity and demand, A_j and θ_d , through expected revenue per worker.

5.5 Adding Labor Sharing

I now add labor sharing as a way for a firm to flexibly adjust its headcount. After observing its demand state, the firm can offer to lend or request to borrow workers through labor sharing. A borrowed worker's type is already known, because the lending firm learned it on hiring (Section 2.4). I assume only skilled workers are exchanged, and a firm can lend at most its own skilled workers. Prices are fixed at the valuations from the firm choice experiment (Section 3):

$$p_{b,j} = w_{H,j} + c_s + \tau, \quad p_{s,j} = w_{H,j} + c_s. \quad (19)$$

The borrowing firm pays the shared worker their own skilled worker wage, plus a fee c_s and incurs transaction costs τ of which the lending firm receives c_s . These costs are estimated by the choice experiments of Section 3. The network on which these firms are connected is left outside the model. I assume lending is a firm decision, in line with the structure documented in Section 2.3. During a spell, a lent worker earns the borrower's skilled wage. Spells last one period, so a worker's choice of home firm depends only on that firm's wage and amenities.

After its demand state is realized, a firm chooses how many skilled workers to borrow or lend, ℓ .

³⁹Appendix Table A9 reports estimates for regressions of log wages on worker types, estimated firm effects, and pass-through.

⁴⁰Each firm takes ψ_j as given, including its pass-through term. Revenue per worker falls slightly as a firm grows, but the effect on its wage is small because β_{pt} is small.

Its profit in demand state d is

$$\begin{aligned} \pi_{d,j}(N_H, N_L) = \max_{\ell} & \left\{ \theta_d A_j (N_H + a_L N_L + \ell)^\kappa - w_{H,j} N_H - w_{L,j} N_L - p_{d,j} \ell \right\}, \\ \text{s.t. } & \ell \geq 0 \text{ if } d = b, \quad -N_H \leq \ell \leq 0 \text{ if } d = s. \end{aligned} \quad (20)$$

Lending ($\ell < 0$) earns $p_{s,j}$ per worker, consisting of the saved wage plus the fee. Each firm moves its effective labor toward the level at which a worker's marginal product equals the price of a shared worker, giving a target for each state,

$$L_{d,j}^* = \left(\frac{\kappa \theta_d A_j}{p_{d,j}} \right)^{\frac{1}{1-\kappa}}, \quad (21)$$

and desired positions $\ell_{b,j}^* = [L_{b,j}^* - L_j]_+$ and $\ell_{s,j}^* = -\min\{[L_j - L_{s,j}^*]_+, N_{H,j}\}$, where L_j is effective labor from Equation (2).

The targets are ordered, $L_{s,j}^* < L_{b,j}^*$, if and only if $\rho < p_{s,j}/p_{b,j}$. Firms below the slow target only borrow, firms above the busy target only lend, and firms in between borrow when busy and lend when slow, creating two-sided relationships without any taste for reciprocity.

Rationing of Shared Workers I assume that prices do not adjust to clear the sharing market. Labor markets in low-income settings often clear through quantities (Breza et al., 2021; Kaur, 2019). The sharing market shows the same pattern, since exchanges carry no cash price, and one in five attempts to borrow from another workshop fails (Section 2.2).

Firms request their desired positions $\ell_{d,j}^*$ and take fill rates as given. Total desired borrowing and lending are the positions summed over firms and weighted by how often each state occurs,

$$D_b = q \sum_j \ell_{b,j}^*, \quad D_s = (1 - q) \sum_j |\ell_{s,j}^*|, \quad \lambda_b = \min\left\{1, \frac{D_s}{D_b}\right\}, \quad \lambda_s = \min\left\{1, \frac{D_b}{D_s}\right\}. \quad (22)$$

The side that wants less is served in full, and each firm on the other side receives the same fraction of its request in expectation.⁴¹ This is a fixed-price equilibrium with rationing on one side of the market (Bénassy, 1993). A firm's realized position is $\lambda_d \ell_{d,j}^*$, and its realized profit $\tilde{\pi}_{d,j}$ is the objective of Equation (20) at that position.

The Manager's Hiring Problem With labor sharing, the firm's vacancy problem in Equation (15) uses realized profit in place of π^0 :

$$\begin{aligned} V_j(N_H, N_L) = \max_{m \geq 0} & \left\{ \mathbb{E}_d [\tilde{\pi}_{d,j}(N_H + \alpha \lambda_e m, N_L + (1 - \alpha) \lambda_e m)] - C(m) + \beta V_j(N'_H, N'_L) \right\}, \\ N'_\omega = & (1 - \delta_{\omega,j})(N_\omega + \alpha_\omega \lambda_e m), \quad \omega \in \{H, L\}. \end{aligned} \quad (23)$$

⁴¹Proportional rationing can in principle be manipulated by inflating requests (Bénassy, 1993). I assume firms request their desired positions.

Firms post vacancies anticipating how much they will borrow or lend in each state. Sharing profit also enters the value of operating, $\bar{\pi}_j$ in Equation (17). Labor sharing gives firms a way to meet a busy period, but also has broader impacts on how firms staff permanent workers. A borrowed worker arrives with known skill only when needed, while lending turns slow-period slack into income.

5.6 Characterization

I use this model to study the role of the labor sharing market in shaping hiring, employment, and production. I state the equilibrium, then state a proposition to describe how sharing impacts each margin of the model. I discuss proof of existence in Appendix D.

Definition of equilibrium A *stationary equilibrium* is a set of operating firms $\mathcal{S}$, firm policies $\{m_j, \ell_{d,j}^*\}$, stocks $\{N_{H,j}, N_{L,j}\}$, wages $\{w_{\omega,j}\}$ with type wage levels $\{\mu_{\omega}\}$, and fill rates (λ_b, λ_s) such that

1. *Managers choose whether to operate.* A manager operates if and only if (17) holds, and $\mathcal{S}$ is the set of firms that operate.
2. *Firms hire and share optimally.* Given wages and fill rates, m_j solves the vacancy problem in Equation (23) and $\ell_{d,j}^*$ solves Equation (20) in each state.
3. *Workers optimize.* Workers participate according to Equation (5), choose firms according to Equation (6), and quit according to Equation (10).
4. *Stocks are stationary.* Each firm's stock satisfies Equation (11).
5. *Wage setting.* $w_{\omega,j}$ satisfies (18) and type wage levels clear the market according to (13).
6. *Sharing market clears.* Fill rates satisfy (22).

To examine comparative statics, I hold prices and rationing fixed at different points so that each result isolates one margin. The counterfactuals in Section 7 relax all of them. Proof of each result is in Appendix D.

Proposition 1. (a) *Fix wages $\{w_{H,j}, w_{L,j}\}$ and fill rates (λ_b, λ_s) , and let headcounts $\{N_j\}$ and the operating set $\mathcal{S}$ respond. Then:*

- (i) **Hiring.** *Access to sharing raises the value of a hire in Equation (16) for lending-only firms and lowers it for borrowing-only firms. Stocks therefore rise for the first and fall for the second. The sign is ambiguous for firms that both borrow and lend.*
- (ii) **Entry.** *Staying out of the sharing market is always feasible, so access to sharing weakly raises every firm's profit. Holding the outside option and the ownership cost fixed, the set of operating firms weakly expands.*

(b) *Fix headcounts, wages, and the operating set $\mathcal{S}$, and let fill rates settle by (22). Suppose firms pay common type wages w_{ω} . Then:*

- (iii) **Utilization.** *Each realized trade moves labor from a firm where its marginal product is at most p_s to one where it is at least p_b . Every realized trade weakly raises total surplus,*

labor in use shifts towards busy firms, and the dispersion of marginal products within a state weakly falls.

(iv) **Welfare.** *Total surplus is weakly ordered, no sharing $\leq$ status quo $\leq \tau = 0$, and the loss from the transaction cost equals τ times realized volume.*

Labor sharing separates who pays to screen a skilled worker from who uses that worker. A verified worker costs less to carry through slow periods when the firm can lend them out, but is worth less to a firm that can borrow instead. Sharing therefore changes who holds permanent workers. Higher-productivity firms meet busy demand by borrowing rather than by hiring, while lower-productivity firms hire more in the external market because lending gives idle labor a price.

The distribution of permanent stocks compresses across productivity even as labor in use concentrates in productive firms in busy periods. Because access raises profit at every stock and vacancies are costly at the margin, a firm needs a smaller permanent workforce to serve the same demand. This lowers the scale at which operating pays and expands the set of viable firms.

The structure of the sharing market pools firm-specific demand risk only. A trade needs a counterparty in the opposite state, and proportional rationing means a productive firm cannot outbid a less productive one when both are busy. Fixed prices are therefore not an innocuous choice. Whichever side is rationed, a clearing price would raise volume and allocate workers by value, so fixed prices and proportional rationing understate the gains from sharing. Correlated demand shocks would thin the set of counterparties and shrink the gains, and are left to future work.

6 Estimation

In this section, I estimate the model. I first set out the parametric assumptions needed for estimation. I then discuss how the parameters of the model are calibrated directly from model objects, taken from the choice experiments of Sections 3 and 4, or estimated jointly by simulated method of moments (SMM).

6.1 Parameterization and Calibrated Parameters

I start by imposing some parametric and distributional assumptions to make the model estimable.

Manager Heterogeneity As mentioned in Section 5, managers differ in their managerial ability and idiosyncratic productivity. Managerial ability z_j is computed from the data and standardized, while idiosyncratic productivity I assume to be normally distributed $u_j \sim \mathcal{N}(0, \sigma_u^2)$. Productivity follows Equation (3), with $u_j \sim \mathcal{N}(0, \sigma_u^2)$.

To smooth the entry and exit decision, managers also differ in their preference for firm ownership. A potential firm owner must expect to earn more than the outside option w_j^o , the wage they could command as a worker given their own characteristics. I estimate this outside option by applying the

coefficients from a regression of wages on observable worker characteristics to the same characteristics in the manager sample.⁴²

The entry payoffs carry an unobserved component ζ_j , which captures non-pecuniary returns to ownership and determinants of the decision I do not measure. I assume this component is logistically distributed with scale parameter σ_e , which governs how responsive participation is to profitability. Because w_j^o is uncorrelated with z_j in the data, ability enters this margin only through profit, so higher ability unambiguously raises the probability of operating. I calibrate the fixed entry cost c_0 so the model reproduces the number of operating firms in the sampling frame.

Wages and Hiring Costs Wages follow the rule in Equation (18). I estimate the type wage levels μ_H and μ_L ; market clearing (Equation (13)) holds at the status quo because I normalize $\Gamma_\omega M_\omega$ to observed employment. The firm premium has a part linked to productivity and an independent part, $\xi_j = \rho_{\xi u} \sigma_\xi (u_j / \sigma_u) + (1 - \rho_{\xi u}^2)^{1/2} \sigma_\xi e_j$ with $e_j \sim \mathcal{N}(0, 1)$. Vacancies cost $C(m) = \phi m^2 / 2$. Separations follow Equation (10), with base rates $\delta_{0,H}$ and $\delta_{0,L}$ and a common elasticity ε_s . The reference wage W_ω is the mean weekly wage of type ω in the data.

Calibrated Parameters The model has 23 parameters. I set six outside the model (q , α , κ , a_L , λ_e , and σ_e) and take four from the choice experiments and the worker survey (c_s , τ , ε , and ε_m). I estimate the remaining 13 jointly in the SMM routine described in the next subsection.

First, I define the probability of the busy demand state as q . I set it to 0.29, the share of firms that report being in a “busy” month at the time of the survey under the demand elicitation protocol described in Section 2.5.

The parameter α is the probability that an externally hired worker is skilled, which in the model is the skilled share of new hires in the external market. For each external hiring channel (walk-ins, employee referrals, and friend or family referrals), owners report how many of ten new workers they believe could produce the firm’s main product at a quality they would sell without further training. I assume these beliefs are accurate. Averaging them across firms, and weighting channels by their shares of the successful hires owners recall over the past twelve months, gives $\alpha = 0.384$.

I pin two production function parameters outside the model. Because my survey does not catalog capital equipment in detail, I use the labor returns-to-scale estimate from Bassi et al. (2022) for carpentry, and fix $\kappa = 0.5$. My own regression of log revenue on labor inputs, with management and demand-state controls and market fixed effects, gives 0.51 (SE 0.09), close to this value. I also require an estimate of the relative productivity between skilled and less-skilled workers, denoted a_L . I set a_L outside of the model by estimating the model’s production function using non-linear least squares, regressing log revenues on observed counts of skilled and less-skilled workers, fixed effects for industry and parish, and controls for demand state. The preferred specification yields $\hat{a}_L = 0.521$. This parameter is not tightly identified, so I report a sensitivity band of $a_L \in [0.40, 0.64]$ to account for this calibration. Appendix Table A13 reports details of the estimation and other specifications.

⁴²I include age and its square, sex, years of education, experience and its square, and market fixed effects in this regression, and report estimates in Appendix Table A12.

The last calibrated parameter is the hiring efficiency on the external market, denoted λ_e . I derive it from the reported vacancy fill rates for each “external” hiring source (walk-ins, friend/family referral, employee referral), calibrated to a weekly time horizon. In the firm survey, respondents report how many times they tried to hire from each hiring source over the previous three months, and how many times they succeeded. A hire counts as successful if the worker produced items that the firm was able to sell. I estimate a weekly vacancy fill rate $\lambda_e = 0.555$.

Parameters from the Choice Experiments I take three parameters from the choice experiments of Sections 3 and 4 and hold them fixed in the SMM. From the firm experiment, a lending firm receives $c_s = 13.95$ thousand UGX per lent worker-week and a borrowing firm pays $c_s + \tau = 29.37$, so the transaction cost is $\tau = 15.42$. From the worker experiment, I take the wage elasticity across employers, $\varepsilon = 1.28$. Its equality across the two types supports Lemma 1, and it enters worker surplus. Stated reservation wages pin the participation elasticity, $\varepsilon_m \approx 0.98$, which governs how market wage levels respond in the counterfactuals.

6.2 Targeted Moments and Identification

I estimate the remaining 13 parameters by simulated method of moments (SMM). I target 21 moments, which leaves 8 over-identifying restrictions. The estimation has two steps. The first employs a diagonal weighting matrix, and the second uses the inverse of the bootstrapped covariance matrix of the data moments (Appendix E.1). I group the moments by their role in the model: wages, firm size and heterogeneity, revenue and demand volatility, turnover and tenure, and use of labor sharing. The parameters are identified jointly. In each paragraph below I discuss the moments each parameter corresponds to most closely. Table 6 reports the parameters and their definitions, and Table A14 lists each moment with the parameters it disciplines.

Wages I target the log mean realized weekly wage of each type. These moments pin μ_H and μ_L because each type’s wage level shifts in response. The mean wage owners report gives a second measure of the same wage levels, which I compare with the model through the ratio of owner- to worker-reported pay in matched pairs. The between-firm standard deviation of log wages pins σ_ξ . It separates this parameter from σ_u because σ_u leaves the moment essentially unchanged while the firm wage premium ξ_j leaves size dispersion essentially unchanged. The pass-through of expected revenue into workers’ wages, estimated within task and within parish-by-industry markets, pins β_{pt} . I also target the slope of the firm mean log wage on log size, estimated within markets, which is small in the data. This slope also speaks to $\rho_{\xi u}$, because if high-premium firms are also more productive, larger firms pay more. Because the premium also enters firm costs, however, $\rho_{\xi u}$ also governs the dispersion of firm size, since a premium that rises with productivity raises costs at productive firms and compresses differences in size. Finally, I target the slope of the mean log wage on the management score. In the model, this slope combines pass-through of the higher revenue at better-managed firms with differences in skill mix, whose effect on the mean wage scales with the

gap between μ_H and μ_L .

Firm Size and Heterogeneity Three moments describe the permanent workforce: the log of mean firm size, the standard deviation of log size across firms, and the slope of log size on the owner’s management score z_j . Size counts permanent workers, excluding the owner.

Holding fixed the wages firms pay and their productivity, a higher vacancy cost ϕ makes the permanent stock N_j more expensive to build. The level of firm size responds to ϕ , but ϕ is only weakly identified: it trades off against the wage rents, which also set how costly the permanent stock is to build, and its estimate depends most on the type wage levels. A higher θ_b also raises size, but it raises revenue directly as well, while ϕ moves revenue only through the size of the stock.

The size level and the revenue level together separate ϕ from θ_b . Because I fix κ outside the model, ϕ cannot instead trade off against the returns to scale. The management loading λ_z ties productivity, and hence size, to the observed score z_j but not with the unobserved component u_j . The size–management slope therefore pins λ_z . The dispersion of u_j , σ_u , then accounts for the spread in size that the management score does not explain.

Revenue and Demand Volatility Three moments describe revenue: the mean across firms of log monthly revenue, weighted by how often each firm reports each demand state; the ratio of mean busy-month revenue to mean revenue in all other months; and the standard deviation of log revenue per worker in a normal month. The model has two demand states, so a busy month maps to b , and normal and slow months together map to s . Holding fixed the wages firms pay, a higher θ_b raises revenue in both states. The revenue level therefore disciplines θ_b . Because I fix q outside the model, the level does not have to separate how often a firm is busy from how productive it is when busy. The busy/slow ratio responds most strongly to ρ , so it pins ρ . No parameter targets the dispersion of revenue per worker directly. It responds to the two type wage levels and to ρ , and so disciplines them. Finally, ρ measures the demand swing that gives firms a reason to share labor.

Turnover and Tenure Four moments describe turnover: the annual separation rate, the log ratio of the tenure of skilled to less-skilled workers, and, for each type, the slope of log tenure on the log wage. I measure tenure as the time since the worker started at their usual firm. This is because most spells that workers recall as completed overlap their current job and are concurrent temporary stints rather than full separations. A fifth moment, the mean skilled share of firms’ workforces, links the pinned probability α that a new hire is skilled to a stock share through the worker retention, which varies by type. Given the wage rents, the base separation rates $\delta_{0,H}$ and $\delta_{0,L}$ set how often each type leaves regardless of pay, so they are pinned mainly by the separation rate and the tenure ratio. The common separation elasticity ε_s makes separations fall with the wage, because a better-paid worker is less likely to receive an outside offer above their wage. Both tenure–wage slopes inform ε_s , and their equality is an over-identifying restriction.

Labor Sharing Flows Three moments describe how much firms rely on labor sharing: the share of workers on owners’ listings who are currently borrowed from another firm, the slope of the owner’s count of borrowing events over the past three months on the management score z_j , and the share of borrowed worker requests which are filled. These moments govern how much sharing is used at the estimated c_s and τ . Given the wage rents, the borrowed share responds most to ρ , because a wider demand swing opens a larger gap in busy months between the permanent stock and the workforce a firm wants. The share also rises with ϕ and θ_b , which set how far that stock falls short. The slope of borrowing on the management score governs the shared hiring margin. Better-managed firms face a larger busy-month gap, and the slope tests whether these firms fill as much of that gap by borrowing as the model predicts at the fixed price. In the model, busy firms request more workers than slow firms lend, so not every request is filled. Among the parameters, it moves most with ρ .

6.3 Estimation Results

I estimate the 13 parameters Θ by simulated method of moments. Some moments are regression coefficients and others are means or dispersions, and I compute each one the same way in the survey data and in data simulated from the model. The estimator is

$$\Theta^* = \arg \min_{\Theta} [\hat{m} - m(\Theta)]' W [\hat{m} - m(\Theta)], \quad (24)$$

where $\hat{m}$ stacks the data moments and $m(\Theta)$ their simulated counterparts. Complete details of the estimation procedure are provided in Appendix E.1.

Results The estimated vector of parameters Θ^* is shown in Table 6, while Table 7 shows the values of moments computed in the data and model, respectively. The reported standard errors treat the inputs I set outside the model as known, so I report how each estimate responds to those inputs, using the local sensitivity measure of Andrews et al. (2017) (Appendix E.1).

The model provides a good fit of the data in many respects, though it is not perfect and struggles to replicate some aspects of the data. In particular, it understates the dispersion of revenue per worker across firms. In the model, firms differ over a long horizon only through their management score and idiosyncratic productivity. The model also has no capital and fixes a common return to labor κ , so it does not generate differences in how labor-intensive firms are in their production processes, leading to under-dispersion in revenue per worker.

The model also overstates the pass-through of revenue into wages and the slope of wages on firm size. The estimated correlation between the firm premium and productivity is high, which helps the model match the dispersion of firm size but makes model wages track revenue more closely than in the data.

Lastly, The model also somewhat overstates the share of listed workers who are borrowed because the model has no extensive margin of access to the sharing market. While a meaningful fraction of surveyed firms do not share labor at all, each simulated firm can borrow at the estimated prices. As

a result, the model somewhat overstates the share of listed workers who are borrowed (16.5% against 12.4%). Overall, the model reproduces the patterns documented in Section 2. Better-managed firms are larger and borrow more, and wages respond to expected revenue, giving me confidence in the estimated parameters.

The estimated parameters reproduce the market conditions which make sharing profitable. First, demand swings are large, making optimal headcounts across states markedly different. The estimate of ρ implies that in a slow week, a firm’s productivity is 54 percent of its busy-week level. Holding its wage fixed, a firm facing this swing wants a slow-week workforce only $\hat{\rho}^{1/(1-\kappa)} \approx 29$ percent of its busy-week workforce. Second, hiring is costly. The vacancy cost is convex, I express it as the cost of the marginal hire, which at the estimates equals 5.4 weeks of a skilled worker’s wage. As an untargeted check, the participation elasticity from stated reservation wages (0.98) lies below the elasticity across employers from the choice experiment (1.28), as the two-margin structure requires.

7 Quantifying the Importance of Labor Sharing

One of the key roles of the firm in these markets is to match customer orders to the right workers. But because hiring permanent workers is a slow process, firms must hire before observing short-term demand, which can misallocate labor across firms. Some firms hold skilled workers in slow weeks while others are left under-staffed at peak demand. I use the estimated model to study how labor sharing changes labor allocation across firms, and how this impacts market composition, firm owners, and workers.

I proceed in four steps. First, I measure what labor sharing is worth by comparing the estimated equilibrium to one where firms cannot borrow or lend workers. Second, I examine where this value comes from by removing each of the model’s main frictions, screening and demand swings, one at a time. Third, I ask how close sharing comes to an efficient allocation by comparing it to a frictionless hiring benchmark, and whether a more standard institution, such as a spot market for casual labor, could serve the same role. Lastly, I evaluate the effects of two skill policies, certification and training. Carpentry and metalworking, along with manufacturing as a whole, are common targets of training and up-skilling programs that aim to improve firms’ access to skilled workers, and almost two-thirds of owners state that support for training and retention would help in busy periods. Since these policies are common and serve similar goals to labor sharing, I ask whether accounting for sharing changes what these policies achieve and who benefits.

7.1 Overall Impacts of Labor Sharing

I first compare the estimated equilibrium with an economy where firms cannot borrow or lend workers to each other. In this economy, modeled in Section 5.3, firms can only post vacancies in the external market, forcing them to pay screening costs for additional workers before seeing demand. Thus, they hire according to expected demand and productivity. In the model, this is equivalent to making transaction costs τ arbitrarily large. Type wage levels μ_ω adjust until each type’s labor

market clears at the new choices (Equation (13)).⁴³ All parameters stay at their original estimates. I report results in the long run, where each manager compares profit from operating with the outside option in Equation (17), and thus firms can exit and enter.

In the long run, sharing raises total welfare by 7.0%, with gains accruing to both firms and workers. Figure 5 reports estimated impacts on welfare measures and other market quantities.

Operating firms Sharing alters which firms operate in the market. The status quo economy supports 4.7% more firms than the economy without sharing (Figure 5a). Total employment is only minimally changed, with 1.0% more workers employed in total with sharing. So the average firm is slightly smaller, with 3.5% fewer workers. There are two forces which produce these results. A firm which can lend out its workers during slow periods faces lower carrying costs for their workforce, thus raising profits. A borrowing firm can also meet its demand peaks via sharing instead of permanently hiring, so they maintain a smaller, cheaper workforce, leading to increased expected profits. Sharing thus compresses the firm-size distribution.

Firms that lend on net are twice as likely to exit without sharing compared to those who net borrow in the status quo, but exiting firms come from across the productivity distribution. At the bottom of the productivity distribution, where firms mostly lend, firms can no longer afford the carrying costs of skilled workers during slow weeks, and exit the market. Near the top, higher-productivity borrowing firms lose access to skilled workers in busy weeks, leading to exits. In the long run, surviving firms reabsorb the workers from exiting firms, leading to the muted aggregate employment effect. Importantly, sharing does shift skilled permanent hiring down the productivity distribution. In the economy without sharing, the most productive third of firms employs 46% of skilled permanent workers, while the least productive third employs 22%. Sharing flips this relationship (45% in bottom third, 29% in top third). Thus, sharing separates who hires and screens workers from who employs them during demand spikes. Skilled workers can be maintained more cheaply during slow periods at lower productivity firms who pay less and can lend them out, so low-productivity firms become a source of skill for productive borrowing firms.

Owner and Firm Impacts I next consider the impacts of sharing on managers, who can choose between operating a firm and taking their outside option. I measure owner surplus as profit minus the fixed operating cost c_0 , plus the taste for ownership ζ_j .⁴⁴ Owner surplus rises 4.5% with sharing, representing 43% of the total welfare gains (Figure 5a). Gains accrue across the productivity distribution and to firms that borrow and firms that lend, but the sources of their gains differ. About half of the gains accrue to borrowing firms through increased output in busy periods, though they experience reduced output and due to smaller permanent workforces producing in slow periods. Lending firms, meanwhile, benefit primarily from saved wages from lending in slow periods. Relative

⁴³Within a market, workers who move between firms cancel out, so μ_ω responds only through participation, at the elasticity ε_m in Equation (12).

⁴⁴Changes in owner surplus include the operating cost, taste for ownership and outside option of every manager who switches between operating and working. I divide these changes by surplus in the economy without sharing measured before those terms. Only the difference $c_0 - \zeta_j$ affects entry, so their sum depends on a normalization.

to their size, these firms gain much more; lending firm profits rise by 15%, against 3% at borrowing firms.

Sharing changes where labor is used and thus where output is produced. In the model, more productive firms are net borrowers. In the data, firms with higher revenue per worker borrow more workers on net (Appendix Table A15). Shared workers are moved to where they are more productive. In the model, a shared worker produces 3.5 times the output they would have produced at their home firm in a slow week. This gap reflects the fact that a skilled worker is 1.8 times more productive in a busy week than a slow week, and that sharing moves workers to firms which are more productive overall. In total, output increases by 6.2% compared to a non-sharing economy.

Worker Impacts Finally, labor sharing improves overall worker welfare, but has differential impacts on skilled and less-skilled workers. Worker welfare is measured as total earnings net of their reservation wage. In total, worker welfare rises by 12.3% with labor sharing, accounting for just over half (57%) of the total gains (Figure 5a). This is driven by gains of skilled workers, who see an average wage-level increase of 4.7%, and also are borrowed by higher-productivity firms who tend to pay more, since wages are linked to productivity. On the other hand, less-skilled workers, who are not shared in the model, see their average wages fall by 12.0%. This reflects where their permanent jobs are in a sharing economy. As mentioned above, labor sharing shifts permanent jobs to lending firms which pay less (Figure 5b). Less-skilled workers, however, do not have loan weeks which make up for this compositional shift. See Appendix Figure A4 for a full decomposition.

In the status quo, lending firms are under-compensated, so they offer fewer workers than borrowing firms request. In the model, I estimate that 77% of borrowing requests get filled, against 81% in the survey. In Appendix F.2, I estimate a “full compensation” economy where transaction costs are fully passed through to lenders. Here, lenders are better compensated, and thus lend more frequently, fulfilling all borrowing requests. However, total surplus only slightly rises about 1 percentage point in the long run. Instead, surplus is shifted from firms to workers. Workers gain 22.6% over the economy without sharing, against 12.3% in the status quo, while owners gain 1.0% rather than 4.5%. This fits what firms report in the survey, that making individual labor transactions more efficient is unlikely to matter much.

7.2 Why Sharing is Valuable

The value labor sharing provides could come from either of the two problems it helps firms overcome, by providing a substitute around high screening costs on the external market or by providing on-call workers in demand peaks. In this section, I examine the role of each individually by resolving one of the frictions at a time, and comparing its value in each case with its value in the estimated economy without sharing. I first examine an economy where firms can effectively screen external hires and, second, where firms face a consistent demand schedule.

The value of sharing does not rest on the screening friction on the external market. When firms can clearly observe worker skill on the external market but still face demand fluctuations, sharing

expands surplus by 8.1% compared to 7.2% in the estimated economy. Skilled workers make up 65% of the workforce when screening frictions exist, with or without sharing. When firms can perfectly observe worker types before hiring, they tilt their permanent workforces towards skilled workers because there is a degree of wage compression in the status quo economy, where skilled workers' pay premium is less than their relative productivity advantage. The skilled share of the workforce rises to 74%, and the number of excess skilled workers at slow-week firms increases by a quarter. With more skilled workers available, sharing volume increases, and the value of sharing in the market correspondingly increases.

Fluctuations in demand are what make individual sharing trades possible and valuable. To examine this, I simulate an economy where each period's demand is set to a weighted average of the busy and slow demand states: $\bar{\theta} = q \cdot \theta_b + (1 - q) \cdot \theta_s$. Each firm can now post vacancies in the external market knowing its optimal hiring target, and thus carry no excess workers, so almost no trades take place when demand is constant. The resulting economy is nearly identical to the no-sharing economy. Remaining differences in marginal products of labor across firms are too small to facilitate sharing, since sharing still carries a fixed cost per worker lent.

Labor sharing's value thus comes from its role providing flexible capacity rather than a way around screening costs. Information about worker skill still plays a vital role, as it is a design feature of the sharing system. Firms vouch for the skills of lent workers in the secondary market. In the next section, I examine the role of information in sharing by comparing sharing as observed to simulated economies with spot markets.

7.3 Comparing sharing to institutional benchmarks

I now compare the estimated economy with labor sharing to an efficient benchmark to give an upper bound on potential gains from policy intervention. In this benchmark, firms can make all hiring decisions with full knowledge of worker type and of their demand state at production, at each type's market wage and no transaction costs. This is, in effect, a weekly spot market with full information. In this case (Table 8), sharing recovers 29.2% of the total gains from moving from the no-sharing economy to this efficient benchmark.⁴⁵ This benchmark also further sheds light on the role of each friction. I decompose the available gains between the efficient benchmark and the non-sharing economy, and find that flexible capacity is worth about three-quarters of the available gains, with screening ability closing the remaining quarter. The remaining gains available from the estimated economy are split evenly between screening and flexibility. Sharing corrects for the screening friction after the fact, giving firms a second chance to access skilled workers, but firms still hire externally without seeing skill. Thus, both frictions remain active and consequential even with sharing.

Sharing helps correct misallocation within firms due to short-run demand shocks, but increases misallocation across firms. Overall, sharing reduces output lost to misallocation from 8.7% to 5.2%

⁴⁵This benchmark is an extreme case where permanent employment collapses to just 13% of its level in the economy without sharing.

(Hsieh & Klenow, 2009). This gain comes from an improvement in allocation of workers within a firm across time, so individual firms are able to staff more efficiently week-to-week (Figure 5c). However, misallocation across firms within period *rises*, because skilled workers are held in permanent roles at lending firms Figure 5b. As a result, the most-productive third of firms uses only 46% of the skilled workforce in busy-weeks, approximately the same as without sharing, compared to the efficient allocation of about 67%. This is because the most productive firms replace permanent skilled workers with borrowing.

An alternative market structure would be for firms to hire temporary labor from a spot market, as is common in construction and agricultural industries (Breza & Kaur, 2025). I compare the sharing economy to an economy where firms can hire for one week in a pooled spot market, subject to the same transaction costs (τ) as estimated in Section 3. In this market, firms cannot observe type and thus pay a single pooled weekly wage. Adverse selection drives out some skilled workers, and the spot market raises welfare by only 5.0% compared to 7.0% in the estimated economy. A spot market only beats sharing when it solves the same worker information problem. If pay perfectly tracked each worker’s output, skilled workers enter the pool, and this spot market beats sharing (10.1%). However, in the data wages are compressed across worker types. Sharing sorts workers through what a firm already knows about their skill, rather than sorting through pay, which is its advantage over a spot market.

7.4 Skill Policies

I now use the model to analyze two common labor market policies, certification and training. Both aim to ease firms’ difficulty finding the skilled labor they need. Certification lets firms better observe a worker’s type before hiring, raising the probability that an external hire is skilled, but holding supply fixed. In the model, this is an exogenous shift of the skilled share of hires, denoted α . I also consider a targeted training policy which converts less-skilled into skilled workers. This policy operates on externally hired workers, where market supply of each type is altered. I construct these simulated policies so the skilled hire rate α rises by the same amount, from its estimated value of 0.38 to $\alpha' = 0.70$, halfway to each external hire being skilled. I evaluate each policy in the economy with and without sharing, allowing for firms to enter and exit the market. An important note is that reported effects exclude the cost of either policy, so they compare benefits only.

Certification Certification does not improve overall welfare in the economy with or without sharing. Overall effects are negative but small (-0.5% with sharing, -0.3, without, Figure 6a). Certification improves visibility of skill to firms, but does nothing to address an underlying shortage of skilled labor. Each firm more effectively hires from the fixed pool of skilled workers, pushing their wage up, and pushing less-skilled workers out of the market. This competition for skilled workers pushes the skilled wage up by a fifth, which cuts into firm profits in the economy without sharing (-6-8%). Less-skilled employment collapses, dropping by about two-thirds. These findings follow a similar pattern to Bassi and Nansamba (2022), who find that gains from certification accrue

primarily to certificate holders through better matches and higher wages at the expense of those who are not certified.

Introducing sharing does not change the aggregate welfare effects, but it substantially shifts which firms benefit. With sharing, losses concentrate around borrowing firms, who tend to have higher productivity. The highest-tercile productivity firms lose 17% profits while the lowest-tercile gains 3.7%. These effects are driven by two forces. First, high-productivity borrowers pay more for the shared workers they rely on, who are now commanding higher wages. Second, since hiring a skilled worker on the external market is now comparatively cheaper, lending firms can hire them externally without paying the maintenance costs to retain them when they are lent out. As such, skilled permanent positions concentrate even more at lower-productivity lending firms, and lending volume increases by 11%. The increased costs of borrowing push high-productivity firms out of the market disproportionately, with 57% of exiting firms belonging to the top productivity tercile.

Training In contrast to certification, training programs expand the supply of skilled labor. In the economy without sharing, a targeted training program which converts less-skilled workers into skilled workers raises total surplus by 20%, with 53% of the gains accruing to workers (Figure 6b). In the estimated economy, labor sharing was constrained by the supply side; more firms wanted to borrow than there was available slack, pointing to a shortage of skilled labor in the market. Training targets this shortage directly, expanding supply to all firms. Firms across the productivity distribution see gains 17-19% through increased profits.

With labor sharing, overall impacts remain highly positive, but gains shift to more productive firms. Increased supply allows high-productivity firms who rely heavily on borrowing to instead hire skilled workers permanently and grow, gaining 12% and increasing permanent firm size by 60%. They therefore have less need for borrowed labor, and sharing flows reduce by a total of 12% among incumbent firms.⁴⁶ Lower-productivity firms, which hold skilled labor and lend in the status quo, have fewer counterparties with whom to share the carrying costs of their workforce, and lend less. They still gain modestly, seeing profits rise about half as much (6%). While certification concentrates skilled workers further at firms that lend, training moves them back toward the most productive firms.

8 Conclusion

Small firms operating in large informal clusters face a variety of problems when it comes to hiring and maintaining a skilled workforce. In this paper, I show that firms respond to screening frictions and demand volatility by hiring directly from their neighbors. This system of labor sharing allows firms to access flexible capacity, relying on the verification from their neighbor to meet their peaks in demand.

⁴⁶Entry offsets most of this reduction in sharing flow, but the total is still a reduction of 1.5% compared to the status quo economy.

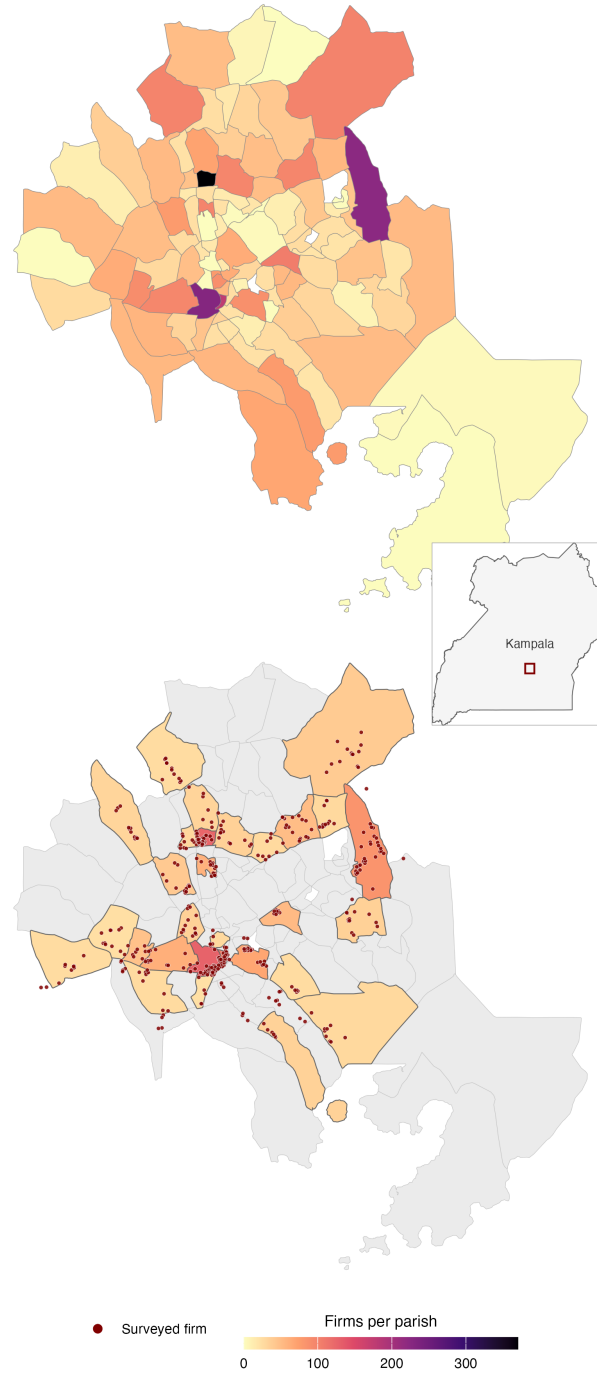
I combine a novel set of linked firm and worker surveys in urban Uganda with a series of stated choice experiments and an equilibrium model of hiring. I first document the characteristics and functions of labor sharing, which reallocates skilled workers from slack to busy firms through a system of uncompensated exchanges between owners. I then use the choice experiments to estimate transaction costs and valuations of labor sharing for both firms and workers and find that, while firm owners value it heavily, workers view it similarly to other types of hiring. Finally, I take the survey data and experimental estimates to a model of hiring in a frictional labor market, and show that sharing raises surplus for both firms and workers, and supports more, smaller firms in the market.

The model shows that labor sharing has strong allocative effects on the market. It helps firms collectively place workers at the firms facing high demand. However, because firms trade off sharing with other types of hiring, it also shifts which firms hold permanent workers. With sharing, permanent jobs shift towards firms that lend, and the most productive firms borrow their workers instead of growing their own permanent workforce. This leads to misallocation across firms, and closes only about a third of the gap to an efficient allocation benchmark.

This paper shows how firms in developing settings can substitute informal systems for missing institutions, and it offers lessons for policy in these markets. In my setting, firms have developed a system which already serves as a partial verification mechanism, operating through firm-to-firm interactions. Labor sharing allows firms to address screening frictions and demand volatility, but it cannot create skilled labor when it is in short supply. As a result, training efforts to expand the supply of skilled labor vastly outperform certification efforts. Certification reshuffles a fixed supply of skilled workers, while training allowing high-productivity firms to expand by hiring skilled workers permanently. Future studies aimed at understanding the formation of firm hiring networks would complement this work.

Figures

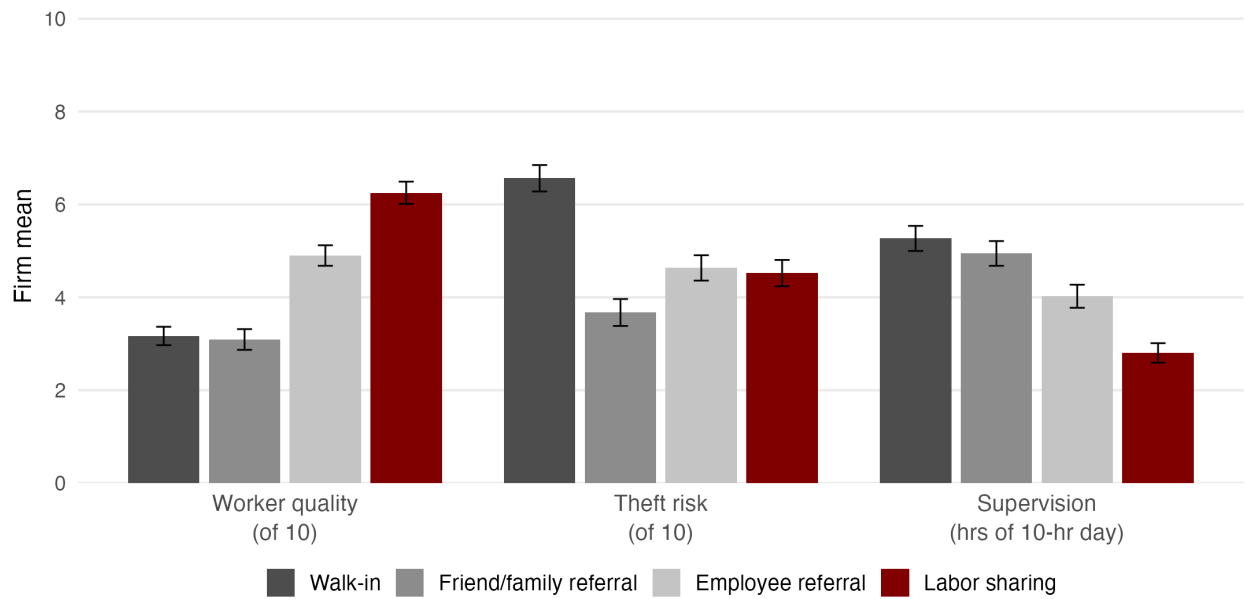
Figure 1: Geographic Distribution of Sampled Firms



Note: This figure shows the sampled regions of Kampala and the surrounding Wakiso District in Central Uganda. The top panel shows density of eligible firms at the parish level according to the 2019/20 Census of Business Establishments. The bottom panel shows selected parishes and locations of firm surveys.

Figure 2: Comparing Hiring Channels: Beliefs and Hiring Costs

(a) Firm beliefs over worker quality by hiring channel

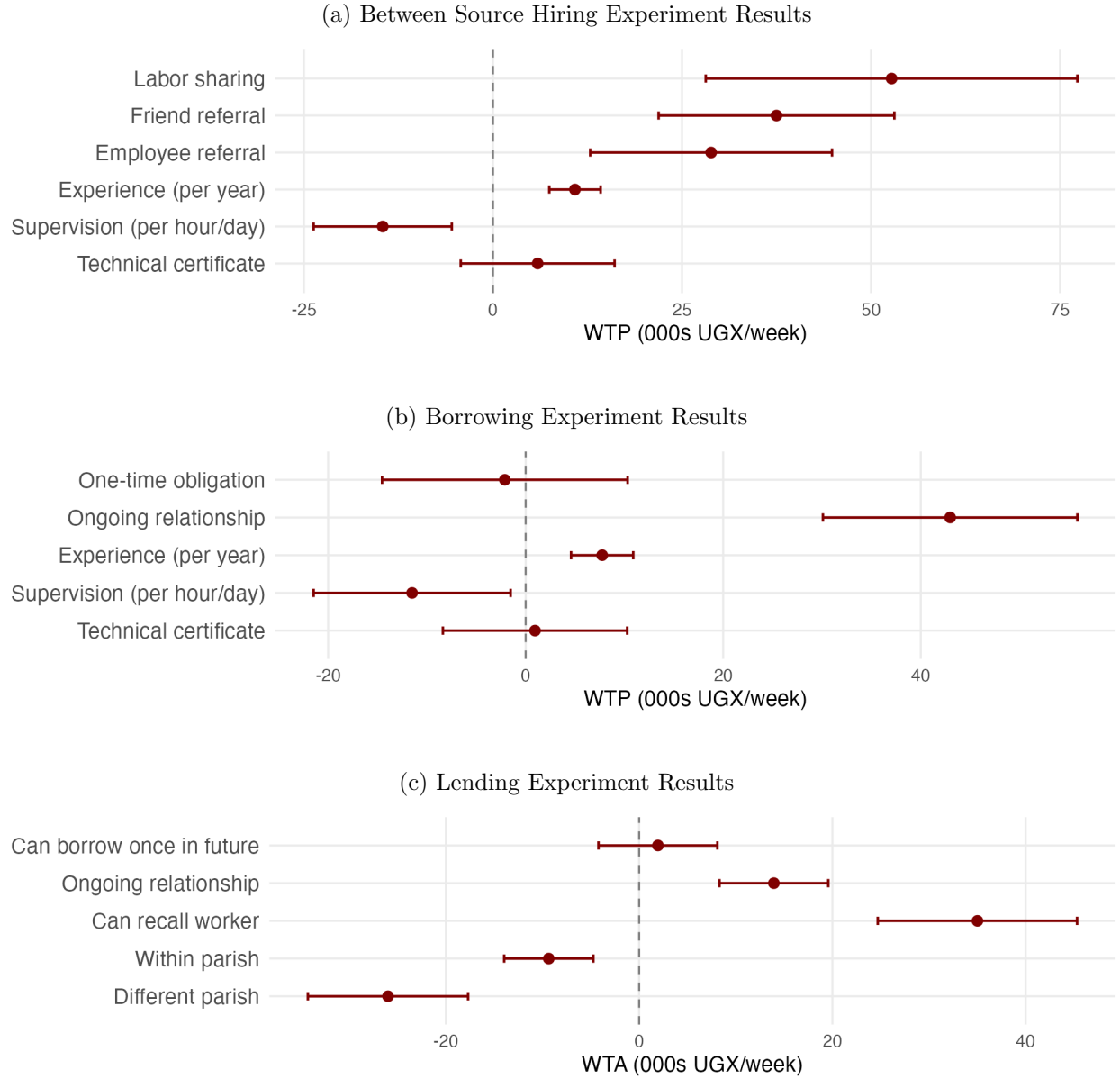


(b) Hiring costs by hiring channel



Note: These figures show firm owner elicited beliefs for worker quality (Panel A) and hiring costs (Panel B) across hiring sources. Panel A questions are all measured on a scale of 0-10. Error bars displayed are 95% confidence intervals.

Figure 3: Firm Stated Choice Experimental Estimates



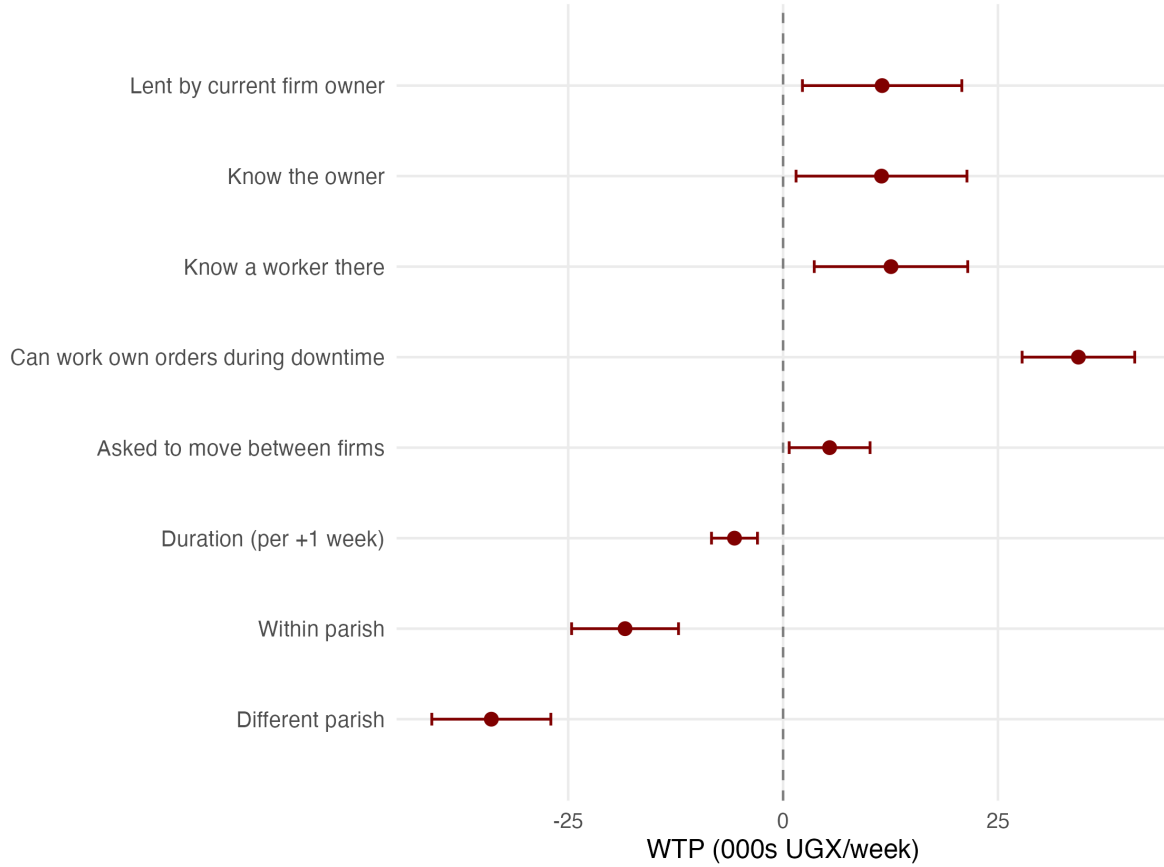
Note: This figure shows willingness to pay (Panels a and b) or accept (Panel c) estimates for worker attributes estimated using multinomial logit. Willingness to pay (accept) is calculated by dividing the coefficient for the attribute by the wage coefficient, and are reported in thousands of Ugandan Shillings (UGX). At the time of survey, 1USD $\approx$ 3,750UGX, and median weekly wage $\approx$ 150,000 UGX. Error bars displayed are 95% confidence intervals.

In Panel (a), the base attributes of a worker are: walk-in hire, 2 years of industry experience, requires no supervision, and does not carry certification from a technical institute.

In Panel (b), the base attributes of a borrowing agreement are: no expectation of reciprocity for a worker with 2 years industry experience, who requires no supervision, and does not carry certification from a technical institute.

In Panel (c), the base attributes of a lending agreement are: no expectation of reciprocity for a worker, lent to a firm within the cluster (or within a 10 min walk), but no guarantee of the ability to recall the worker immediately should they be needed.

Figure 4: Worker Job Offer Experiment Estimates



Note: This figure shows willingness to pay estimates for job attributes estimated using both mixed logit. Willingness to pay is calculated by dividing the coefficient for the attribute by the offered wage coefficient, and are reported in thousands of Ugandan Shillings (UGX). At the time of survey, 1USD $\approx$ 3750UGX, and median weekly wage $\approx$ 150,000 UGX. Error bars displayed are 95% confidence intervals.

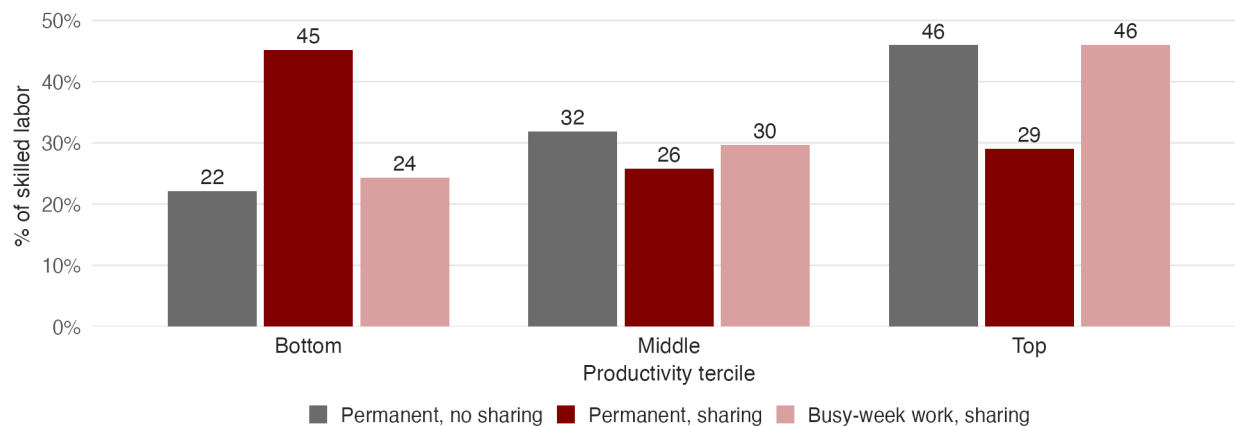
The base attributes are for a job where the worker has no connection to the firm, they cannot work on their own orders during downtime, they are not asked to shift between firms, for a duration of 1 week at a firm within the cluster (or within a 10 min walk).

Figure 5: Estimated Counterfactuals

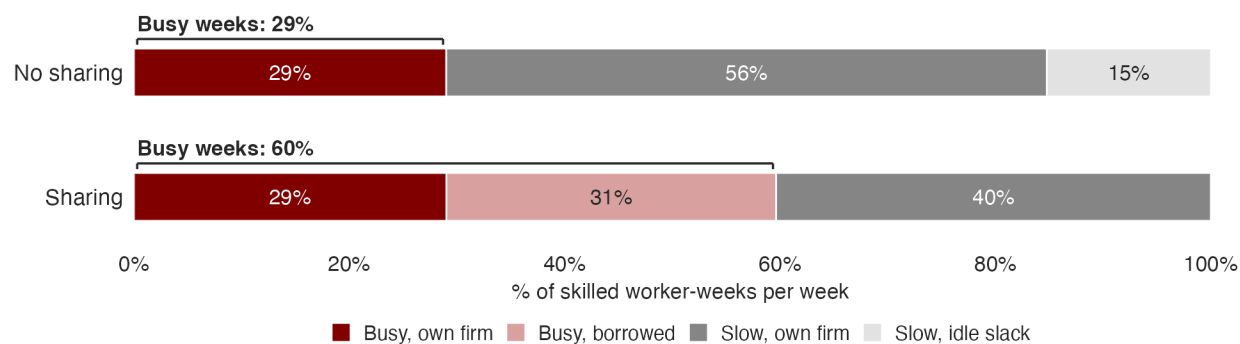
(a) Estimated Aggregate Impacts of Labor Sharing



(b) Allocative Impacts of Labor Sharing by Firm Productivity Tercile



(c) Distribution of skilled workers across demand states



Note: These figures show estimated impacts of labor sharing, comparing the status quo economy to an economy without sharing. Panel (a) reports aggregate surplus outcomes and market characteristics. Panel (b) examines the placement of skilled workers across firms by terciles of firm productivity (TFPQ), with terciles defined among firms operating in the status quo. Panel (c) reports the distribution of skilled worker-weeks across demand states with and without sharing. Idle slack is skilled workers held beyond a firm's slow-week labor target, net of workers lent out. Reported values are long run, with firm entry and exit, not evaluated on a fixed population.

Figure 6: Estimated Policy Experiments



Note: These figures show estimated impacts of labor market policies counterfactual economies compared to a no sharing baseline economy. The sharing economy measures the economy as observed with two counterfactual policy experiments: certification which increases the probability of an external worker being skilled (a), and training where less-skilled are converted to skilled workers (b). In each case, the probability of an external worker being skilled is calibrated to 69% (vs 38%). Reported values long run values inclusive of entry and exit.

For worker surplus, aggregate values are indicated by the white diamond shapes. Results are reported by worker type pre-policy intervention.

Tables

Table 1: Firm Summary Statistics

	All		Carpentry		Metal		N
	Mean	[p20; p80]	Mean	[p20; p80]	Mean	[p20; p80]	
<i>Panel A: Firm characteristics (515 firms: 333 carpentry, 182 metal)</i>							
Workers employed	3.25	[2.00; 4.00]	2.98	[2.00; 4.00]	3.76	[2.00; 4.00]	515
Workers engaged, past month (incl. absent)	5.95	[3.00; 7.00]	5.34	[3.00; 7.00]	7.06	[3.00; 8.00]	515
Monthly revenue, last month (USD/month)	1,005	[267; 1,333]	873	[227; 1,280]	1,264	[400; 1,813]	484
Orders, last month	7.81	[2.00; 10.00]	7.77	[2.00; 10.00]	7.88	[2.00; 11.00]	506
Items produced, last month	52.77	[6.00; 61.20]	51.59	[4.50; 59.70]	54.95	[7.10; 61.80]	504
Busy months per year	3.49	[2.00; 4.00]	3.42	[2.00; 4.00]	3.61	[2.80; 4.00]	512
Slow months per year	3.74	[3.00; 5.00]	3.75	[3.00; 5.00]	3.72	[3.00; 5.00]	512
<i>Panel B: Workforce and hiring (1,539 listed workers: 966 carpentry, 573 metal)</i>							
Share on a permanent contract	0.80		0.76		0.87		1,534
Tenure, permanent workers (years)	3.67	[1.00; 5.00]	3.36	[1.00; 5.00]	4.11	[1.24; 6.00]	1,212
Length of last stint, non-permanent workers (days)	11.19	[2.00; 6.00]	12.45	[2.00; 6.00]	7.12	[2.00; 6.00]	274
Weekly pay (USD/week)	30	[16; 40]	27	[13; 40]	34	[19; 48]	1,344
Share currently borrowed (all listed workers)	0.12		0.15		0.08		1,534
<i>Panel C: Labor-sharing participation (515 firms: 333 carpentry, 182 metal)</i>							
Any sharing, past 3 months	0.78		0.79		0.76		515
Borrowed workers, past 3 months	0.75		0.76		0.74		515
Lent workers, past 3 months	0.55		0.56		0.54		515
Borrowed worker on site, survey day	0.37		0.40		0.32		515
Partner firms (partner roster)	1.73	[1.00; 3.00]	1.71	[1.00; 3.00]	1.75	[0.00; 3.00]	515
Distinct workers borrowed, past 3 months (partner roster)	2.03	[0.00; 3.00]	1.89	[0.00; 3.00]	2.30	[0.00; 4.00]	515
Distinct workers lent, past 3 months (partner roster)	1.77	[0.00; 3.00]	1.56	[0.00; 3.00]	2.14	[0.00; 3.00]	515

Note: Panel A reports firm characteristics in the sample from all surveyed firms in the final sample, split by industry. Panel B reports workforce characteristics from the worker listing module in the firm survey. Finally, Panel C reports labor sharing statistics. In all panels, I report the mean, and 20th to 80th percentile ranges for continuous variables. At the time of survey, 1 USD $\approx$ 3750 UGX.

Table 2: Worker Summary Statistics

	All		Carpentry		Metal		N
	Mean	[p20; p80]	Mean	[p20; p80]	Mean	[p20; p80]	
<i>Panel A: Worker characteristics (1,001 workers: 647 carpentry, 354 metal)</i>							
Age (years)	27.18	[22.00; 31.00]	27.64	[22.00; 32.00]	26.33	[21.00; 30.00]	1,001
Share male	0.98		0.97		1.00		1,001
Years of education	9.88	[7.00; 13.00]	9.83	[7.00; 13.00]	9.96	[7.00; 11.00]	1,001
Share with technical/vocational training	0.19		0.19		0.18		1,001
Received training from current firm	0.72		0.69		0.76		1,000
Experience in the industry (years)	4.98	[2.00; 7.00]	4.92	[2.00; 7.00]	5.08	[2.00; 7.00]	1,001
Skills test, share correct	0.79		0.79		0.77		992
<i>Panel B: Labor-market outcomes</i>							
Firms worked for, past 12 mo	2.05	[1.00; 3.00]	2.02	[1.00; 3.00]	2.10	[1.00; 3.00]	1,001
Current weekly wage (USD/week)	41	[18; 57]	39	[17; 56]	45	[20; 67]	971
Reservation weekly wage (USD/week)	21	[10; 30]	21	[10; 30]	22	[10; 30]	1,000
Days searching, past month	1.33	[0.00; 3.00]	1.31	[0.00; 2.00]	1.37	[0.00; 3.00]	1,001
Idle days, past month	3.34	[0.00; 7.00]	3.11	[0.00; 6.00]	3.78	[0.00; 7.00]	964
Capacity utilization at the firm	0.71	[0.55; 0.92]	0.71	[0.52; 0.95]	0.72	[0.58; 0.88]	993
Any self-employment, past month	0.53		0.54		0.50		973
Days in self-employment, past month	2.34	[0.00; 4.00]	2.55	[0.00; 4.40]	1.96	[0.00; 3.00]	973
Monthly self-employment income (USD/month)	91	[27; 120]	83	[27; 120]	108	[27; 117]	499
<i>Panel C: Labor-sharing exposure</i>							
Ever involved in labor sharing	0.55		0.52		0.59		1,001
... worker-reported only	0.49		0.45		0.57		1,001

Note: Panel A reports worker observable characteristics in the sample from all surveyed workers in the final sample, split by industry. Panel B reports summary statistics on labor market outcomes for workers. Finally, Panel C reports labor sharing statistics. In all panels, I report the mean, and 20th to 80th percentile ranges for continuous variables. At the time of survey, 1 USD $\approx$ 3750 UGX.

Table 3: Firm Hiring Statistics

	Share	N
<i>Panel A: Channel use, past 12 months (firm level)</i>		
Hired at least one worker	0.95	515
Share of all firms that hired through:		
Walk-in	0.49	515
Friend or family referral	0.45	515
Employee referral	0.42	515
From another firm	0.59	515
<i>Panel B: First hiring channel of listed workers</i>		
Walk-in	0.30	1,536
Friend or family referral	0.34	1,536
Employee referral	0.16	1,536
From another firm	0.18	1,536
Other	0.02	1,536
<i>Panel C: Worker lifecycle and conversion</i>		
Share converted to permanent, by first-hire channel:		
From another firm	0.49	270
Walk-in	0.89	460
Friend or family referral	0.89	528
Employee referral	0.75	239
Median years since hire, converted another-firm workers	3	133
Currently borrowed (share of listed workers)	0.12	1,534
... of whom first hired from another firm	0.61	190
... first hired through conventional channels	0.39	190
Converted another-firm hires since lent out	0.67	133
... all permanent workers, for comparison	0.52	1,217
First hired from another firm, converted, never subsequently shared	0.03	1,534

Note: This table reports statistics on firm hiring patterns. Panel A reports recent hiring intensity and use of hiring sources. The channel comparison uses only questions asked about every channel. Adding the relationships module, which exists only for labor sharing, raises the share of firms that hired from other firms to 79%. Panel B displays the distribution of hiring sources for the firm's observed workforce at the time of survey. Panel C displays statistics for listed worker life-cycles at their current firm.

Table 4: Determinants of Labor Sharing Reliance

(a) Worker Beliefs and Labor Sharing

	(1) Any sharing	(2) Partners	(3) Workers shared	(4) Borrowed	(5) Lent	(6) Transactions
Believed quality advantage: another firm (z)	0.036** (0.018)	0.193*** (0.055)	-0.062 (0.217)	0.082 (0.180)	-0.144 (0.164)	-0.002 (0.588)
Management ability (z)	0.024 (0.015)	0.247*** (0.074)	0.871*** (0.275)	0.378** (0.163)	0.493*** (0.160)	1.226* (0.639)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Parish $\times$ Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	493	493	493	493	493	493
R^2	0.226	0.253	0.295	0.265	0.231	0.245

(b) Demand Variability and Labor Sharing

	(1) Any sharing	(2) Partners	(3) Workers shared	(4) Borrowed	(5) Lent	(6) Transactions
Demand CV	0.094 (0.064)	0.102 (0.251)	2.235** (0.877)	1.186** (0.510)	1.049** (0.461)	2.335 (1.598)
Management ability (z)	0.019 (0.018)	0.235*** (0.078)	0.809** (0.307)	0.358** (0.163)	0.452** (0.188)	1.139 (0.687)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Parish $\times$ Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	479	479	479	479	479	479
R^2	0.224	0.220	0.304	0.275	0.235	0.242

Note: This table reports regressions of labor sharing outcomes on firm beliefs about workers from other firms (Panel A) and on demand variability (Panel B). Outcomes are: (1) an indicator for any sharing relationship; (2) the number of distinct sharing partners; (3) distinct workers borrowed or lent in the past three months; (4) workers borrowed and (5) workers lent; and (6) sharing transactions in the past three months.

In Panel A, the regressor is the standardized gap between the number of 10 workers from another firm the owner expects to produce sellable work and the average across walk-ins, employee referrals, and friend or family referrals.

In Panel B, the regressor is the coefficient of variation of monthly output across busy, normal, and slow months, weighted by months spent in each state. All regressions control for the share of the year spent in busy and slow months and a standardized management ability index, and include market (parish $\times$ industry) fixed effects. Standard errors in parentheses are wild-cluster bootstrapped by market.

Coefficients are descriptive and do not identify causal effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Stated Choice Experiment Designs

(a) Experiment 1: Between Hiring Source Design Attributes

Attribute	Levels
Weekly wage (000s UGX/week)	80, 130, 150, 200, 250
Hiring source	[Walk-in], Friend referral, Employee referral, From other nearby workshops
Experience (years)	2, 4, 6
Supervision (hrs/day)	0, 1, 2
Technical certificate	[No certification], Has certificate

(b) Experiment 2: Borrowing Design Attributes

Attribute	Levels
Weekly wage (000s UGX/week)	80, 130, 150, 200, 250
Experience (years)	2, 4, 6
Supervision (hrs/day)	0, 1, 2
Technical certificate	[No certification], Has certificate
Reciprocity terms	[No relationship], Must lend once, Ongoing relationship

(c) Experiment 3: Lending Design Attributes

Attribute	Levels
Lending fee (000s UGX/week)	10, 30, 55, 80
Reciprocity terms	[No relationship], Can borrow once, Ongoing relationship
Recall right	[Cannot recall], Can recall
Borrower location	[Within cluster], Within parish, Different parish (same division)
Demand state at lending firm	[Slow], Normal, Busy

(d) Experiment 4: Worker Job Offer Design Attributes

Attribute	Levels
Weekly wage (000s UGX/week)	40, 60, 100, 150, 200, 250
Contract duration	1 week, 2 weeks, 1 month
Location	[Within cluster], Within parish, Different parish
Relationship to firm	[No connection], Know a worker there, Know the owner, Sent by current firm owner
Required Mobility	[Full-time at one firm], Split time / moves between firms
Self-employment	[Cannot work own orders], Can work own orders during idle time

Note: Panels (a), (b), and (c) report the attribute spaces for the firm survey stated choice experiments described in Section 3. Panel (d) reports the attribute spaces for the worker survey stated choice experiments described in Section 4. For categorical variables, the base attribute is displayed in brackets.

Table 6: Parameter Definitions and Estimates

Parameter	Description	Enters	Value	SE
A. SMM estimates				
ϕ	Convex vacancy-cost curvature	Hiring	537.0	3,191
θ_b	Busy-state TFP scale	Production	862.3	48.9
ρ	Slow-to-busy TFP ratio	Production	0.5469	0.0210
σ_u	SD of idiosyncratic firm TFP	Production	0.4329	0.0572
λ_z	Management loading on firm TFP	Production	0.06603	0.0208
μ_H	Type-H log wage component	Wages	4.337	0.928
μ_L	Type-L log wage component	Wages	4.191	0.838
σ_ξ	SD of firm wage component	Wages	0.2496	0.0840
β_{pt}	Revenue passthrough into wages	Wages	0.1363	0.177
$\delta_{0,H}$	Type-H exogenous churn floor	Separations	0.003660	0.000397
$\delta_{0,L}$	Type-L exogenous churn floor	Separations	0.01086	0.00113
ε_s	Separation elasticity	Separations	0.1487	0.0601
$\rho_{\xi u}$	Corr. of firm wage rent with firm TFP	Wages	0.9430	0.0438
B. Estimated outside the model				
c_p	Lender-received per-worker pool fee	Sharing	13.95	2.87
τ	Borrower's additional per-worker wedge	Sharing	15.42	3.11
ε	Worker acceptance elasticity, firm level	Supply	1.28	0.0581
ε_m	Market labor-supply elasticity	Supply	0.976	[0.835, 1.381]
b_j	Owner outside-option wage	Ownership	133.6	—
C. Calibrations and pins				
a_L	Low-type relative productivity	Production	0.521	—
κ	Effective-labor returns to scale	Production	0.5	—
q	Probability of busy state	Demand	0.29	—
λ_e	Worker meeting rate	Hiring	0.5551	—
α_{in}	Inflow share of type-H hires	Hiring	0.384	—
W_H	Type-H reference wage	Separations	158.4	—
W_L	Type-L reference wage	Separations	124.4	—

Note: Panel A reports parameters estimated by simulated method of moments, targeting the moments in Table A14 with the two-step efficient weighting matrix described in Section 6. Panel B reports parameters estimated directly from the survey and choice experiments, outside the model: the lender's sharing fee and the transaction cost from the firm hiring and lending experiments (Section 3), the firm-level acceptance elasticity from the worker experiment (Section 4), and the participation elasticity from stated reservation wages, for which the 95% confidence interval is shown in brackets. Panel C reports parameters calibrated to survey moments or fixed by assumption. Monetary values are in thousands of UGX per worker-week.

Table 7: Empirical Moments and Model Estimates

Moment	Data	SE	Model
<i>Panel A: Targeted moments</i>			
Wages			
Log mean skilled wage	5.065	0.070	5.004
Log mean less-skilled wage	4.824	0.072	4.770
Log mean wage, owner-reported	4.675	0.074	4.752
Between-firm SD of log wages	0.377	0.031	0.321
Revenue passthrough, within task	0.104	0.056	0.367
Firm mean log wage on log size	0.030	0.092	0.192
Firm mean log wage on management score	0.032	0.031	0.004
Firm size and heterogeneity			
Log mean firm size	1.167	0.081	1.248
SD of log firm size	0.436	0.060	0.500
Log size on management score	0.069	0.037	0.133
Revenue and demand volatility			
Mean log monthly revenue, state-weighted	15.372	0.097	15.283
Busy- to other-month revenue ratio	3.049	0.306	3.026
SD of log revenue per worker, normal month	0.885	0.045	0.781
Turnover and tenure			
Annual separation rate	0.281	0.025	0.268
Log skilled/less-skilled tenure ratio	0.997	0.086	1.090
Log tenure on log wage, skilled	0.212	0.112	0.149
Log tenure on log wage, less-skilled	0.182	0.065	0.150
Mean skilled share of workforce	0.699	0.038	0.650
Labor sharing			
Share of listed workers borrowed	0.124	0.017	0.166
Borrowing on management score	0.211	0.077	0.128
Sharing fill rate, firm mean	0.806	0.048	0.766
<i>Panel B: Untargeted moments</i>			
Log revenue on management score	0.106	0.065	0.140
Log revenue per worker on management score	0.042	0.064	0.007
Median labor share of revenue	0.290	0.030	0.252
Median reservation wage relative to wage	0.625	0.061	0.624
Sharing fill rate, pooled ratio	0.814	0.030	0.766

Note: Data reports the survey moment and SE its standard error, clustered by enumerator (500 bootstrap replications). Model reports the same statistic computed on 2,000 firms simulated at the estimated parameters (Table 6). Panel A lists the 21 moments targeted in estimation; 17 lie within two standard errors of their data value. Panel B lists untargeted moments. Tenure is measured as time since the worker started at their usual firm, and management score is the standardized management index.

Table 8: Benchmarking Labor Sharing

Estimated Economy Description	Welfare gain (%)	Share of benchmark gain (%)
<i>A. Frictionless-hiring benchmark</i>		
Benchmark gain	23.98	—
Sharing (estimated economy)	7.01	29.2%
<i>Shapley split of the benchmark gain, over no sharing</i>		
Perfect screening	6.52	27.2%
Hiring after demand is seen	17.46	72.8%
<i>Shapley split of eff. benchmark gain, over economy with sharing</i>		
Perfect screening	6.83	40.4%
Hiring after demand is seen	10.10	59.6%
<i>B. Spot market instead of sharing (types hidden, fee τ per traded week)</i>		
One price per worker-week	4.98	—
Sharing (estimated economy)	7.01	—
Spot minus sharing (pp)	−2.02	—

Note: Panel A: the benchmark removes both frictions (perfect screening and hiring after demand is seen); the Shapley split divides the benchmark gain between perfect screening and hiring after demand is seen, starting from no sharing and from sharing, with their interaction shared equally. Panel B: the spot market pays one price per worker-week to skilled and less-skilled workers alike; firms cannot see a spot worker’s skill, and every traded week costs τ .

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Supplementary Appendix

A Data and Sampling

A.1 Sampling Procedure Details

Sampling frame construction.

- Frame drawn from the 2019/20 Uganda Census of Business Establishments: ISIC classes 3110 (furniture) and 2511 (structural metal products), 2–25 employees, located in Kampala district or a parish bordering it in Wakiso. Yields 1,363 eligible firms in the 30 selected parishes.
- Parishes ranked by count of eligible firms; top 30 retained.
- Targets allocated proportionally: 500 firms (322 carpentry, 178 metal), a 36.7% sampling rate.

Field protocol.

- Seed firms randomly selected within each parish from census records, subject to a minimum spatial-separation buffer so that seeds fan out across the parish rather than clustering.
- Enumerators then followed reported firm-to-firm ties (snowball). Where a firm reported no ties, or a named partner was unavailable, they approached every third establishment until finding an eligible firm.
- Up to two workers per firm, randomly selected within the survey instrument from a roster constructed during the firm interview. Realized ratio 1.94 workers per firm; 95.3% of workers matched to their interview firm.

Representativeness under tie-based sampling.

- *Concern.* Locating firms by following reported ties makes inclusion probability increasing in network connectivity, which is the object of study; measured sharing prevalence could be inflated.
- *Composition.* Sectoral mix matches the frame: 64.7% carpentry in the sample against 64.2% in the frame (62.2% in the pilot).
- *Saturation test.* Enumerator discretion over which firms to locate exists only where parish coverage is incomplete, so tie-based selection predicts higher measured sharing in *low*-coverage parishes. Coverage ranges from 0.19 to 0.87 across parishes (mean 0.40). Regressing an indicator for borrowing within three months on parish coverage gives +0.259 (clustered s.e. 0.123, $p = 0.044$); network membership gives +0.211 ($p = 0.118$). The sign is the opposite of what selection would produce.
- *Pilot benchmark.* In a randomly sampled 2025 pilot in the same areas, 93.3% of firms report at least one sharing partner, and 85.7% report borrowing, against 83.5% network membership in the full sample. The random sample shows prevalence at least as high.

- *Residual exposure.* Isolated firms outside the visible roadside clusters are least likely to be referred or encountered; their under-coverage would bias measured prevalence *upward*, so the direction is known and works against the paper’s headline magnitudes.

A.5 Sampling Frame Representativeness Surveyed firms appear smaller than in the CoBE, but this largely reflects a measurement difference. The CoBE includes total engaged workers and the owner (avg. 8.8), and my survey headline size measure is workers present at time of survey. Adjusting my survey to resemble the CoBE gives an average firm size of 7.0. Sectoral composition closely matches the sampling frame, at 65% carpentry firms in the sample against 64% in the sampling frame. Compliance rates were high, with over 90% of selected firms and workers completing the survey.

Table A1: Sample to Data Frame Comparison

	Frame	Sample	Sample – Frame	Norm. diff.
<i>Panel A. Industry</i>				
Wood / carpentry share	0.642	0.650	0.008	0.016
<i>Panel B. Geography (share of firms)</i>				
Kampala district	0.847	0.843	–0.004	–0.011
Wakiso district	0.153	0.157	0.004	0.011
Kampala: Central	0.060	0.047	–0.013	–0.059
Kampala: Kawempe	0.207	0.215	0.008	0.020
Kampala: Makindye	0.191	0.196	0.004	0.011
Kampala: Nakawa	0.105	0.102	–0.003	–0.010
Kampala: Rubaga	0.284	0.284	0.000	0.000
Wakiso: Kira/Namugongo	0.091	0.088	–0.003	–0.010
Wakiso: Nabweru	0.019	0.027	0.008	0.055
Wakiso: Nansana	0.023	0.022	–0.002	–0.013
Wakiso: Nsangi (Kyengera)	0.019	0.020	0.000	0.004
<i>Panel C. Size (workers)</i>				
Present on survey day: mean	8.77	3.09	–5.68	–1.685
Present + past month + owner: mean	8.77	6.72	–2.05	–0.468
<i>Panel D. Owner / respondent</i>				
Female respondent	0.040	0.035	–0.005	–0.027
Respondent age (years)	–	38.1	–	–
Respondent schooling	–	11.6	–	–
Respondent completed O-level or higher (share)	–	0.841	–	–
Observations	1,363	515		

Note: This table compares surveyed firms with the sampling frame, the 1,363 carpentry and metalworking establishments (ISIC 3110 and 2511) with 2–20 employees in the 30 sampled parishes, as recorded in the 2019/20 Census of Business Establishments (CoBE). Normalized differences are the difference in means divided by the square root of the average of the two groups’ variances; they are not reported for medians. Kira and Namugongo divisions are combined because one sampled parish spans both. Panel C reports surveyed firm size under three definitions, because the CoBE counts all persons earning income from the establishment, including part-time and temporary workers and proprietors of incorporated firms, whereas the survey’s headline measure counts workers present on the interview day; the closest survey analog adds workers who worked in the past month and the owner. In Panel D, the CoBE records the owner’s sex, while the survey records the respondent’s, who is a manager rather than the owner in 183 firms; the CoBE records neither age nor schooling.

Table A2: Industry composition and parish coverage: frame, full-scale sample, and pilot

	Frame	Sample	Pilot
Wood / carpentry share	0.642	0.647	0.622
Metal / welding share	0.358	0.353	0.378
Establishments	1,363	515	45
Parishes covered	29	29	–
Mean parish saturation	–	0.395	–
Min parish saturation	–	0.189	–
Max parish saturation	–	0.870	–
Any sharing tie	–	0.835	0.933
Borrowed in past 3 months	–	0.674	0.857

Notes: Frame is the 1,363 CoBE establishments (ISIC 3110 wood or 2511 metal, MSM, 2–25 employees, Kampala or a bordering district) in the 30 sampled parish cells (29 distinct parish names); Sample is the 515-firm analytic sample (April–May 2026) and Pilot is the randomly-sampled November 2025 pilot (45 firms). Parish saturation is firms surveyed divided by frame establishments.

Table A3: Sharing prevalence is higher, not lower, where parish coverage is more complete

	(1)	(2)	(3)	(4)	(5)	(6)
Parish saturation	0.259** (0.123)	0.259** (0.121)	0.211 (0.131)	0.213 (0.126)	0.259** (0.125)	0.102** (0.040)
Firm size (workers)		-0.001 (0.006)		0.001 (0.005)		
Metal/welding		-0.022 (0.069)		-0.043 (0.051)		
Outcome	Borrowed (3mo)	Borrowed (3mo)	Any tie	Any tie	Borrowed (3mo)	Borrowed (3mo)
Unit of observation	Firm	Firm	Firm	Firm	Parish	Firm
Saturation denominator	Frame	Frame	Frame	Frame	Frame	Target
Standard errors	Parish	Parish	Parish	Parish	HC1	Parish
Fixed effects	None	None	None	None	None	None
Observations	515	515	515	515	29	515
R^2	0.006	0.006	0.006	0.009	0.054	0.007

Notes: Parish saturation is firms surveyed divided by frame establishments in the parish (mean 0.395, range 0.189–0.870 across 29 parishes; frame as in Table A2). Outcomes are borrowing in the past three months and reporting any sharing partner, from the firm survey (Section 2.3). Columns (1)–(4) and (6) are firm-level linear probability models clustered by parish; column (5) is at the parish level, weighted by firms sampled; column (6) uses the sampling target as denominator. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Firm labor-sharing prevalence by source and recall window (percent of firms)

Window	Roster	Listing	Union	Both	Union + Q1a.0-12m
<i>Borrowing</i>					
At survey	20.4	30.3	37.3	13.4	37.3
Past 3 months	69.3	30.3	75.0	24.7	75.0
Past 12 months	69.3	35.0	75.7	28.5	80.2
Ever	79.6	35.0	82.9	31.7	83.1
<i>Lending</i>					
At survey	16.9	–	16.9	–	16.9
Past 3 months	55.3	–	55.3	–	55.3
Past 12 months	55.3	–	55.3	–	55.3
Ever	68.9	–	68.9	–	68.9
<i>Any sharing (borrow or lend)</i>					
At survey	31.3	30.3	46.0	15.5	46.0
Past 3 months	73.8	30.3	78.1	26.0	78.1
Past 12 months	73.8	35.0	78.6	30.1	81.0
Ever	81.2	35.0	83.9	32.2	83.9

Notes: Firms $n = 515$. Roster is the partner roster of the firm relationships module (Section 2.3; ever = any named partner, no time bound) and Listing is the worker listing; Union is roster or listing and Both is roster and listing. Lending is roster-only because the listing has no lending item with a recall window. The last column adds firms' reports of sharing with other workshops, counted only alongside other sharing evidence.

A.2 Shared Worker Classification

This appendix describes how workers are classified as shared workers using both evidence from the firm and worker survey.

A.2.1 Classification Construction

On the worker side, each work-history stint asks two questions. One is: “Were you sent to work here or referred by another firm’s owner or manager?” The other is: “Have you ever been sent by this firm’s owner or manager to work at another firm?” On the firm side, the worker listing asks every non-permanent listed worker: “Is this worker currently being borrowed from another firm?” It also asks every listed worker, regardless of contract status: “Have you ever sent this worker directly to work at another firm?” The preferred measure classifies a worker as ever shared if any worker-side signal is true, or the firm flags the worker as being both temporary and actively being borrowed during the worker listing.

Two exclusions are deliberate. Firm reports that a permanent worker was ever sent to another firm are excluded from the canonical measure, because that recall is one-sided and the worker cannot corroborate it. A worker’s hiring source of “hired from another firm” is not treated as a sharing signal, because a transfer recorded at hire cannot be distinguished from ordinary poaching.

A.2.2 Classification Agreement and Validation

Three nested measures bound the classification on the 1,001-worker analytic sample. The worker-reported measure alone puts 49.5 percent of workers as ever shared. The canonical measure adds firm-listing evidence on non-permanent workers and reaches 54.6 percent. A measure that also admits firm reports about permanent workers reaches 64.7 percent.

Among the 900 interviewed workers matched to a firm-listing row, Table A5 cross-tabulates worker-reported and firm-reported evidence, without the permanent requirement. The firm corroborates 80.1 percent of workers who self-report sharing, and workers corroborate 70.6 percent of firm flags. Overall agreement is 72.9 percent, rising to 76.8 percent among workers interviewed under version-2 forms. Under the permanent employee requirement, only a minority of matched workers are ever eligible for a firm-side flag, so conditional agreement is mechanically lower. The two sides measure different windows, worker career recall against firm current status and lifetime-sent reports, so this is concordance across measurement and recall windows rather than validation against ground truth.

Table A5: Concordance between worker-reported and firm-reported sharing evidence

	Firm flags sharing	Firm silent	Total
Worker reports sharing	367	91	458
Worker silent	153	289	442
Total	520	380	900

Notes: Sample is the 900 of 1,001 interviewed workers (89.9%) matched by name to a firm-listing row (Jaro–Winkler distance at most 0.20). *Worker reports sharing* is the worker-side two-signal indicator; *Firm flags sharing* is either firm-listing flag, including reports about workers the firm classes as permanent. Overall agreement is 72.9%, and 76.8% among the 723 workers interviewed under version-2 worker forms.

Table A6: Who gets shared? Worker characteristics by ever-shared status

	Never shared		Ever shared		Difference (Ever – Never)	<i>p</i> -value
	N	Mean	N	Mean		
Age (years)	454	26.80	547	27.49	0.97*	0.081
Industry experience (years)	454	4.31	547	5.53	0.98***	0.003
Skills test score (%)	448	79.93	544	77.53	0.14	0.913
Firms worked, past 12 months	454	1.48	547	2.52	1.02***	<0.001
Education (years)	454	9.69	547	10.03	0.25	0.255
Technical training (%)	454	18.50	547	19.20	-0.19	0.953
Self-employment evidence (%)	454	48.46	547	53.56	5.20	0.186
Current wage (USD/week)	432	38.9	539	42.7	1.7*	0.081
Reservation wage (USD/week)	454	20.3	546	21.9	1.5*	0.072

Note: This table displays observable characteristics of workers split by whether the worker has ever been a shared worker. Differences are estimated net of market (parish $\times$ industry) fixed effects. At the time of survey, 1 USD $\approx$ 3750 UGX. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

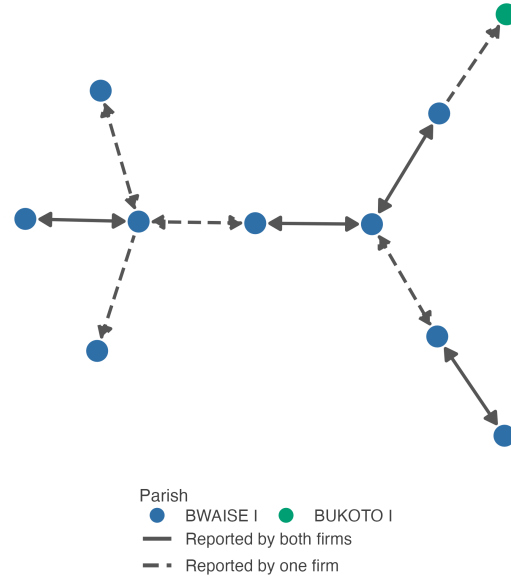
Table A7: The structure of firm-to-firm labor sharing: relationship features and intensity

<i>Panel A: Characteristics of reported sharing relationships (tie level)</i>			
	Share	Ties	
Reciprocal: firm both sends to and receives from the partner	0.753	802	
No direct compensation exchanged	0.830	805	
Partner located within the same parish	0.792	804	
Coordinated or approved by the owner or manager	0.887	604	
<i>Panel B: Sharing intensity among firms with any sharing tie</i>			
	Mean	Median	Firms
Any sharing tie (share of all firms)	0.812		515
Sharing partners	2.13	2.00	418
Sharing stints, past three months	9.10	6.00	418
Workers exchanged, past three months	4.68	3.00	418

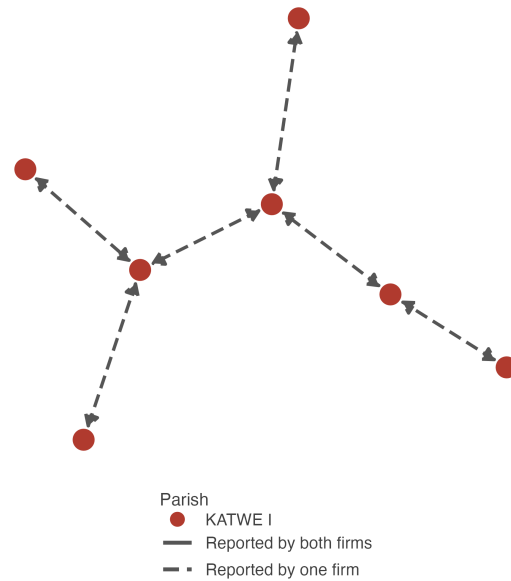
Notes: Panel A describes firm-reported sharing ties from the relationships module (Section 2.3), each unique tie counted once; the rows use the 604 of 802 detailed ties, and reciprocity over all 890 reported ties is bounded below at 0.679 (0.740 imputing the 68 ties beyond the three-slot detail cap). Panel B conditions on the 402 of 515 firms (0.781) reporting any labor sharing in the three months before the interview, using the union definition of Table 1, Panel C; intensity rows use the partner roster only, and a stint is one occasion on which a worker moved.

B Descriptive Evidence

Figure A1: Example Firm Labor Sharing Network Clusters



(a) Example Carpentry Hiring Network



(b) Example Metalworking Hiring Network

Notes: These figures show example network clusters constructed from the firm relationships module of the firm survey described in Section 2.3. Dotted lines represent relationships reported by one firm, while solid lines represent bilaterally reported relationships. Arrowheads represent reported labor sharing directions (from lender to borrower).

Table A8: Measures of Firm Demand Variation

	Busy	Normal	Slow
<i>Panel A: Demand by reported state (typical months)</i>			
Monthly revenue (USD)	3,210	1,383	596
Monthly orders	14.70	8.56	5.03
Monthly items produced	172.91	59.48	28.20
Months per year	3.49	4.77	3.74
<i>Panel B: Current cycle position, by at-survey demand state</i>			
Cycle position (log gap from own mean), mean	0.267	-0.331	-1.141
(market-clustered SE)	(0.107)	(0.062)	(0.088)
Busy – slow difference: 1.407 (SE 0.152), $n = 468$			
<i>Panel C: Firm-specific vs. market variation</i>			
Within-market share of variance in cycle position (ICC = 0.120)			0.880
Pairwise correlation of cycle positions, same-market pairs			0.040
Pr(two same-market firms report the same demand state)			0.502
vs. independence benchmark			0.469
Share of markets (≥ 3 firms) with firms in different states			0.942
Market-specific cycle share of state-level demand variance			≤ 0.028
Within-market share of variance in demand CV			0.750

Notes: Panel A reports months per year and typical monthly revenue, orders and items by self-reported demand state; Panel B the current cycle position (log revenue gap from the firm’s own mean) by at-survey state; Panel C firm-specific versus market-shared variation; Panel D the variance decomposition of log monthly revenue. Data are from the demand module of the firm survey (Section 2.5; 515 firms, fewer in Panels B–D). Revenues are cleaned; Panel A converts them to US dollars at 3,750 UGX per dollar. Panel B standard errors are clustered by market.

Table A9: Wage Determinants

	(1) Type wage gap	(2) Passthrough	(3) Size-wage slope
Log wage gap, H – L type	0.242*** (0.048)		
log expected revenue/worker		0.109*** (0.032)	
log firm size (total workers)			-0.001 (0.079)
log mean wage, H-type	5.065*** (0.039)		
log mean wage, L-type	4.824*** (0.036)		
Task (main product) FE		Yes	
Worker type FE		Yes	
Market (parish×industry) FE		Yes	Yes
Dependent variable	Log wage	Log piece rate	Log firm-mean wage
Observations	412 / 530	796	483

	SD of log wage
Raw log wage	0.730
Residual (task/worker controls, product FE)	0.682
Between-firm	0.375*** (0.024)
Within-firm (residual net of firm)	0.569
Firms / workers	480 / 1,606

Notes: The upper table reports the log wage gap between high- and low-type workers (column 1), the passthrough of log expected revenue per worker to piece rates with task, worker-type and market (parish × industry) fixed effects (column 2), and the size-wage slope with market fixed effects (column 3); the lower table decomposes the dispersion of log wages. Standard errors are bootstrapped over firms and workers, except column (2), clustered by firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Firm beliefs about workers and realized search, by hiring channel

	(1) Walk-in	(2) Employee ref.	(3) Friend/family	(4) Another firm	(4) – (1)
<i>Panel A: Beliefs about 10 unknown workers from this channel</i>					
Would produce sellable quality (of 10)	3.15	4.89	3.08	6.24	3.04***
Still employed in 3 months (of 10)	2.72	3.18	3.55	3.71	1.04***
Risky — may steal from the firm (of 10)	6.57	4.63	3.67	4.52	-2.04***
<i>Panel B: Screening and supervision costs</i>					
Supervision needed (hours of a 10-hour day)	5.25	4.00	4.92	2.78	-2.47***
Days needed to assess skill	4.08	2.95	3.84	1.88	-2.21***
<i>Panel C: Realized search, past three months</i>					
Hiring attempts, past 3 months	1.29	1.40	1.07	2.90	1.68***
Successful hires, past 3 months	0.61	0.89	0.66	2.41	1.84***
Success rate (successes ÷ attempts)	0.56	0.61	0.65	0.81	0.21***
Firms (N)	474–510	469–510	476–510	482–510	463–509

Notes: Firm owners' beliefs about new workers hired through each channel and realized search over the past three months (firm survey, Section 2.4; 515 firms). Cells are unconditional means, except the success rate, which uses firms with at least one attempt ($N = 201, 251, 208$ and 347 across the four channels). The last column is the mean within-firm difference between from-another-firm and walk-in hiring ($N = 467–513$), tested with a paired t -test. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Seasonal demand variability and worker capacity utilization

<i>Panel A: Seasonal demand states (firm level)</i>				
	Busy	Normal	Slow	Busy – Slow
Months per year, mean	3.49	4.76	3.75	-0.26***
Months per year, SD	1.32	1.58	1.22	
Monthly revenue, mean (USD)	3,197	1,377	587	2,614***
Monthly revenue, median (USD)	2,133	1,067	400	
Firms (N)	476	482	478	470
<i>Panel B: Demand variability (firm level)</i>				
	Mean	SD	Median	Firms (N)
Busy-to-slow revenue ratio	11.23	33.15	5.42	445
Demand CV (winsorized p1/p99)	0.75	0.30	0.71	485
Demand CV (raw)	0.75	0.31	0.71	485
<i>Panel C: Worker capacity utilization, by home firm's demand state at survey</i>				
	Busy	Normal	Slow	Busy – Slow
Capacity utilization (%), mean	72.0	73.9	66.9	5.1
Capacity utilization (%), SD	23.2	22.0	22.4	

Notes: Panel A reports months per year and typical monthly revenue by demand state from the demand module of the firm survey (Section 2.5; 515 firms, N varies by item), in US dollars at 3,750 UGX per dollar after winsorizing shilling values at the 99th percentile with a 50 million UGX cap; the last column is the mean within-firm busy-minus-slow difference with a paired t -test. Panel B summarizes the per-firm busy-to-slow revenue ratio and the coefficient of variation (CV) of physical demand, winsorized at [0.167, 1.602] as in the regressions. Panel C reports worker capacity utilization from the time-use diary by the home firm's survey-day demand state (946 of 954 matched workers; standard errors clustered by firm). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Estimation of the discrete choice experiments

This appendix records how the three discrete choice experiments (DCEs) are taken from choice data to the objects the paper uses: the willingness-to-pay premia of Section 3, the lender’s price c_s , the borrower’s price $c_s + \tau$, and the labor supply elasticity ε . Attribute definitions and level sets are described in the main text and are not repeated here.

Notation. The idiosyncratic logit error is written ν_{ijt} . The taste coefficients β in this appendix are DCE preference parameters. All monetary quantities are in thousands of Ugandan shillings per worker-week, the same units as the structural model.

C.1 Setup and notation

Choice environment. Each experiment presents respondent i with $T_i = 6$ choice tasks. Every task t offers two designed alternatives, labeled A and B , plus an outside alternative o that lets the respondent decline both. The firm sample completes three experiments in sequence: Block 1 (hiring across sources), Block 2 (borrowing a shared worker), and the lending experiment. The worker sample completes one job-offer experiment. Tasks are generated from a Bayesian D-efficient design, and are randomly assigned to respondents in blocks so that choice task attributes are uncorrelated with respondent observable characteristics.

Random utility. Let $x_{jt} \in \mathbb{R}^{K_x}$ collect the designed attributes of alternative j in task t , and let $d_{jt} = (\mathbf{1}\{j = B\}, \mathbf{1}\{j = o\})'$ collect two alternative-specific constants (ASCs). Respondent i derives utility

$$U_{ijt} = d'_{jt}\alpha_i + x'_{jt}b_i + \nu_{ijt}, \quad j \in \{A, B, o\}, \quad t = 1, \dots, T_i, \quad (25)$$

and chooses the alternative with the highest utility, so that $y_{ijt} = 1$ if and only if $U_{ijt} \geq U_{ikt}$ for all k . Two normalizations make (25) estimable. Utility scale is fixed by assuming ν_{ijt} is i.i.d. Type-I Extreme Value with unit scale. Utility location is fixed by taking alternative A as the reference, so no ASC enters U_{iAt} . The outside alternative carries no designed attributes, $x_{ot} \equiv 0$, so its systematic utility is the outside ASC alone.

Throughout what follows the ASCs and the designed attributes are stacked, $x_{jt} \leftarrow (d'_{jt}, x'_{jt})'$ and $\beta_i \leftarrow (\alpha'_i, b'_i)'$, so that $K = 2 + K_x$ and the systematic utility is $x'_{jt}\beta_i$.

Conditional logit probability and log-likelihood. Conditional on β_i , the extreme-value assumption gives the multinomial logit probability

$$P_{ijt}(\beta_i) = \Pr(y_{ijt} = 1 \mid \beta_i) = \frac{\exp(x'_{jt}\beta_i)}{\sum_{k \in \{A, B, o\}} \exp(x'_{kt}\beta_i)}. \quad (26)$$

The conditional logit estimator imposes homogeneity, $\beta_i = \beta$ for all i , and maximizes

$$\ell(\beta) = \sum_{i=1}^N \sum_{t=1}^{T_i} \sum_{j \in \{A, B, o\}} y_{ijt} \log P_{ijt}(\beta) \quad (27)$$

The score and Hessian of (27) are globally well behaved: ℓ is concave in β whenever the stacked design matrix has full column rank, so $\hat{\beta}_{\text{MNL}}$ is unique.

Lender’s compensation c_s . The lending experiment (Choice Experiment 3) varies the weekly fee the borrower pays, along with recall rights, reciprocity, location and the demand state. A conditional logit, (27), gives a separate fee slope in each demand state. The marginal utility of money is the slow-state slope at a fee of 40, because lenders in the model are slack firms. Dividing the coefficient on an ongoing relationship by it gives the fee a lender forgoes to lend within an ongoing relationship rather than to a partner with no reciprocity, which I read as what the lender receives in kind for a one-week loan. Values are in thousands of UGX per worker-week. The estimate is $c_s = 13.94$ (SE 2.87; 95% interval [8.3, 19.6]). The main caveat is that demand states appeared in a fixed task order, so state and order cannot be separated.

Borrower’s price $c_s + \tau$ and the transaction cost τ . The hiring experiment (Choice Experiment 1) varies the worker’s wage and hiring source. From a conditional logit, (27), I value each source relative to a walk-in at a wage of 150. Because a firm short of workers would otherwise use its usual channels, I net out a composite non-shared hire weighted by twelve-month hiring shares (walk-ins 0.283, employee referrals 0.409, friend or family referrals 0.308):

$$c_s + \tau = \frac{\beta_{\text{share}} - 0.409 \beta_{\text{emp}} - 0.308 \beta_{\text{fr}}}{-(\beta_w + 2 \cdot 150 \beta_{w^2})} = 29.37,$$

with the walk-in coefficient set to zero (95% interval [10.0, 50.3]). The transaction cost is the part of this price the lender does not receive, $\tau = 29.37 - 13.94 = 15.42$. The two are nearly uncorrelated in a bootstrap (0.04). The main caveat is that the premium is measured on a hiring choice rather than a loan, so I assume that a borrower’s alternative to a shared worker is its usual hire.

Labor supply elasticity ε . The job-offer experiment varies each offer’s weekly wage (40 to 250) and several job characteristics. I estimate a mixed logit with normally distributed coefficients on the wage and on being asked to move between firms. I define ε as the elasticity of the probability that an offer is chosen with respect to its wage, $\varepsilon = (\beta_w + 2\beta_{w^2}\bar{w})\bar{w}(1 - \bar{P})$, at the mean coefficients, the mean offered wage $\bar{w} = 148.1$ and the mean choice share $\bar{P} = 0.455$. This gives $\varepsilon = 1.28$ (SE 0.058), the value the model uses; it is 1.27 for skilled and 1.35 for less-skilled workers ($p = 0.52$). Workers decline both offers in only 9 percent of tasks, so ε captures substitution between employers; the participation elasticity ε_m comes from stated reservation wages (Section 4). The main caveat is that ε depends on the menu: a firm with many rivals would face a larger elasticity, about 2.3.

Interpreting the lending WTA as a bound. Two features of the lending experiment make the estimated WTA a lower bound on the lender's compensation c_s , and hence the implied transaction cost τ an upper bound. First, the valued bundle excludes the right to recall the worker, which lenders value. Second, because lending is typically uncompensated, there was no natural fee analog to the payments in the hiring experiments; fees of comparable size were judged unrealistic in piloting and were scaled down for the full survey. If the marginal value of money declines with the amount, a price coefficient estimated over small fees overstates the value of money at the scale of the hiring premium, understating the WTA.

Figure A2: Example Stated Choice Experiments

(a) Firm Experiment 1 – Between Hiring Sources

Choice 1 of 6

You receive an order for 10 four-panel door which need to be produced very quickly. In addition to your usual workers, which of these workers would you prefer to hire?

Note that you can choose to not hire either worker, but this may result in delays or difficulties.

	Worker A	Worker B
Weekly wage	200K	80K
Experience	6 years	2 years
Source	Employee referral	Walk-in
Supervision	None	1 hour/day
Certification	No certification	Has technical certificate

(b) Worker Job Offer Experiment

Choice 4 of 6

Consider a situation where you are not employed. You are offered the following jobs at different firms in this industry. Which of the following would you accept?

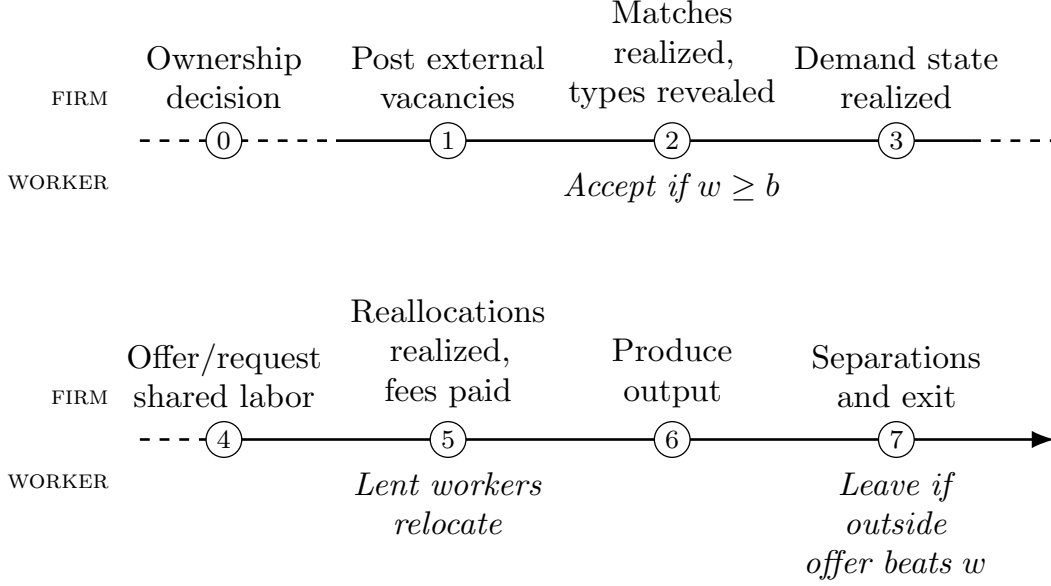
Note that you can say no to both if you believe you could find a better job elsewhere or would rather remain unemployed.

	Offer A	Offer B
Weekly wage	100K	150K
Guaranteed duration	1 month	1 month
Location	Within cluster	Same parish outside cluster
Relationship to firm	Know a worker there	Sent by owner of another firm
Stability	Full-time at same firm	Asked to move between multiple firms
Personal orders	Cannot work on own orders	Can work on own orders during downtime

Notes: Panel A shows an example firm choice experiment decision and Panel B an example worker job offer choice experiment decision, as displayed to respondents (Sections 3 and 4). Each experiment has 6 choices per respondent, with values drawn from a D-efficient set of profiles; see Appendix C for construction.

D Model Propositions and Derivations

Figure A3: Model timing within a period.



Notes: This figure shows the model timing of firm manager and worker decisions within a period. Firm actions above the line, worker decisions below. Hires from step 2 join the stock and face separation alongside incumbents in step 7. In steady state, inflows equal separations.

D.1 Proof of Lemma 1.

Proof. Substituting Equation (8) into Equation (7) gives $\ln R_{\omega,j} = (\Lambda_{\omega} + \varepsilon\mu_{\omega}) + (a_j + \varepsilon\psi_j)$. The firm term cancels in the ratio. $\square$

The lemma is the case of the two-group model in Card et al. (2018) in which both groups share the wage coefficient and value amenities equally.

D.2 Proof of Proposition 1

Preliminaries. Let $R_d(L) = \theta_d A_j L^{\kappa}$ be revenue and $MRP_d(L) = \kappa\theta_d A_j L^{\kappa-1}$ its slope, which falls with L . A firm with effective labor L uses $\tilde{L}_d = L + \lambda_d \ell_{d,j}^*$ after trading. The objective in Equation (20) is concave in ℓ and peaks at $\ell_{d,j}^*$, so any position between zero and $\ell_{d,j}^*$ earns at least as much as not trading. The target sets $MRP_d(L_d^*) = p_d$. A borrower therefore ends between its own labor and its target, with $MRP_b(\tilde{L}_b) \geq p_b$. A lender ends between its target and its own labor, with $MRP_s(\tilde{L}_s) \leq p_s$.

Part (a)(i). When a firm trades, an extra worker of type ω replaces part of the trade. Its marginal benefit in state d is $a_{\omega}[(1 - \lambda_d) MRP_d(\tilde{L}_d) + \lambda_d p_d]$, a weighted average of the marginal product

after trading and the sharing price.⁴⁷ For a borrowing-only firm, both terms are at most $MRP_b(L)$ in the busy state, and nothing changes in the slow state, so the marginal benefit in Equation (16) weakly falls. For a lending-only firm, both terms are at least $MRP_s(L)$ in the slow state, so it weakly rises. Wages and separation rates are fixed. In steady state, hiring costs rise with the stock while the marginal benefit falls with it, so the stock moves in the same direction as the marginal benefit. A lender's stock rises, so it stays above the busy target; a borrower's falls, so it stays below the slow target. For a firm that does both, the busy-state term falls and the slow-state term rises, so the sign is ambiguous.

Part (a)(ii). Not trading is feasible in every state, so profit with sharing is at least profit without it at every stock. Any hiring plan earns weakly more, so the value of operating weakly rises. Reading $\bar{\pi}_j$ in Equation (17) as this value per period, any manager who operates without sharing also operates with it.

Part (b)(iii). Fix stocks, wages and the operating set. Each borrower's marginal product falls toward p_b and stays above it; each lender's rises toward p_s and stays below it. Labor in use moves from slow firms to busy firms.

Part (b)(iv). Let V be expected volume, the same on both sides of the market. Wage and fee payments are transfers, so the change in total surplus is the change in revenue less τV . Because revenue is concave, a borrower gains at least p_b per unit borrowed and a lender loses at most p_s per unit lent. Total surplus therefore rises by at least $(p_b - p_s - \tau)V = 0$. Holding positions fixed, each unit traded uses up τ , so the loss from the transaction cost is τV .

Firm-specific wages. If skilled wages differ across firms, a borrower pays $p_{b,j} = w_{H,j} + c_s + \tau$ and a lender saves $p_{s,k} = w_{H,k} + c_s$. The same steps bound the gain in (b)(iv) below by $V(\bar{w}_H^b - \bar{w}_H^s)$, where $\bar{w}_H^b$ and $\bar{w}_H^s$ are the volume-weighted skilled wages of borrowers and lenders. Part (iv) therefore holds whenever borrowers pay their skilled workers at least as much as lenders, on average over trades. Parts (a)(i), (a)(ii) and (b)(iii) do not depend on this.

D.3 Common skilled share of the stock

The skilled share of the stock in Equation (11), α^N , is the same at every firm. By Lemma 1, a share α of every firm's hires is skilled. Wages are type-neutral (Equation (8)), so a firm's premium ψ_j raises both types' wages by the same proportion. In Equation (10), the ratio of separation rates,

$$\frac{\delta_{L,j}}{\delta_{H,j}} = \frac{\delta_{0,L}}{\delta_{0,H}} \left[\frac{e^{\mu_L}/W_L}{e^{\mu_H}/W_H} \right]^{-\varepsilon_s},$$

⁴⁷If a lender already lends all its skilled workers, an extra less-skilled worker adds $a_L MRP_s(\tilde{L}_s)$, which is also at least $a_L MRP_s(L)$.

therefore does not depend on the firm. Each type's steady-state stock is its hires divided by its separation rate, so

$$\alpha^N = \frac{\alpha}{\alpha + (1 - \alpha) \delta_{H,j} / \delta_{L,j}}$$

is common to all firms. Sharing exchanges workers for one period at a time and does not change the stock, so the result holds with and without sharing.

D.4 Existence of an equilibrium

I show existence for a given set of operating firms, then turn to entry.

Given wages and fill rates, each firm's problem has a unique solution. The sharing choice in Equation (20) maximizes a strictly concave function over an interval, so positions are unique and continuous in the firm's stock. In the vacancy problem in Equation (23), the marginal benefit of a hire weakly falls with the stock (proof of Proposition 1, part (a)(i)) while the marginal hiring cost rises. The stationary stock is therefore the unique root of Equation (16), and it is continuous in wages and fill rates.

The aggregate objects are the fill rates, the type wage levels μ_ω , and each firm's wage premium through revenue per worker. Given these, firms choose stocks and positions. Fill rates then update by Equation (22), type wage levels by Equation (13), and firm wages by Equation (18). Each step is continuous.⁴⁸ Fill rates lie in $[0, 1]$, type wage levels lie in a bounded interval because participation is bounded, and stocks are bounded because hiring costs are convex. The map takes a compact, convex set into itself, so a fixed point exists by Brouwer's theorem.

With a finite set of managers, the operating set is discrete, and a fixed point in that set need not exist: one firm's entry can lower fill rates or raise wages enough that another firm exits. With the taste for ownership drawn from a continuous distribution, the share of managers who operate is continuous in profit, which restores the argument. In the counterfactuals, I iterate on the operating set as described in Appendix F.3.

Uniqueness is not guaranteed, because a higher fill rate raises the value of a hire, and therefore stocks and positions on both sides of the market. At the estimated parameters, the solver reaches the same equilibrium from different starting points.

D.5 Solution algorithm

For a given parameter vector, I solve the stationary equilibrium on a fixed set of 2,000 simulated firms. Their productivity, wage premium and demand draws are held fixed across evaluations. The solver has three nested steps. First, given wages, the sharing targets in Equation (21) are closed form, and each firm's stock is the root of the steady-state hiring condition in Equation (16), which I find by bisection. Second, given stocks and targets, I solve for the fill rates in Equation (22) by bisection. Third, wages update by the wage rule in Equation (18), placing weight 0.3 on the new value, and

⁴⁸Fill rates are continuous when desired borrowing and lending are both positive; I set a fill rate to one when the other side of the market is empty.

separation rates and stocks are recomputed at the new wages. Starting from observed mean wages, I iterate until the average relative change in skilled wages falls below 10^{-6} . In estimation, the type wage levels μ_ω are parameters. In the counterfactuals, they adjust to clear each type's market by Equation (13), and the set of operating firms updates as in Appendix F.3.

E Estimation Details

Table A12: Worker Wage Regression Used to Construct the Outside Option

	(1)
Years of education	0.022*** (0.007)
Age	0.021 (0.024)
Age ² / 100	−0.025 (0.037)
Male	0.630*** (0.233)
Experience in industry (years)	0.068*** (0.016)
Experience ² / 100	−0.253*** (0.081)
Market (parish×industry) FE	Yes
Dependent variable	Log weekly wage
Observations	966
Markets	57
R ²	0.198
Within adj. R ²	0.069

Notes: The dependent variable is the log of the worker’s realized weekly wage, for the 966 workers with a positive wage and complete covariates (worker survey). Experience is years in the worker’s industry. Owners’ industry experience is not observed, so when predicting each owner’s outside option I use potential experience, age minus years of schooling minus six (Section 6). The regression includes market (parish × industry) fixed effects (57 markets), and standard errors are clustered by market. Only 17 workers in the sample are women, so the gender coefficient is imprecise. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A13: Productivity Function Parameter Estimates

	(1)	(2)	(3)	(4)	(5)
$\hat{a}_L$	0.436 (0.280) [-0.063, 0.934]	0.523 (0.347) [-0.057, 1.104]	0.532 (0.362) [-0.088, 1.152]	0.479 (0.336) [-0.094, 1.052]	0.600 (0.279) [0.153, 1.047]
Industry FE	X	X			X
Parish FE		X			X
Market (parish $\times$ industry) FE			X	X	
Survey-day demand-state FE					X
Manager ability control				X	
Revenue measure	Normal month	Normal month	Normal month	Normal month	Current state
Observations	486	486	486	479	473
Markets	56	56	56	56	56

Notes: Estimates of a_L , the productivity of an owner-assessed non-skilled worker relative to a skilled one, from non-linear least squares of log revenue on a labor aggregate counting the owner as one skilled unit, with the size elasticity fixed at 0.5 (firm survey; Section 6). Standard errors are clustered by market (56 markets); brackets are bootstrap 95% intervals.

Table A14: Moment Definitions

Moment	Notation	Disciplines
Wages		
Log mean skilled wage	$\log \bar{w}_H$	ϕ, μ_H
Log mean less-skilled wage	$\log \bar{w}_L$	ϕ, μ_L
Log mean wage, owner-reported	$\log \bar{w}^F$	μ_H, μ_L
Between-firm SD of log wages	$\text{sd } \log \bar{w}_j$	σ_ξ
Revenue passthrough, within task	$\partial \log w / \partial \log(Y/N)$	β_{pt}
Firm mean log wage on log size	$\partial \log \bar{w} / \partial \log N$	$\rho_{\xi u}$
Firm mean log wage on management score	$\partial \log \bar{w} / \partial z$	λ_z
Firm size and heterogeneity		
Log mean firm size	$\log \bar{N}$	ϕ, θ_b
SD of log firm size	$\text{sd } \log N_j$	$\sigma_u, \rho_{\xi u}$
Log size on management score	$\partial \log N / \partial z$	λ_z
Revenue and demand volatility		
Mean log monthly revenue, state-weighted	$\mathbb{E} \log \bar{Y}_j$	θ_b
Busy- to other-month revenue ratio	$\bar{Y}_b / \bar{Y}_s$	ρ
SD of log revenue per worker, normal month	$\text{sd } \log(Y_j/N_j)$	—
Turnover and tenure		
Annual separation rate	δ^{ann}	$\delta_{0,H}, \delta_{0,L}$
Log skilled/less-skilled tenure ratio	$\log(\bar{T}_H/\bar{T}_L)$	$\delta_{0,H}, \delta_{0,L}$
Log tenure on log wage, skilled	$\partial \log T_H / \partial \log w$	ε_s
Log tenure on log wage, less-skilled	$\partial \log T_L / \partial \log w$	ε_s
Mean skilled share of workforce	$\bar{\alpha}$	$\delta_{0,H}, \delta_{0,L}$
Labor sharing		
Share of listed workers borrowed	s_B	ρ, θ_b
Borrowing on management score	$\partial d_B / \partial z$	λ_z
Pool fill rate (other workshops), firm mean	λ_B	ρ

Notes: The 21 moments targeted in the SMM objective (Section 6), grouped in blocks, with the parameters each principally disciplines in the Jacobian.

E.1 SMM Estimation Procedure

Estimator. I estimate $\Theta = (\phi, \lambda_z, \sigma_u, \theta_b, \rho, \mu_H, \mu_L, \sigma_\xi, \rho_{\xi u}, \beta_{pt}, \delta_{0,H}, \delta_{0,L}, \varepsilon_s)$ as

$$\hat{\Theta} = \arg \min_{\Theta} [\hat{m} - m(\Theta)]' W [\hat{m} - m(\Theta)], \quad (28)$$

where $\hat{m}$ stacks the $N = 20$ targeted moments of Table A14 and $m(\Theta)$ is the same vector computed on a panel simulated at Θ . Each moment is a mean, ratio, dispersion or regression slope. Its model counterpart applies the same statistic to the simulated firms.

Simulation. I simulate $S = 2,000$ firms for $T = 200$ weeks and drop the first 100 as burn-in. Each firm resamples its management score z_j with replacement from the 503 surveyed firms that have one, and draws $\tilde{u}_j \sim \mathcal{N}(0, 1)$. Productivity $A_j = \exp(\lambda_z z_j + \sigma_u \tilde{u}_j)$ scales θ_b and $\theta_s = \rho \theta_b$. Its firm premium is $\xi_j = \rho_{\xi u} \sigma_\xi \tilde{u}_j + (1 - \rho_{\xi u}^2)^{1/2} \sigma_\xi \tilde{e}_j$, with $\tilde{e}_j \sim \mathcal{N}(0, 1)$. A firm is busy in a week when a uniform draw, independent across firms and weeks, falls below q . A second uniform draw perturbs weekly headcount by at most 2.5 percent. Separations follow Equation (10): a type- ω worker at firm j leaves with probability $\delta_{0,\omega}(w_{\omega,j}/W_\omega)^{-\varepsilon_s}$, where W_ω is the mean weekly wage of type ω in the data. Tenure moments follow from these hazards in closed form. All draws come from fixed seeds and stay constant across evaluations (common random numbers).

Weighting and search. In the first step, $W_1 = \text{diag}(\hat{S})^{-1}$ on the targeted moments, so the objective is a sum of squared residuals, each divided by its bootstrap standard error. The second step uses

$$W_2 = D^{-1/2}(R + \lambda I)^{-1}D^{-1/2}, \quad \hat{S} = D^{1/2}RD^{1/2}, \quad (29)$$

where D is the diagonal and R the correlation matrix of $\hat{S}$ on the targeted moments. I then minimize on the full panel with the Nelder and Mead simplex method, capped at 3,200 evaluations. The starts are the first-step minimum, the previous version's estimate, the first-step minimum with $\rho \times 1.25$ and $\sigma_\xi \times 0.8$, and further first-step points. I keep the lowest-objective point.

$\hat{S}$ is the covariance of the data moments across $B = 500$ bootstrap replications. Each replication recomputes every moment, regressions included. I resample the 515 surveyed firms with replacement, each with its linked workers, so cross-survey covariances are estimated, not set to zero.

Inference. The estimated covariance matrix of $\hat{\Theta}$, conditional on the choice-experiment and calibrated inputs, is

$$\hat{V} = \left(1 + \frac{1}{n_s}\right)(G'W_2G)^{-1}G'W_2\hat{S}W_2G(G'W_2G)^{-1}, \quad (30)$$

where n_s counts simulated firms per surveyed firm, and $G = \partial m / \partial \Theta'$ at $\hat{\Theta}$ is a central finite difference on the full panel. I compute the sandwich in log parameters and map it to levels by the delta method. Identification requires the smallest singular value of $W_2^{1/2}G \text{diag}[\hat{\Theta}]$ to exceed

10^{-8} times the largest, and no finite-difference point may lower the objective below its value at $\hat{\Theta}$. I compare the over-identification statistic $J = \hat{g}'W_2\hat{g}/(1 + 1/n_s)$, where $\hat{g} = \hat{m} - m(\hat{\Theta})$, against $\chi^2(N - 13) = \chi^2(7)$. It has no sample-size factor because $\hat{S}$ is the covariance of the moment estimates.

Propagating choice-experiment error. The firm experiment identifies the borrower's price $c_s + \tau$ and the lender's price c_s ; their difference is τ . I propagate their sampling error by simulation (Krinsky and Robb 1986). For the preferred conditional logit estimates, I draw each model's coefficients from their asymptotic normal distribution, independently for the pooling and lending experiments, and map each draw into the two prices. For the hierarchical Bayes alternative, I use posterior draws of the population means. I keep $R = 200$ draws, replace any with a nonpositive price or a borrower price below 1,000 UGX per week, and set $\tau = 0$ if a draw implies $\tau < 0$. For each draw, I re-estimate on the second-step objective with W_2 and the simulation draws fixed, by BOBYQA from $\hat{\Theta}$ (at most 400 evaluations, 500-firm panel). I report standard errors from

$$\hat{V}_{\text{total}} = \hat{V} + \widehat{\text{Cov}}_R(\hat{\Theta}^{(r)}), \quad (31)$$

where the second term is the sample covariance of the R re-estimates.

Table A15: Sharing patterns with firm productivity and managerial ability

	All firms			Firms that share		
	(1)	(2)	(3)	(4)	(5)	(6)
	Workers borrowed	Workers lent	Net borrowed	Workers borrowed	Workers lent	Net borrowed
<i>Panel A. Management score alone</i>						
Management score (z)	0.329** (0.162)	0.395** (0.177)	-0.065 (0.170)	0.323 (0.216)	0.499* (0.257)	-0.176 (0.219)
Observations	503	503	503	360	360	360
Markets	56	56	56	49	49	49
<i>Panel B. Revenue per worker alone</i>						
Log revenue per own worker (z)	0.301** (0.130)	-0.295 (0.364)	0.596* (0.299)	0.454*** (0.140)	-0.391 (0.462)	0.845** (0.386)
Observations	453	453	453	327	327	327
Markets	53	53	53	48	48	48
<i>Panel C. Both together</i>						
Management score (z)	0.349** (0.171)	0.483** (0.230)	-0.134 (0.190)	0.296 (0.219)	0.540* (0.317)	-0.244 (0.256)
Log revenue per own worker (z)	0.285** (0.127)	-0.321 (0.352)	0.606* (0.303)	0.447*** (0.149)	-0.397 (0.443)	0.844** (0.384)
Observations	447	447	447	326	326	326
Markets	53	53	53	48	48	48
Mean of dep. var. (Panel A sample)	2.060	1.803	0.256	2.811	2.447	0.364
Parish $\times$ Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Respondent type	Yes	Yes	Yes	Yes	Yes	Yes

F Counterfactual Details

This appendix sets out three pieces of the counterfactuals in Section 7: how I measure welfare, how the two compensation structures for shared workers differ, and how firms enter and exit. I compare three economies: the status quo, the economy without sharing of Section 5.3, and the fully compensated economy (FC). All values are per week, in thousands of UGX.

F.1 Welfare Accounting

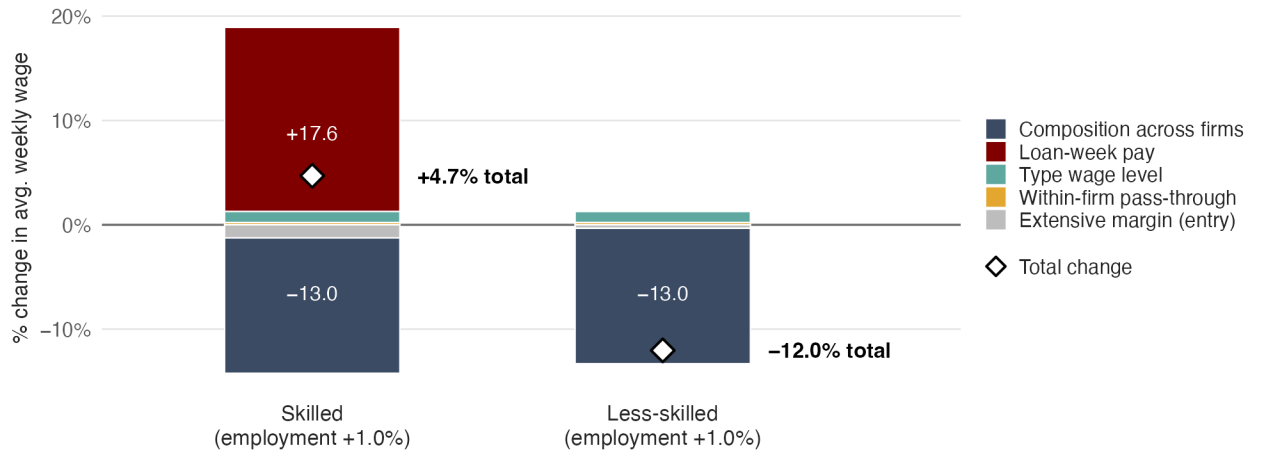
Owners. For a manager who operates, owner surplus is expected profit per period, $\bar{\pi}_j$ in Equation (17), minus the operating cost c_0 , plus the taste for ownership ζ_j . Profit is cash profit. It nets the firm's wage bill, its vacancy costs, and its payments in the sharing market (Equation (20)). A manager who does not operate earns the outside option w_j^o .

Workers. Worker welfare is earnings net of reservation wages. Earnings include the weeks a worker spends on loan. During those weeks the worker earns the borrower's skilled wage, and the home firm pays nothing. I count this pay in full. I measure reservation wages from the participation curve in Equation (12). With that curve, the reservation wages of a firm's employed workers add up to a share $\varepsilon_m/(1 + \varepsilon_m)$ of its own wage bill. I apply this share to the home firm's wage in every week a worker is employed, including loan weeks. Let b_j be the workers firm j borrows when busy and n_j the workers it lends when slow, both after rationing. Worker welfare at firm j is then

$$WS_j = \frac{1}{1 + \varepsilon_m} \sum_{\omega} w_{\omega,j} N_{\omega,j} + q w_{H,j} b_j - (1 - q) w_{H,j} n_j. \quad (32)$$

The second term is the pay borrowed workers receive at firm j . The third is the pay firm j 's own workers do not receive from it while on loan. A worker on loan therefore counts the borrower's wage in full, net of a reservation cost priced at the home wage.

Figure A4: Worker Wage Decomposition



Total surplus. Total surplus W sums profit and worker welfare over operating firms. Payments for shared workers are transfers between firms and workers, so they cancel. So does the part of the fee that reaches the lender. Let $V = q \sum_j b_j = (1 - q) \sum_j n_j$ be the volume of trade. Then

$$W = \sum_j \left[\text{expected output}_j - C(m_j) - \frac{\varepsilon_m}{1+\varepsilon_m} \sum_\omega w_{\omega,j} N_{\omega,j} \right] - \tau V. \quad (33)$$

The last term is the loss from the transaction cost in Proposition 1(b)(iv). Wages and the firm premium move surplus between owners and workers. They change W only through where workers are employed, and through the reservation cost.

Long-run ledger. With entry and exit, some managers switch between operating and working. Their operating cost, taste for ownership, and outside option enter the ledger. Let $\mathcal{S}_{SQ}$ be the managers who operate in the status quo and $\mathcal{S}_e$ those who operate in economy e . Net surplus in e is

$$W_e^{net} = W_e + \sum_{j \in \mathcal{S}_e} (\zeta_j - c_0) + \sum_{j \in \mathcal{S}_{SQ}, j \notin \mathcal{S}_e} w_j^o - \sum_{j \in \mathcal{S}_e, j \notin \mathcal{S}_{SQ}} w_j^o. \quad (34)$$

Managers who stop operating take up their outside option. Managers who start give theirs up. Outside options are valued at the wages of economy e (Section F.3). A person who operates in neither economy adds nothing, since their earnings as a worker are already part of worker welfare. Owner surplus is W_e^{net} minus total worker welfare. With a fixed set of firms, no one switches and $W_e^{net} = W_e$.

Normalization. I report the change $W_e^{net} - W_{NP}^{net}$ as a share of W_{NP} , gross surplus in the economy without sharing, measured before the c_0 , ζ_j and w_j^o terms. For a manager who operates in both economies, $\zeta_j - c_0$ cancels in the change. Only managers who switch contribute, each by $\zeta_j - c_0 - w_j^o$. The level of $\sum_j (\zeta_j - c_0)$ is a different matter. Only the difference $c_0 - \zeta_j$ is identified, from who operates, so the level of $\sum_j (\zeta_j - c_0)$ is a normalization. Its level, and so the level of W^{net} , is a normalization. I therefore keep it out of the denominator. Owners' and workers' changes are divided by the same base, so the two add up to the total.

F.2 Compensation Structures

Status quo. Prices follow Equation (19). A borrower pays its own skilled wage plus $c_s + \tau$. A lender saves the wage of the worker it lends and receives c_s . No one receives τ . It is a transaction cost that uses up resources, and total surplus falls by τ for every worker traded (Equation (33)).

Fully compensated. In FC, the borrower's price is unchanged and the lender receives all of it, $c_s + \tau$ above the wage. The transaction cost becomes a transfer from borrowers to lenders, and the τV term in Equation (33) drops out. Everything else stays at its estimate. I report outcomes for this counterfactual economy, compared to the status quo estimated economy, in the table below.

Fill rates. In both economies, firms request their desired positions and fill rates follow Equation (22). The side that wants less is served in full. The busy target in Equation (21) is the same in both economies, because the borrower’s price does not change. The slow target falls in FC, because lending pays more, so slow firms offer more workers. In the status quo, lenders offer fewer workers than borrowers request, and borrowers are rationed ($\lambda_b \approx 0.77$). In FC, offers exceed requests. Every borrowing request is filled, $\lambda_b = 1$, and lenders are rationed instead ($\lambda_s \approx 0.81$ in the long run). Because the lender’s and borrower’s prices are equal in FC, the two targets are ordered for every firm.

Relation to Proposition 1. FC turns the transaction cost into a transfer: the borrower pays the same price, and all of it reaches the lender. Proposition 1(b)(iv) holds headcounts, wages and the set of firms fixed. It shows that sharing raises total surplus relative to no sharing, and that the transaction cost uses up τ per unit traded. It does not rank the status quo against FC, because FC also changes who lends and how much. The comparison in Section 7 is therefore computed rather than implied.

Table A16: Fully Compensated Counterfactual Outcomes

	Long run		Fixed firms	
	Status quo	FC	Status quo	FC
<i>Panel A: Change relative to no sharing</i>				
Total welfare (%)	7.01	8.03	7.20	9.42
Owners (pp)	3.02	0.69	4.27	1.80
Owners (%)	4.47	1.03	6.33	2.67
Workers (pp)	3.98	7.33	2.93	7.62
Workers (%)	12.27	22.59	9.02	23.45
<i>Panel B: Sharing volume (levels)</i>				
Fill rate, firms that borrow	0.77	1.00	0.77	1.00
Fill rate, firms that lend	1.00	0.82	1.00	0.86
Borrowed worker-weeks per week	1,383	1,702	1,383	1,808

F.3 Entry Closure

Horizons. I solve each economy at two horizons. In the fixed-firm horizon, the set of firms is the status quo set of 2,000 simulated firms. Headcounts, wages, type wage levels and fill rates all re-solve. In the long run, the set of firms also responds: every manager operates if and only if Equation (17) holds at that economy’s equilibrium. Results in Section 7 are long run. I note the fixed-firm results where they differ.

Who can operate. The incumbents are the 2,000 simulated firms. Potential managers are surveyed workers. I draw as many as the number of firms times mean firm size in the data. Each potential manager’s ability comes from the owner ability regression at their own characteristics, plus a residual drawn from the owners’ residuals. An incumbent’s outside option w_j^o is the wage predicted for the owner from a wage regression on owner characteristics. A potential manager’s outside option is their observed wage. In a counterfactual, each outside option moves one-for-one with the average wage of the manager’s own skill type.

Taste for ownership and the operating cost. The taste ζ_j is drawn from a logistic distribution with mean zero and scale σ_e . Given σ_e , I set c_0 so that the expected number of managers who operate in the status quo equals the number of firms,

$$\sum_i \Pr(\zeta_i \geq c_0 + w_i^o - \bar{\pi}_i) = |\mathcal{S}_{SQ}|, \quad (35)$$

where the sum runs over incumbents and potential managers and $\bar{\pi}_i$ is status quo profit. I then draw each ζ_i from the logistic distribution cut to match the person’s status: incumbents above the threshold, potential managers below it. The status quo is therefore an exact equilibrium of the closure.

Solving for the set of firms. I find the operating set by iteration. Given a set, I solve the equilibrium. Managers for whom Equation (17) fails leave. Potential managers for whom it holds, at the prevailing wages and fill rates, join. I repeat until the set stops changing. If the iteration cycles between two sets that differ by a few marginal firms, I keep the firms common to both. Entry and exit do not change the number of workers. Entry and exit do not change the pool of workers. In the long run, the workers of exiting firms are reallocated across operating firms in proportion to their recruitment, and type wage levels re-clear by Equation (13).

Table A17: Fixed vs. Long Run Estimates

	Fixed firms	Long run
<i>Panel A: Welfare, sharing relative to no sharing</i>		
Total surplus (%)	7.20	7.01
Owners (pp)	4.27	3.02
Workers (pp)	2.93	3.98
Owner surplus (%)	6.33	4.47
Worker surplus (%)	9.02	12.27
<i>Panel B: Output, firms and employment (% change)</i>		
Output	3.11	6.17
Number of firms	0.00	4.66
Average firm size	-0.31	-3.49
Employment	-0.31	1.00
<i>Panel C: Average wage (% change)</i>		
Skilled	3.01	4.70
Less-skilled	-13.45	-12.04
<i>Panel D: Allocation of skilled workers</i>		
Skilled busy-week share (%)		
No sharing	29.0	29.0
Sharing	59.6	59.6
Misallocation gap (% of output)		
No sharing	8.69	8.66
Sharing	5.23	5.23

Why exit is measured against the economy without sharing. I calibrate c_0 and ζ_j on the status quo, the economy I observe. The counterfactual question is which of these managers would still operate if sharing were removed. Each manager compares the profit they would earn in the no-sharing equilibrium with their outside option at that equilibrium's wages. Firms that fail this test are the firms that would exit without sharing. Wages are higher without sharing, so outside options rise too. This cushions the loss for managers who exit, and it is why the long-run gain is smaller than the fixed-firm gain. FC is solved the same way, and its entries and exits are counted against the status quo set.

Calibrating σ_e . The scale σ_e governs how many managers sit near the margin. I estimate it from workers' stated likelihood, on a 0–10 scale, of starting their own business. I compute each worker's predicted profit as a manager at status quo prices and fill rates. I then fit an ordered logit of the stated likelihood on predicted profit and on the worker's wage, entered separately, with controls for

age, age squared, gender, education and market fixed effects. The logit's error has unit scale, so the coefficient on profit is $1/\sigma_e$. This gives an estimate of $\sigma_e = 882$. It is the most elastic ownership margin the data admit, so it gives the largest response of entry and exit. The alternative is the point estimate, $\sigma_e = 3,023.57$. I re-solve c_0 at the value of σ_e , $c_0 = 1,588$. A larger σ_e spreads tastes out, leaves fewer managers near the margin, and so produces less entry and exit when sharing is removed.

F.4 Frictions and Alternative Institutions

Table A18: The Value of Labor Sharing When Each Friction Is Removed

Economy	Screening	Demand	Value of	Of which (pp)		Fill rate		Borrowed
	problem	swings	sharing (%)	Owners	Workers	Borrowers	Lenders	worker-weeks
Estimated economy	Yes	Yes	7.01	3.02	3.98	0.77	1.00	1,383
Perfect screening	No	Yes	7.72	0.65	7.06	1.00	0.99	1,669
No demand swings	Yes	No	-0.02	-0.01	-0.01	1.00	0.50	9
Neither	No	No	0.00	-0.01	0.01	1.00	0.06	2

Table A19: Friction Decomposition

Economy	Long run			Fixed firms		
	Value of sharing (%)	Of which (pp)		Value of sharing (%)	Of which (pp)	
		Owners	Workers		Owners	Workers
<i>Panel A: Value of sharing</i>						
Estimated economy	7.01	3.02	3.98	7.20	4.27	2.93
Perfect screening	7.72	0.65	7.06	8.08	2.38	5.70
No demand swings	−0.02	−0.01	−0.01	0.03	0.00	0.03
Neither	0.00	−0.01	0.01	0.02	−0.04	0.06
Type-blind sharing	3.45	0.70	2.74	3.77	0.84	2.92
Value of known skill (row 1 − row 5)	3.56	2.32	1.24	3.43	3.43	0.01
Economy	Long run			Fixed firms		
	Fill rate		Borrowed worker-weeks	Fill rate		Borrowed worker-weeks
	Borrowers	Lenders		Borrowers	Lenders	
<i>Panel B: Sharing volume</i>						
Estimated economy	0.77	1.00	1,383	0.77	1.00	1,383
Perfect screening	1.00	0.99	1,669	0.92	1.00	1,622
No demand swings	1.00	0.50	9	0.66	1.00	14
Neither	1.00	0.06	2	1.00	0.45	9
Type-blind sharing	1.00	0.27	726	1.00	0.31	803