Search Costs and Relational Contracting

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Abstract

We experimentally investigate the link between search costs and relational contracts for small firms in Tanzania. Our analysis takes advantage of random assignment to a digital telephone directory that reduces the cost of search. One treatment group was made visible upstream, to suppliers in nearby cities, and another was made visible downstream, to customers. Relative to a control group, firms in both treatment groups increase relational contracting with their suppliers and decrease it with their customers. Most effects are larger and more statistically precise for women firm owners and for more remote firms. We do not find that the number of new customers or suppliers increases; rather, results suggest that exposure on the directory provided a reputation boost to firms that led them to negotiate better terms with suppliers and customers.

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1 Introduction

Markets in low-income countries tend to be highly fragmented (Jensen and Miller, 2018). Integration is hampered both by poor physical infrastructure, and by the high cost of information (Allen, 2014; Startz, 2024; Aggarwal et al., 2022). Firms have almost no ways to market their products to buyers that are not physically present. Buyers, in turn, cannot search the web or access a central depository of information about nearby firms, making it difficult to compare product attributes or engage in price search (Dillon et al., 2024). High search costs trap final consumers in their local markets, and can also constrain innovation by firms. An ambitious firm that seeks new products or suppliers must engage in extensive in-person travel, and usually cannot screen potential suppliers on quality.

A consequence of high search costs is that buyers and sellers form relationships based on mutual trust and repeated exchange (Fafchamps, 2006). These relationships are embedded in relational contracts, which are sustained not by recourse to third party enforcement, but by the future value of the relationship (Baker et al., 2002). For sellers, relational contracts reduce demand uncertainty. For buyers, they provide assurance of access to supply in the face of stock-outs or quality problems, and may provide other benefits such as trade credit (Sexton, 2013; Macchiavello and Morjaria, 2015; Casaburi and Reed, 2022; Macchiavello and Morjaria, 2023). In low-income countries, relational contracting helps resolve persistent failures in the markets for credit, insurance, and verifiable information about quality (Mcmillan and Woodruff, 1999).

In this paper we experimentally examine the connection between search costs and relational contracting for firms in Tanzania. When upstream information frictions fall, do firms switch suppliers? Do they forego the benefits of longstanding relationships in favor of anonymous sourcing from the market? When downstream information frictions fall and firms become visible to a wider range of customers, do they reduce the relationship-based benefits that they provide to their regular customers? Addressing these questions sheds light on both the fundamental link between search costs and second-best contracting arrangements, and on how firms in low-income countries navigate the transition to digital economies with lower information costs.

To address these questions we built a digital Yellow Pages, accessible for free on any mobile phone, to provide basic information about firms. Prior work has established the feasibility and impact of the platform in the same setting (Weld et al., 2018; Dillon et al., 2024). We used the platform to exogenously reduce search costs in input and output markets. Specifically, we randomly assigned 507 rural firms into three groups: *Upstream Treatment* firms were made visible on the platform to suppliers in nearby urban areas, and were able to find information about those suppliers and about each other; *Downstream Treatment* firms were made visible to customers in the surrounding area, and were able to find information about each other; *Control* firms were given access to a placebo directory. The two treatments both reduce search costs, but in different directions, allowing us to examine the relative importance of supplier-facing and customer-facing information frictions. Because there are no other marketing services in the area, the directory listing could also have acted as an endorsement or a boost to the reputation of the listed firms.

We study how the telephone directory treatments affect firm relationships and business outcomes. Study firms are in the retail and services sectors, and are based in small and medium-sized villages that are on average 65km from the nearest city. These firms engage in relational contracting in two directions: upstream with suppliers, and downstream with customers. In a discrete choice experiment at baseline we show that firms highly value receiving favorable delivery terms and credit from suppliers, and will pay a 6% premium to purchase from a known supplier even in the absence of other relationship benefits. For some of their regular customers, study firms provide credit on purchases, place special orders, and give price discounts. A novel feature of our study is that we are able to examine how firms' relationships in both directions evolve as a consequence of exogenous changes in the information environment.

Our analysis leads to three main sets of findings. First, using administrative data from the back end of the directory service, we find that take-up of the treatments is substantial. Treated firms are much more likely than Control firms to use the directory. Upstream treatment firms search for suppliers and have their listing found by suppliers at the highest rates, while Downstream treatment firms are most likely to be found by rural consumers.[1]

[1] We conducted promotional events across villages in the study area, to make consumers aware of the

Study firms also engage in substantial search for other study firms, indicating that they see each other, not just the city-based suppliers, as potential new trading partners. Overall, high rates of directory usage are evidence of pent-up demand for information.

Second, we find that firms' relationships evolve when search costs fall. Upstream treated firms increase the extent of their relational contracting with suppliers by 0.07 standard deviations, measured by an index that captures a variety of relationship-based benefits. The primary underlying mechanism is an increase in the receipt of credit from suppliers. Both groups of treated firms decrease the relationship-based benefits that they extend to customers, by 0.1-0.12 standard deviations. These changes do not seem to be driven by switching to new trading partners: if anything, treated firms report less search and a lower likelihood of trading with agents outside the village, compared to Control firms. While we find no significant effects on input prices, treated firms increase output prices by 0.08-0.14 standard deviations.

This collection of findings is not consistent with a simple search model in which the directories allow Upstream firms to reduce input costs and allow Downstream firms to reach a larger set of customers. We find many similarities between the Upstream and Downstream treatment effects, and little evidence of changes mediated by lower cost search. We interpret these patterns as evidence that both the listed firms and other directory users saw the directory as an endorsement or a signal of quality about listed firms. Because all treated firms could find others in their treatment group on the platform (and they did so frequently), the similarity between Upstream and Downstream treatment effects may also be due to increased interaction between study firms. Finally, while it is not *ex ante* likely that all firms would benefit from the directory treatments in the medium term—low productivity firms may lose business when their customers can search more widely (Melitz, 2003; Jensen and Miller, 2018; Dillon et al., 2024)—our findings are consistent with the average treated firm believing that the directory would lead to an increase in demand, which induced them to raise prices and withdraw some of the relationship benefits extended to regular customers.

Our third set of findings relates to heterogeneity. We pre-specified three dimensions

directory. At those events we collected phone numbers from attendees. We matched those phone numbers to those that queried the digital directory, allowing us to identify some rural consumers among users of the service.

of heterogeneity: gender of the owner, remoteness, and sector. From our prior work and knowledge of the context we conjectured that women-owned and remotely located firms would benefit more from the interventions, because they face higher costs to travel, search, and access market information in the prevailing equilibrium. Our findings are consistent with this hypothesis. For women-owned firms and remote firms we find that treatment reduces input prices and increases the transportation share of inputs costs, consistent with switching to source some inputs from farther away. Treated firms in both subgroups also see substantial increases in the value of the supplier-facing relational contracting index.

Estimated effects on service and retail firms are broadly similar, except in regard to sourcing. Treated service firms decrease the transport share of inputs, and begin purchasing more inputs locally. There is no similar effect for retail firms. This pattern reflects the fact that the relative cost of traveling to cities is lower for retail firms, because input prices are lower in urban areas and they can spread transport costs over larger order sizes.[2] For some service firms, simply receiving contact information for nearby firms is sufficient to induce them to search locally and avoid traveling to urban suppliers.

These findings contribute to three lines of literature. The first is on constraints to the growth of small firms in developing countries. Prior work has examined the role of relaxing input-related constraints to firm growth—such as access to capital and credit (De Mel et al., 2008), or management and business training (Bloom et al., 2013; McKenzie and Woodruff, 2014; Anderson et al., 2018))—and has begun unpacking the role of networks to disseminate knowledge and improve business practices (Fafchamps and Quinn, 2018; Cai and Szeidl, 2018; Hardy and McCasland, 2021). Few studies have experimentally relaxed both upstream and downstream constraints in a single setting (with the notable exceptions of Anderson et al. (2018) and Anderson and McKenzie (2022)). We add to this line of work by exploring how reducing search frictions in both input and output markets influences firm relationships and other outcomes.

Our second contribution is to the literature on relational contracts. Since the pioneering work of Fafchamps (2003), economists have increasingly recognized the importance of relationships and repeated exchange for firms in low-income countries, who face substantial

[2]At baseline, the transport share of inputs costs for service firms is twice that of retails firms.

uncertainty along the supply chain and have little recourse when contracts are violated. Recent work has focused on relationships in the context of international trade (Macchiavello and Morjaria, 2015; Startz, 2024), manufacturing (Mcmillan and Woodruff, 1999; Fafchamps and Quinn, 2018), or seasonally active agricultural supply chains where buyers and sellers only transact during harvest season (Fafchamps and Minten, 2002; Casaburi and Reed, 2022; Macchiavello and Morjaria, 2021). Within this body of work our paper is most closely related to Ghani and Reed (2022) and Macchiavello and Morjaria (2021), both of which study how seller-buyer relationships evolve when cost structures change. What is novel here is that we are able to exogenously reduce information frictions in two directions—toward suppliers, and toward customers—and to study the implications of lower search costs for relationships in both directions.

Lastly, we contribute to a line of work on information and search in the digital age, particularly in low-income countries. The arrival of mobile phone technology increased market efficiency in some contexts (Jensen, 2007; Aker, 2010), but evidence on the impact of digital information services in developing economies is decidedly mixed (Aker and Cariolle, 2023). Dillon et al. (2024) study the impacts on firm business outcomes of a paper version of a Yellow Pages directory in a different part of Tanzania. They document large impacts on customer contact and sales for the firms, and show that treatment effects are larger in magnitude for firms that were more productive at baseline. Iacovone and McKenzie (2022) study a digital platform designed to aggregate orders of small vendors, and found that it had limited use in the long-run. We extend this nascent line of work on information services by examining how a telephone directory alters firm relationships via both search and endorsement channels.

2 Search, Information, and Relational Contracts

The proliferation of mobile phone networks in the 2000s reduced price disperion in some agricultural markets by lowering the cost of communication (Jensen, 2007; Aker, 2010; Aker and Fafchamps, 2015). However, even with lower-cost communication, search and information frictions persist. Startz (2024) shows that information costs, including those related to maintaining supplier relationships, explain a substantial portion of overall transaction costs in Nigerian wholesaler supply chains. Allen (2014) estimates that nearly half of price dispersion in agricultural markets in the Philippines is explained by information frictions. In Tanzania, Aggarwal et al. (2022) estimate that non-pecuniary costs of travel (including information frictions, opportunity costs, and other) accounted for 57% of total travel costs. Also in Tanzania, Dillon et al., 2024 show that firms listed in a telephone directory experience substantial increases in customer contact and sales, highlighting the importance of information frictions related to identifying new partners.

As the costs of learning about and trading with new partners increase, agents become more likely to establish repeat relationships with suppliers and customers (Fafchamps, 2006). After establishing mutual trust, parties may enter into a relational contract sustained by the future value of the relationship (Baker et al., 2002). With no third party enforcement, agents employ informal mechanisms to validate the quality of business partners, and rely on repeated exchange to build trust. Informal mechanisms include asking social networks to recommend new business partners, or sharing negative experiences to sanction business partners who have reneged on contract terms (Mcmillan and Woodruff, 1999; Macchiavello and Morjaria, 2021; Ghani and Reed, 2022).

Firms in our setting act as both *recipients* of relational contracts (agents in a principal-agent relationship), with their suppliers, and as *providers* of relational contracts (principals), with their customers. With their suppliers, firms use relationships to access benefits that are imperfectly provided by markets (e.g., credit, shipping), or to receive price discounts on inputs. Their suppliers receive the benefit of demand assurance—or at least, less volatility in demand—in at atmosphere of substantial uncertainty. As principals, firms use relational contracting to build a loyal customer base and reduce demand uncertainty, typically by offering price discounts or trade credit, placing special orders, or accepting mobile money. A unique feature of our study is that we are able to examine how relational contracts in both directions evolve when information frictions are reduced.

The fact that high search costs and information frictions co-exist with relational contracting points to a central tension in this setting. Rural firms stand to benefit from innovations that reduce search frictions, because they can locate new trading partners. Yet, the risks associated with forming new relationships can be substantial when third party enforcement is absent. Firms may choose to forego new relationships, and thereby fail to realize the benefits of easier search, because they know that they will bear the full cost of any contract violations (e.g., if inputs are of poor quality, or if delivery is late). For this reason we are interested in a second channel by which our interventions can influence firm relationships: a directory listing could be interpreted as an endorsement of the firm or a signal of quality, as observed in Hasanain et al. (2023). In Section 4.2 we discuss these two mechanisms—search and endorsement—in more detail.

3 Experimental Design and Sample

3.1 Study setting and sample

Our study is set in the Dodoma and Singida regions of central Tanzania. The area is semi-arid, with a single rainy season. The primary crops are maize and sunflower. The study area consists of the rural wards (sub-districts) served by the three urban centers of Singida, Dodoma, and Manyoni. Within this area we identified 54 villages that had at least 3,000 residents in the most recent census (see map in Figure A4 in the Appendix).[3] We randomly selected 25 of those villages for the study, stratifying on primary urban center, distance to urban center, and population.

Firms in the study villages are small, and operate in a range of retail subsectors—food, household goods, clothing, and spare parts—as well as in services such as restaurants, barber shops, welders, garment makers, and mechanics. Within study villages, the team recruited participant firms by walking systematically through each village and approaching local businesses. Most of the recruited firms had a physical stall or storefront. The team also looked for mobile businesses, such as truck drivers and motorcycle taxis. The only inclusion criterion was that the firm manager or owner must have a mobile phone. This proved to be non-binding, as no firms declined to participate because of lack of phone access. We enrolled

[3] We excluded smaller villages because they tend to have few firms. Appendix Table A2 compares characteristics from the sample regions with national averages. All three regions are less urban than the national average, have lower rates of non-farm employment, and have lower mobile phone ownership rates.

a total of 507 rural firm across the 25 villages.

3.2 Description of Interventions

The interventions in this study are based on *listing firms in* and *giving firms access to* digital telephone directories that are viewable on any type of mobile phone. The directories, called *Kichabi*, operate like a Yellow Pages (see Weld et al., 2018 for more details). Each firm listing includes the owner name, firm name, location, phone number, sector, and subsector (51 subsectors split between 8 primary sector categories). Phone users reach the directory via a USSD short code, the same technology used to purchase phone credit or send mobile money. Users navigate the directory by sequentially choosing options from a series of menus (location, sector, subsector, firm). When a user reaches a screen displaying the firms matching the selected criteria, the display order is randomized (Varian, 2007; Athey and Ellison, 2011; de Cornière, 2016). The directory is free to use, and our team is able to route specific phone numbers to different versions of the directory.

We made three versions of the digital directory, one for each treatment arm:

1. **Upstream Treatment Directory.** Study firms in Upstream Treatment group were able to access a directory with listings for (i) all other firms the Upstream Treatment group (including their own listing), and (ii) 348 urban firms. The urban firms are not members of the study population. They are wholesale and retail firms located in the three cities in the study area, who are potential suppliers for study firms. These urban firms were recruited by walking systematically through all commercial areas of Singida, Dodoma, and Manyoni.[4] The Upstream Treatment directory was viewable only by the firms listed in it, i.e., the Upstream Treatment firms and the urban firms. The objective of the Upstream treatment was to reduce the cost of connecting with new potential suppliers.

2. **Downstream Treatment Directory.** Study firms in the Downstream Treatment group were able to access a directory with listings for all other firms in the Downstream Treatment group (including their own listing). The Downstream Treatment directory

[4]The urban firms are not subjects of the study, except in their role as entries in the directories.

was viewable by three groups: (i) the firms listed in it, (ii) any unknown phone number that accessed the directory, and (iii) 540 local residents whose phone numbers we gathered through community meetings to promote the directory. These community meetings were held in the month after recruitment of study firms, in 14 villages that we randomly selected from those in the study area with populations below 3,000. The meetings gave us the opportunity to promote the directory, and allowed us to collect phone numbers with which we could identify the home village of some directory users. The objective of the Downstream treatment was to lower the cost for new potential customers to find the firms in this group.

3. **Placebo Directory.** Study firms in the Control group were able to access a placebo directory that listed firms in a neighboring area of Tanzania. These firms were too far away to be of use for the typical study firm.[5] The goal of this placebo directory was to replicate for firms in the Control group the experience of receiving a directory and thinking about the implications for their business, without providing actionable information.

3.3 Treatment Assignment and Compliance

We randomly assigned the 507 rural firms, at the firm level, with equal probability, to Upstream Treatment, Downstream Treatment, or Control. Assignment was stratified on village, sector, respondent gender, and a self-reported measure of the relative importance of upstream (supplier) vs. downstream (customer) contacts.

Compliance with treatment assignment was guaranteed as long as firms queried the directory using the phone number(s) they registered with us. It is possible that someone at a study firm queried the directory using a different phone. If this happened to a member of the Downstream group, compliance would have been maintained because unknown numbers were routed to the Downstream directory. If an Upstream or Control firm manager used an unknown phone number, they would have been exposed to the Downstream treatment. Be-

[5] Specifically, the 1,200 firms listed in the placebo directory were from another part of the Dodoma region, and the adjacent Manyara region. These firms are on the far side of the commercial centers that serve as the boundaries of typical trading areas for the small village-based firms in our study.

cause this form of non-compliance was possible, we interpret estimated regression coefficients as intent-to-treat (ITT) estimates.

3.4 Data Collection

Our analysis utilizes data from surveys with study firms, and administrative data from the back end of the digital directories.

3.4.1 Surveys with Study Firms

We collected four rounds of survey data from the study firms. The first survey was an in-person enrollment and baseline survey, in June 2019. After interventions began, at the start of October 2019, we conducted follow-up phone surveys in October-November 2019, January-March 2020, and July-Sep 2020.[6] Appendix Figure A3 shows the study timeline. Survey topics include communication with suppliers and customers (in-person and by phone), inventory sourcing, features of relational contracts with suppliers and customers, revenue, and input and output prices.

Only 5.3% of sample firms fully exited the study after the baseline survey, with no difference by treatment groups. Appendix A5 provides more details on attrition rates and tests of differential attrition by treatment group.

3.4.2 Administrative Data

The USSD service stored details for all queries to the directories, including time/date, phone number, time spent on each screen, and selections made from the displayed menus. Using phone numbers that we collected through various field efforts, we are able to categorize the querying phone numbers into four groups: study firms, urban firms, consumers that attended promotional meetings, and unknown.

[6] The last round of survey data corresponds to a period of significant Covid-19 disruption in the United States and Europe. However, infections in Tanzania did not start to rise until after data collection was completed. In our endline survey, 92% of firms said that Covid-19 did not restrict their travel.

4 Empirical framework

In this section we describe the possible effects of the interventions and the econometric framework for our analysis. First, we characterize the study sample.

4.1 Characterizing Study Firms and Their Relationships

4.1.1 Firm Characteristics from the Baseline

Panel A of Table 1 presents descriptive statistics from the baseline survey. The average study firm is 5.5 years old, and is run by a 35-year old with seven years of education. Just over a third (36%) of firms are owned by women. About half are in retail, with the rest divided between different types of service activities.

Three features of study firms are of particular note. First, study firms are small. Most are sole proprietorships: the average firm has 1.36 employees, including the owner. On an average day, firms complete 15 sales transactions, earning 50,500 TZS (18.50 USD) in revenue, or 1.87 USD per sale per day. Second, firms are relatively isolated from central markets. The average firm is located 65km from the nearest city, a distance that precludes same-day travel in response to stock-outs. While all firm owners or managers have a mobile phone, only a quarter have a smartphone, and smartphones are of limited value in this setting.[7] Third, despite their relative isolation from major markets, some study firms are not isolated from competitors. Firms report having an average of nearly five competitors in their same sector and village, with wide variation.[8]

While the majority of firms (93%) report that they sell to customers from their own village, which increases the likelihood of repeated contact and lowers the cost of social sanctions when contracts are violated, not all business is local: 58% of study firms report having customers from neighboring villages, and 13% reported having customers from distant villages or from the city.[9]

[7]Data is relatively expensive in Tanzania, and there are few apps or Internet-based information sources that are relevant to study firms. We know from our conversations with study firms that many of those with smartphones do not download apps or access the Internet.

[8]Competing firms may not be immediately adjacent to each other: in large villages, they could be located in separate subvillages, a 5-20 minute walk apart.

[9]We define nearby and distant villages according to their location within administrative boundaries of

4.1.2 Relationships with Suppliers: A Discrete Choice Experiment

In the context of repeated relationships with known suppliers, firms in our setting may receive a range of relational contracting benefits, including trade credit, price discounts, favorable shipping terms, and the ability to make payments via mobile money.[10] When sourcing business inputs, 9% of firms receive credit from suppliers, 29% receive price discounts for being regular customers, 17% had goods shipped to their storefront, and 19% sent payments using mobile money (Table 1, panel B). Just over a third of firms receive no relational contracting benefits from suppliers; zero firms receive all four benefits. Firms also vary in where they source inputs: 35% of firms purchase inputs locally, while 60% travel to the city (panel C; these are not mutually exclusive).

To understand how firms value the components of their relational contracts with suppliers, we administered a discrete choice experiment prior to launching our RCT. The goal of the discrete choice experiment was to measure willingness-to-pay (WTP) for the benefits commonly associated with retailer-supplier relationships. During the baseline survey, firms were asked to compare a series of hypothetical input purchases with four variable features: a known/unknown supplier, different levels of transportation costs, an option to defer payment (i.e., access to trade credit), and a variable cost. We varied the cost of the hypothetical input—analogous to varying a price discount—in order to provide a financial benchmark for estimating WTP (see Appendix A7 for more details).

Table 2 shows mixed logit results from the discrete choice experiment. The findings of this experiment reveal substantial variation in how a typical firm values the benefits associated with supplier relationships. The average firm is willing to pay a 33% premium for goods to be delivered, relative to traveling to a city to make a purchase. Trade credit is also highly valued: the average WTP for receiving goods on credit is an 18% premium, relative to paying cash at the time of purchase. The high value placed on these relationship attributes are indicative of the relatively poor transport infrastructure and underdeveloped

wards and districts. It is plausible for firms to have customers from the city because some villages are located on primary trunk roads where travelers pass.

[10]Paying with mobile money is a privilege that many firms still reserve for known or favored customers. Because mobile money is still not widely used in the study area, a cash-out may be required to make use of any funds received via mobile money, and there are fees associated with cashing out (Finscope 2023).

financial markets that serve study firms.[11] Finally, study firms indicate an average WTP of a 6% premium to purchase inputs from a known supplier (relative to unknown); firms value dealing with familiar sellers even in the absence of other benefits.

4.1.3 Relationships with Customers

The firms in our study are not just recipients of relationship services from their suppliers; they also act as principals that extend offers of relational contracts to their customers. Customer relationships provide firms with implicit insurance in the face of demand uncertainty, by ensuring that a subset of potential buyers prioritize shopping from the firm in order to maintain the relationship. The types of benefits that firms provide to customers are similar to those that they receive from suppliers: selling on credit, offering price discounts, making on-demand orders for customers, and accepting mobile money payments. On average, rural firms offer these benefits to their customers more often than they receive them from their suppliers. At baseline, 57% of study firms provided services or goods on credit over the last three months, 16% accepted mobile money, 53% sometimes gave price discounts to frequent customers, and 23% placed special orders (Table 1, panel D).

4.2 Linking the interventions to firm relationships and outcomes

Our directory interventions can affect study firms through two channels. First, the directories reduce search costs. Relative to the status quo, directory users can discover and communicate with new trading partners, learn about businesses in other sectors, and update beliefs about the number of competitors in their same sector. These reductions in search costs are enjoyed directly by treated firms, in that they can search for and contact other firms in the directory, and also by customers or other businesses that can more easily find and contact treated firms (relative to control firms).

The second channel relates to endorsement. Our implementation team was careful to describe the directory as a neutral source of information about firms. Nonetheless, some users may have interpreted the directory as an endorsement or signal of quality for the listed

[11] In settings like ours, market inter-linkages (e.g. between wholesale trade and credit), which are sustained within relationships, tend to emerge in response to market frictions (Casaburi and Reed, 2022).

firms. A reputation boost of this kind could influence not only how others perceive a firm, but also how the firm views its own status when bargaining with suppliers or considering its importance to customers. An endorsement effect could be active even in the absence of any new communication or sales transactions; simply seeing a firm in the directory may lead to updating about the firm's sophistication or productivity.

Reputational effects may be especially relevant in a developing country context. In rural Tanzania there is little to no advertising, and no preexisting source of information that is similar to the *Kichabi* directory. The sheer novelty of the directory could bring more attention to listed firms than would be expected in a richer information environment. The reputation/endorsement mechanism is also likely to be of greater importance when contract enforcement is weak. As we described in Section 2, firms in our study stand to gain from exposure to new trading partners via reduced search costs. But trading with new partners is risky, perrhaps all the more so when those partners are found through an exogenous information product like a telephone directory. Treated firms that are unwilling to switch to new suppliers could still use their listing in the directory as a bargaining chip to seek better terms in their relational contracts.

With these mechanisms in mind, we consider the potential effects of the two treatments on supplier-related and customer-related outcomes.

Potential effects of Upstream Treatment. Relative to the Control group, firms in the Upstream treatment group could potentially (i) access new and better suppliers, via lower search costs; (ii) receive better terms in the relational contracts offered by their existing suppliers, either because those suppliers recognize that the firm's choice set has expanded, or because they interpret the directory as a signal of quality for the listed firm; or (iii) increase or decrease the prices that they charge and the value of the relational contracts that they offer to their customers, depending on whether they believe the listing will lead to a net increase or net decrease in demand to their firm. The direction of the third effect is ambiguous because reductions in market segmentation can increase demand to more productive firms while simultaneously reducing demand to less productive firms (Melitz, 2003; Jensen and Miller, 2018). Consumers did not have access to the Upstream version of the directory, so any changes in customer-facing outcomes must arise from choices made by the firms.

Potential effects of Downstream Treatment. Relative to Control firms, Downstream treatment firms that expect a net *increase* in demand from being listed could potentially (i) negotiate better relational contracting terms from their suppliers; or (ii) reduce the value of the relational contracts that they offer their customers. Those potential effects will move in the opposite direction for firms that expect a net *decrease* in demand, because they perceive that previously captive customers now have more options. The Downstream treatment did not make firms easier to find for the urban suppliers, unless one of those suppliers accessed the directory using an unknown phone number. Hence, any impacts on supplier-facing outcomes for this group would most likely arise from choices made by the treated firms themselves.

4.3 Possible dimensions of heterogeneity

We preregistered three sources of heterogeneity: gender of the owner, remoteness from urban markets, and firm sector (retail vs. service).[12]

Women business owners tend to operate in sectors with low profit margins, face greater pressure than men to split time between work and home, and must navigate varying degrees of gender bias in access to inputs and business networks, all of which can reduce productivity (De Mel et al., 2008; Fafchamps et al., 2014; Bernhardt et al., 2019; Hardy and McCasland, 2021; Jayachandran, 2021). Prior evidence shows that women-owned businesses benefit from policies that expand their networks (Brooks et al., 2018; McKenzie and Puerto, 2021). At baseline, women firm owners in our sample were not disadvantaged in their access to relationship benefits from suppliers, but they were more likely to purchase all inputs locally, and less likely than men to travel to the city for any supplies (Table A1, columns 1-2). If the directory interventions reduce gender differences in search and information access, then we expect to find greater impacts on women than men; conversely, if information is complementary to other factors that are differentially available to men and women (e.g.

[12]In response to comments we became interested in another dimension of heterogeneity, related to the number of same-sector competitors in a firm's local market, after completing the field study. Ultimately we found that most results do not vary by this measure of competition; those results are provided in Appendix A3.

credit), then treatment effects will be smaller for women.

We define "remote firms" as those that are above the median distance to the nearest urban center. The average remote firm is 97km from the city, compared to 43km for the non-remote firms (Table A1, columns 3-4). In our sample the more remote firms are slightly less likely to receive relationship-based benefits from their suppliers, and slightly less likely to provide them to their customers. Transport costs as a share of input costs are higher for the remote firms. When search costs decrease, remote firms may increase trade with urban areas if those costs were a barrier to learning about and obtaining inputs; or, they may decrease trade with urban areas if better access to information makes it clear that traveling is not worth the cost, akin to how remoteness lowers input adoption in agricultural markets because travel costs erode the returns to adoption (Suri, 2011; Aggarwal et al., 2022). Firms in remote areas may also be less able to adjust their output prices, if the accumulation of transfer costs along the supply chain means that they face more price-sensitive consumers (Atkin and Donaldson, 2015).

Retail and service firms in the study area differ in their input sourcing costs. At baseline, 83% of retailers and 46% of service firms acquired inputs from a city, either through travel or shipping. The average input purchase value for a retail firm is five times that of a service firm (377,000TSH vs. 78,000TSH, or approximately $158USD and $35USD; Table A1, columns 5-6). However, transport costs per unit of input expenditure are twice as high for service firms, at 10% to 5%, because service firms incur the fixed costs of travel but purchase smaller volumes. For this reason, service firms have greater scope for reducing sourcing costs by reducing the number of trips they take to urban markets.

4.4 Outcome Variables

Our analysis focuses on outcomes in four categories: directory usage and engagement, supplier relationships, customer relationships, and other business outcomes (primarily prices and costs). See Appendix A2 for more details on the construction of outcome variables.

Directory usage and engagement. To assess uptake and engagement with the directory, we use administrative data from the back-end of the service to estimate ITT effects on using the directory, searching for different types of firms, and being found in the directory by different types of agents.

Supplier relationship outcomes. The supplier relationship outcome in our analysis is an index of services that the firm receives from its suppliers. Index components include receiving goods on credit, receiving price discounts, having goods shipped by the supplier, paying suppliers via mobile money, and knowing all suppliers.[13] The index is constructed using the inverse covariance-weighted approach of Anderson (2008). We also estimate ITT effects on an index of input search activities, which includes variables that reflect communication with suppliers in-person and by phone.

Customer relationship outcomes. The customer relationship outcome is an index of the relationship services that the firm offers to its customers, defined analogously to the supplier relationship index. We also estimate ITT effects on communicating with customers over the phone for business activities, and on having any customers from outside their home village.

Other business outcomes. To examine whether firms react to the directory-induced change in the information environment by adjusting their prices or paying lower costs, we estimate impacts on the following pre-specified outcomes: input prices, the transport cost share of input costs, output prices, and sales revenue.

4.5 Empirical specification

Our main analysis is based on the following ANCOVA specification (McKenzie, 2012):

$$Y_{it} = \alpha + \beta_1 Upstream_i + \beta_2 Downstream_i + \gamma Y_{i0} + \theta X_i + \lambda_t + \epsilon_{it} \tag{1}$$

where Y_{it} represents the outcome of firm i in post-treatment round $t = 1, 2, 3$; $Upstream_i$ and $Downstream_i$ are treatment indicators; Y_{i0} is the baseline value of the outcome variable; X_i

[13] Many sellers only accept mobile money from preferred buyers. Agents in the study area cannot use mobile money for most payments, so they must cash out any funds received as mobile money, which incurs an additional fee.

includes strata effects and an indicator if the outcome is missing at baseline; λ_t are survey round effects; and ϵ_{it} is the error term. We interpret β_1 and β_2 as the estimated Intent-to-Treat (ITT) effects of the Upstream and Downstream treatments.[14] When necessary for heterogeneity analysis, we include in (1) additional variables and their interactions with the treatment dummies. In the results tables we cluster standard errors at the level of the firm, which is the unit of treatment assignment.

5 Results

5.1 ITT Effects on Directory Usage and Engagement

Table 3 shows estimated ITT effects on firms using the directory or having their listing found by other users. The outcome variables for this analysis are binary variables constructed from the administrative data from the mobile directory service.

The main takeaway from Table 3 is that the interventions successfully generated the expected forms of engagement. Upstream and Downstream treatment firms were 21% and 27% more likely to use the directory than Control firms (column 1). As intended by the design, only Upstream firms were able to locate the listings of urban (wholesaler) firms (column 2), and only Downstream firms were found on the platform by phone numbers known to belong to rural customers (column 4). Firms in both treatment groups were substantially more likely than Control firms to search for the listings of other study firms (excluding their own listing; column 3), and were more likely to have their listing found by at least one other study firm (column 6). Finally, treated firms were substantially more likely than Control firms to be found by an urban wholesale firm (column 5).[15]

A caveat for these analyses is that we define a firm as "found" on the platform when a user navigates to the full listing page for that firm. A user could encounter a firm name on an earlier screen, in a list of firms that meet search criteria, and so become aware of the firm

[14]We interpret these coefficients as ITT estimates, rather than Average Treatment Effects (ATEs), because although compliance was assured with the directory listings, we cannot rule out that some participant may have used another person's phone and been routed to a different version of the directory.

[15]A small share of Downstream firms were found by urban firms (7%). This occurred because some urban firms began using new phone numbers during the course of the experiment . By default, new phone numbers were shown the Downstream version of the directory.

in a way that is not reflected in the outcomes in Table 3. Hence, we interpret these findings as lower bounds on exposure of and directory usage by treated firms.

5.2 ITT Effects on Supplier Outcomes

The directory listing improved some firms' positions with their suppliers. Relative to the Control group, the average Upstream treated firm saw an increase of 0.07 standard deviations in the value of the supplier-facing relational contracting index (Table 4, column 1). The analogous effect for Downstream firms is smaller, and is not statistically different from zero. In Appendix Table A5 we report separate effects on the components of the supplier-facing relational contracting index (panel A). The most substantial treatment effect is on credit, with a 73% increase in the share of Upstream treated firms that receive goods on credit (relative to firms in the Control group).

The increase in relationship benefits for Upstream firms appears to be based on improved relationships with preexisting suppliers, rather than switching to new suppliers. Firms in both treatment arms *decreased* search activities by 0.09-0.11 standard deviations compared to the control group (Table 4, column 2). Similarly, firms in both treatment arms were 0.08-0.10 percentage points less likely to transact with suppliers outside their village (Table 4, column 3).

5.3 ITT Effects on Customer Outcomes

Table 4 reports that firms in both treatment arms decreased the value of the relational benefits extended to customers by 0.10-0.12 standard deviations (column 4). In Panel B of Appendix Table A5 we report treatment effects on the individual index components. None of the individual effects is statistically significant, although almost all are negative.

As with the supplier-related outcomes, the change in relational contracts with customers does not appear to be driven by a shift to selling to a new base of customers from farther away. The effect on having any customers from outside the village is negative and marginally significant for the Downstream treatment group, and null for the Upstream group (column 6). The Downstream treatment group also saw a statistically significant *decrease* of 0.16

standard deviations in an index of self-reported phone-based communication with customers (column 5). This drop in phone activity may at first seem inconsistent with the finding that Downstream treatment firms were found by directory users nearly three times as often as Upstream treatment firms, reported in Section 5.1. This difference may be related to recall periods: survey questions about phone activity with customers covered the prior week, while directory-related outcomes reflect the entire post-treatment period. Another possibility, discussed below, is that the directory effects had more to do with endorsement than search.

5.4 ITT Effects on Other Business Outcomes

In Table 5 we present ITT effects on a pre-specified set of other business outcomes. We find no effects on input prices paid by treated firms (column 1). However, firms in the Downstream arm enjoyed a 1.3 percentage point (25%) reduction in the per-unit transaction cost of their orders. The Downstream treatment firms could search for other rural firms the directory, but were not able to search for urban firms. Some of the these firms appear to have begun using each other as suppliers, reducing the costs incurred for travel to the city.

We find that firms in both treatment groups increased their output prices relative to the Control group, by 0.08-0.14 standard deviations, although the Downstream effect is statistically imprecise (column 3). These price increases align with the drawdown in relationship-based services offered to customers that we presented above (Table 4, column 4). Taken collectively, these findings are consistent with firms believing that the directory listing would lead to an increase in demand, making it less necessary for them to reduce demand uncertainty by extending benefits to customers. It is not clear that this belief was correct, as we find no increase in sales revenue for either treated group (Table 5, column 4).

5.5 Heterogeneity Analysis

We estimated heterogeneous effects by gender of the owner, remoteness, and sector (retail v. service). Because we have found only minor differences between the Downstream and Upstream treatment effects thus far, for the heterogeneity analysis we pool the two treatments into a single "Treated" variable equal to 1 for both treated groups.

5.5.1 Heterogeneity by Gender of Firm Owner

We find meaningful differences between male and female firm owners in the estimated treatment effects on relational contracts, sourcing strategies, and prices (Table 6). Women firm owners experience a statistically significant increase of 0.1 standard deviations in the value of supplier relational contracts (column 1); for male firm owners the effect is half the magnitude, and is not statistically significant. While male firm owners experience a modest but statistically significant increase in their costs, women do not (column 2). Women firm owners also experience a marginally significant increase of 1.7 percentage points (28%) in the transport share of input costs, which men do not, consistent with women increasing the relative share of inputs that they source from more remote suppliers.

Collectively these findings suggest the directory treatments had larger impacts on supplier relationship for women than men. One interpretation of this pattern is that under the status quo women are disadvantaged relative to men in their access to suppliers, so that the marginal benefit of the directory on supplier relationships is greater for women than men.

We reported above that the treatments induce firms to increase prices and reduce the value of the relationship services they provide to customers. Those effects turn out to be largely driven by men. Treated men reduce the relationship benefits they extend to their customers by 0.14 standard deviations (column 5), and increase their output prices by a similar magnitude, relative to untreated men (column 6). For female firm owners these effects are around half the magnitude, and are not statistically significant. These patterns are consistent with men being more optimistic than women that the directory listing would increase demand and improve their bargaining position vis-a-vis their customers.

5.5.2 Heterogeneity by Remoteness

The ITT effects on relationships that we reported above—namely, that the directory treatments lead firms to receive more relationship benefits from suppliers and to extend fewer such benefits to customers—are driven by the more remote firms. For the more remote firms these relationship effects are statistically precise and of large magnitude; for the less remote firms they are smaller and not statistically significant (Table 7, columns 1 and 4).[16] Conversely, our findings that treatment lowers the probability of purchasing inputs outside the village (Table 4) and reduces the transport cost share of total input costs (Table 5) turn out to be driven by the non-remote firms; for remote firms, there are no effects on the location of input sourcing or the transport share (Table 7, columns 3-4). On the customer-facing side, we find that both the remote and non-remote firms increase their output prices, but only for remote firms does this lead to a statistically significant increase in sales revenue (Table 7, columns 3-4).

The main takeaway from this set of estimates is that the benefits of the directory listing accrued primarily to the more remote firms in our sample.

5.5.3 Heterogeneity by Firm Sector

Treated firms in both retail and service sectors see increases in relationship services offered by suppliers, and decrease the relationship services that they extend to customers (Table 8).

We find multiple differences in estimated effects on retail and service firms. While both groups reduce the relationship benefits that they extend to customers (column 5), only retail firms see an improvement in the relational benefits they receive from suppliers (column 1). Treated service firms, however, experience significant changes in the location and cost of inputs: they are 24% more likely to purchase inputs locally, and they see 34% reduction in the transport share of input costs, relative to service firms in the Control group (columns 3 and 4). At baseline we found that the transport share of inputs for service firms was much higher than that of retail firms. The directory treatments enabled Service firms to adjust their sourcing strategies in a way that closed this gap.

The other difference of note between sectors is that the estimated positive effect on output prices is much larger in magnitude and more statistically precise for retail firms than service firms (column 6). The difference between the effects is not statistically significant, but only the retail firm effect is different from zero.

[16] In the case of customer-facing relationships, the difference between the effects on remote and non-remote firms is statistically significant.

6 Discussion and Conclusion

Earlier, we provided evidence from a discrete choice experiment that firms value relational contracting with their suppliers (or at least value the benefits that are associated with relational contracting). These results provide consistent evidence that when search costs to locate new suppliers decrease, firms use the information to affirm their pre-existing relationships and bargain for better trading terms. It supports the prediction that the digital phonebook raises the value of the outside option for rural firms when they search in their upstream arm. And, they use the information to attain better terms from the suppliers whom they previously knew, consistent with theory on relational contracts.

Firms seem to have acted like their market positions had improved, even though we find no impact on revenues, except for more remote firms. Our measures of search and communication with suppliers and customers show a negative impact of treatment. This is surprising given that this group was by far the most likely to both search and be found by others in the phonebook platform (see usage data in Table 3). One potential explanation is that increased engagement with the platform crowded-out the firms typical engagement with their pre-existing customers relative to the control group. It is also possible that rural customers sought out new firms in face-to-face interactions that is not captured by the number of phone calls. Another possibility is that timing of phone surveys were too infrequent to pick up the timing of phone calls from new contacts. For upstream outcomes, survey questions were oriented around the "most recent input purchase," an event that typically occurs 1-2 times per month. On customer questions, questions were oriented over the previous week or over the past two days because firms engage with customers on a daily basis. Therefore, it is more difficult to pick up net changes in composition of the customer base.

We show that search in input markets exhibits notable heterogeneity. Women-owned firms and firms in remote markets save input costs and increase transportation costs, suggesting that these groups had more pent up demand for information from suppliers outside their immediate network. We see that firms in the services sector make the opposite trade-off; they increase transportation costs and are *more likely* to purchase locally, suggesting that it is not always worth it to travel to cities to procure inputs.

New information and communication technologies have shifted how agents engage within their networks. Digital phonebooks that are accessible on any type of phone are a bridge technology that allows users in rural areas to access new contacts from outside their known contacts. Rural firms often face substantial information frictions that lower total productivity, ultimately constraining firm growth and their capacity to bear shocks. Increasing access to contact information for suppliers and customers lowers search costs and changes incentives to provide and seek relational contracting. we show that when rural firms have access to new contacts, the value of their outside option increases and they succeed in increasing relational contracting with their suppliers at the same time as decreasing their relational contracting with their customers.

References

Aggarwal, S., Giera, B., Jeong, D., Robinson, J., and Spearot, A. (2022). Market access, trade costs, and technology adoption: Evidence from northern tanzania. *Review of Economics and Statistics*, pages 1–45.

Aker, J. C. (2010). Information from markets near and far: Mobile phones and agricultural markets in niger. *American Economic Journal: Applied Economics*, 2(3):46–59.

Aker, J. C. and Cariolle, J. (2023). *Mobile Phones and Development in Africa*. Springer International Publishing AG.

Aker, J. C. and Fafchamps, M. (2015). Mobile phone coverage and producer markets: Evidence from west africa. *The World Bank Economic Review*, 29(2):262–292.

Allen, T. (2014). Information Frictions in Trade. *Econometrica*, 82(6):2041–2083.

Anderson, M. L. (2008). Multiple Inference and Gender Differences in the Effects of Early Intervention: A Reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects. *Journal of the American Statistical Association*, 103:1481–1495.

Anderson, S. J., Chandy, R., and Zia, B. (2018). Pathways to Profits: The Impact of Marketing vs. Finance Skills on Business Performance. *Management Science*, 64(12):5559–5583.

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

Athey, S. and Ellison, G. (2011). Position auctions with consumer search. *Quarterly Journal of Economics*, 126(3):1213–1270.

Athey, S. and Imbens, G. (2017). The Econometrics of Randomized Experiments. *Handbook of Economic Field Experiments*, 1:73–140.

Atkin, D. and Donaldson, D. (2015). *Who's Getting Globalized?: The Size and Implications of Intra-national Trade Costs*. Number w21439. National Bureau of Economic Research Cambridge, MA.

Baker, G., Gibbons, R., and Murphy, K. J. (2002). Relational Contracts and the Theory of the Firm. *Quarterly Journal of Economics*, (February):39–84.

Benjamini, Y. and Hochberg, Y. (2018). Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing. *Journal of the Royal Statistical Society: Series B (Methodological)*, 57(1):289–300.

Bernhardt, A., Field, E., Pande, R., and Rigol, N. (2019). Household matters: Revisiting the returns to capital among female microentrepreneurs. *American Economic Review: Insights*, 1(2):141–160.

Bloom, N., Eifert, B., Mahajan, A., McKenzie, D., and Roberts, J. (2013). Does management matter? Evidence from india. *Quarterly Journal of Economics*, 128(1):1–51.

Brooks, W., Donovan, K., and Johnson, T. R. (2018). Mentors or teachers? Microenterprise training in Kenya. *American Economic Journal: Applied Economics*, 10(4):196–221.

Cai, J. and Szeidl, A. (2018). Interfirm Relationships and Firm Performance. *Quarterly Journal of Economics*, pages 1229–1282.

Campos, F. and Gassier, M. (2017). Gender and enterprise development in sub-saharan africa: a review of constraints and effective interventions. *World Bank Policy Research Working Paper*, (8239).

Casaburi, L. and Reed, T. (2022). Using individual-level randomized treatment to learn about market structure. *American Economic Journal: Applied Economics*, 14(4):58–90.

de Cornière, A. (2016). Search advertising. *American Economic Journal: Microeconomics*, 8(3):156–188.

De Mel, S., McKenzie, D., and Woodruff, C. (2008). Returns to capital in microenterprises: Evidence from a field experiment. *Quarterly Journal of Economics*, 123(4):1329–1372.

Dillon, B., Aker, J. C., and Blumenstock, J. (2024). Yellow Pages: Information, Connections, and Firm Performance. *Economic Journal*, Accepted.

Fafchamps, M. (2003). *Market institutions in sub-Saharan Africa: Theory and evidence.* MIT press.

Fafchamps, M. (2006). Spontaneous Markets, Networks, and Social Capital : Lessons from Africa. *Institutional Microeconomics of Development*, 44(November):1–50.

Fafchamps, M., McKenzie, D., Quinn, S., and Woodruff, C. (2014). Microenterprise growth and the flypaper effect: Evidence from a randomized experiment in ghana. *Journal of development Economics*, 106:211–226.

Fafchamps, M. and Minten, B. (1999). Relationships and traders in Madagascar. *Journal of Development Studies*, 35(6):1–35.

Fafchamps, M. and Minten, B. (2002). Returns to social network capital among traders. *Oxford Economic Papers*, 54(2):173–206.

Fafchamps, M. and Quinn, S. (2018). Networks and manufacturing firms in africa: Results from a randomized field experiment. *The World Bank Economic Review*, 32(3):656–675.

Ghanem, D., Hirshleifer, S., and Ortiz-Becerra, K. (2023). Testing attrition bias in field experiments. *Journal of Human Resources.*

Ghani, T. and Reed, T. (2022). Relationships on the rocks: Contract evolution in a market for ice. *American Economic Journal: Microeconomics*, 14(1):330–365.

Hardy, M. and Kagy, G. (2018). Mind The (Profit) Gap: Why Are Female Enterprise Owners Earning Less Than Men? *AEA Papers and Proceedings*, 108(August 2016):252–55.

Hardy, M. and McCasland, J. (2021). It takes two: Experimental evidence on the determinants of technology diffusion. *Journal of Development Economics*, 149:102600.

Hasanain, S. A., Khan, M. Y., and Rezaee, A. (2023). No bulls: Experimental evidence on the impact of veterinarian ratings in pakistan. *Journal of Development Economics*, 161:102999.

Iacovone, L. and McKenzie, D. (2022). Shortening supply chains: Experimental evidence from fruit and vegetable vendors in bogota. *Economic Development and Cultural Change*, 71(1):111–149.

Imbens, G. W. and Rubin, D. (2015). *Causal Inference in statistics, social, and biomedical sciences.* Cambridge University Press.

Jayachandran, S. (2021). Microentrepreneurship in developing countries. *Handbook of labor, human resources and population economics*, pages 1–31.

Jensen, R. (2007). The Digital Provide: Information (Technology), Market Performance, and Welfare in the South Indian Fisheries Sector. *Quarterly Journal of Economics*, CXXII(August):879–924.

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

Kling, J. R., Liebman, J. B., and Katz, L. F. (2007). Experimental Analysis of Neighborhood Effects. *Econometrica*, 75(1):83–119.

Ludwig, J., Mullainathan, S., and Spiess, J. (2019). Augmenting Pre-Analysis Plans with Machine Learning. *AEA Papers and Proceedings*, 109:71–76.

Macchiavello, R. and Miquel-Florensa, J. (2018). Vertical Integration and Relational Contracts in the Costa Rica Coffee Chain.

Macchiavello, R. and Morjaria, A. (2015). The Value of Relationships: Evidence from a Supply Shock to Kenyan Rose Exports. *American Economic Review*, 105(9):2911–2945.

Macchiavello, R. and Morjaria, A. (2021). Competition and relational contracts in the rwanda coffee chain. *The Quarterly Journal of Economics*, 136(2):1089–1143.

Macchiavello, R. and Morjaria, A. (2023). Relational contracts: Recent empirical advancements and open questions. *Journal of Institutional and Theoretical Economics*, 179(3-4):673–700.

McFadden, D. and Train, K. (2000). Mixed MNL models for discrete response. *Journal of Applied Econometrics*, 15(5):447–470.

McKenzie, D. (2012). Beyond baseline and follow-up: The case for more T in experiments. *Journal of Development Economics*, 99(2):210–221.

McKenzie, D. and Paffhausen, A. L. (2019). Small firm death in developing countries. *Review of economics and statistics*, 101(4):645–657.

McKenzie, D. and Puerto, S. (2021). Growing markets through business training for female entrepreneurs: A market-level randomized experiment in kenya. *American Economic Journal: Applied Economics*, 13(2):297–332.

McKenzie, D. and Woodruff, C. (2014). What are we learning from business training and entrepreneurship evaluations around the developing world? *World Bank Research Observer*, 29(1):48–82.

Mcmillan, J. and Woodruff, C. (1999). Interfirm Relationships and Informal Credit in Vietnam. *The Quarterly Journal of Economics*, 114(4):1285–1320.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, 71(6):1695–1725.

Michler, J. and Wu, S. (2020). Relational Contracts in Agriculture: Theory and Evidence. *Annual Review of Resource Economics*, 12(1):1–17.

Moore, R. T. (2012). Multivariate continuous blocking to improve political science experiments. *Political Analysis*, 20(4):460–479.

Reardon, T., Echeverria, R., Berdegue, J., Minten, B., Liverpool-Tasie, S., Tschirley, D., and Zilberman, D. (2019). Rapid transformation of food systems in developing regions: Highlighting the role of agricultural research & innovations. *Agricultural Systems*, 172(June):47–59.

Sexton, R. J. (2013). Market power, misconceptions, and modern agricultural markets. *American Journal of Agricultural Economics*, 95(2):209–219.

Startz, M. (2024). The value of face-to-face: Search and contracting problems in nigerian trade. *Available at SSRN 3096685*.

Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica*, 79(1):159–209.

Train, K. (2009). *Discrete choice methods with simulation*. Cambridge University Press, Cambridge, MA.

Varian, H. R. (2007). Position auctions. *International Journal of Industrial Organization*, 25(6):1163–1178.

Wager, S., Du, W., Taylor, J., and Tibshirani, R. J. (2016). High-dimensional regression adjustments in randomized experiments. *Proceedings of the National Academy of Sciences of the United States of America*, 113(45):12673–12678.

Weld, G., Perrier, T., Aker, J. C., Blumenstock, J., Dillon, B., Kamanzi, A., Kokushubira, E., Webster, J., and Anderson, R. (2018). eKichabi: Information Access through Basic Mobile Phones in Rural Tanzania. *CHI Conference on Human Factors in Computing Systems*, Montreal,.

Young, A. (2019). Channeling fisher: Randomization tests and the statistical insignificance of seemingly significant experimental results. *The quarterly journal of economics*, 134(2):557–598.

Table 1: Baseline Characteristics

	Mean	sd
Panel A: General Characteristics		
Woman-Owned Firm	0.36	0.48
Owner Age	35.45	11.06
Owner Years of Education	7.41	3.43
Owner has Smartphone	0.24	0.43
Age of Firm	5.46	6.80
Number of Workers (including owner)	1.36	0.64
Has Electricity	0.61	0.49
Daily Average Number of Sales	15.36	21.11
Daily Average Sales (Tzs)	50518.54	98308.29
Distance to City (km)	65.26	31.32
Retail Sector (0=Services Sector)	0.53	0.50
Number of Competitors	4.77	3.84
Panel B: Receives Supplier Relationship Benefits		
Receives Goods on Credit	0.09	0.29
Receives Price Discount	0.29	0.45
Sends Mobile Money to Suppliers	0.19	0.39
Inventory Shipped	0.17	0.37
Receives None	0.36	0.48
Receives All	0.002	0.04
Panel C: Inventory Sourcing		
Number of Suppliers Contacted	1.70	1.11
Inventory Purchased within Village	0.35	0.48
Inventory Purchased Outside Village	0.60	0.49
Inventory Expenditure (Tzs)	245830.00	501566.49
Transport Costs Share of Inventory Expenditure	0.08	0.17
Panel D: Offers Customer Relationship Benefits		
Offers Goods/Services on Credit	0.57	0.50
Offers Frequent Customer Discount	0.53	0.50
Receives Mobile Money from Customers	0.16	0.36
Makes Special Orders for Customers	0.23	0.42
Offers None	0.18	0.38
Offers All	0.02	0.15
Panel E: Customer Sources (does not sum to 100)		
Customers from same village	0.92	0.28
Customers from neighboring villages	0.58	0.49
Customers from distant villages or city	0.13	0.34

Table 2: Mixed Logit Results of Discrete Choice Experiment

	Dependent Var: Contract Choice		
	Mean	SD	WTP (Percent)
	(1)	(2)	(3)
Price	-6.11***		
	(0.58)		
Supplier Known	0.33***	0.72***	0.06
	(0.12)	(0.19)	[0.02, 0.10]
Goods Delivered	2.01***	2.05***	0.33
	(0.19)	(0.18)	[0.25, 0.40]
Mpesa payment	-0.05	-0.21	-0.01
	(0.18)	(0.29)	[-0.06, 0.05]
50% cash now	1.13***	-0.51	0.18
	(0.18)	(0.35)	[0.12, 0.25]
80% cash now	-0.04	1.67***	-0.01
	(0.23)	(0.25)	[-0.08, 0.06]
Observations	4510	4510	

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The sample size comes from the 376 firms that completed the choice experiment multiplied by the 12 contracts they reviewed. The full sample of 507 firms did not complete the discrete choice experiment due to piloting and some cases of non-response. One firm only managed 10 contracts, thus 376×12-2=4510. Coefficients are the mean and standard deviation of a distribution of tastes in the population that participated in the discrete choice experiment. Standard errors are in parenthesis in columns 1 and 2 and confidence intervals are in brackets in column 3.

Table 3: Directory Usage and Engagement

	(1) Used Phonebook	(2) Searched Urban Area	(3) Searched Rural Area	(4) Found by Rural Customer	(5) Found by Urban Firm	(6) Found by Study Firm
Upstream Treat	0.104*	0.255***	0.247***	-0.010	0.117***	0.367***
	(0.055)	(0.035)	(0.052)	(0.016)	(0.026)	(0.040)
Downstream Treat	0.136**	0.018	0.357***	0.579***	0.065***	0.608***
	(0.054)	(0.020)	(0.050)	(0.037)	(0.020)	(0.040)
Control Mean	0.500	0.012	0.165	0.000	0.000	0.000
Observations	507	507	507	507	507	507
Adj. R-squared	0.02	0.18	0.07	0.49	0.04	0.31

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table reports results from treatment effects regressions of a phonebook usage outcomes on a treatment indicator and strata fixed effects. All dependent outcome variables are categorical (0/1) and denote any usage over the entire treatment period. Coefficients identify the effect of treatments on study firm searches in phonebook (Cols 1-3) and whether their listing was found by different user types (Cols 4-6). All outcome variables exclude instances where firms searched for their own listing. Positive means in the control group reflect control firms using the placebo directory.

Table 4: ITT Effects on Supplier and Customer Outcomes

	Supplier Outcomes			Customer Outcomes		
	(1) Supplier Relational Contracting Index	(2) Supplier Search Index	(3) Transact w/ Suppliers Outside Village	(4) Customer Relational Contracting Index	(5) Customer Comm. Index	(6) Transact w/ Customers Outside Village
Upstream Treat	0.071**	-0.091**	-0.081***	-0.097***	-0.033	-0.023
	(0.030)	(0.039)	(0.029)	(0.032)	(0.047)	(0.034)
Downstream Treat	0.027	-0.112***	-0.099***	-0.115***	-0.164***	-0.061*
	(0.031)	(0.038)	(0.030)	(0.032)	(0.048)	(0.033)
Control Mean	0	0	0.794	0	0	0.488
Observations	1230	1230	1190	1253	1253	1253
Adj R-Squared	0.046	0.289	0.383	0.121	0.123	0.195

Robust standard errors in parenthesis clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table reports ANCOVA regressions for relational contracting with suppliers and customers, search and communication with suppliers and customers, and trade across villages. Controls include strata indicators, survey round indicators, baseline outcomes, and an indicator if baseline outcome was missing.

Table 5: ITT Effects on Other Business Outcomes

	(1) Input Price Index	(2) Transport Cost Share	(3) Output Price Index	(4) Sales Revenue Index
Upstream Treat	0.059	-0.006	0.140***	-0.003
	(0.051)	(0.006)	(0.053)	(0.056)
Downstream Treat	-0.001	-0.013**	0.080	0.017
	(0.053)	(0.005)	(0.053)	(0.059)
Control Mean	-0.016	0.052	-0.101	0
Observations	1110	1198	1055	1253
Adj R-Squared	0.185	0.103	0.068	0.126

Robust standard errors in parenthesis clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table reports ANCOVA regressions for pricing and sourcing outcomes. Controls include strata indicators, imbalance prediction index, survey round indicators, baseline outcomes, and an indicator if baseline outcome was missing.

Table 6: Heterogeneous Treatment Effects by Gender of the Firm Owner

	Supplier Outcomes				Customer Outcomes		
	(1) Supplier Relational Contracting Index	(2) Input Price Index	(3) Transport Cost Share	(4) Purchased Inputs Locally	(5) Customer Relational Contracting Index	(6) Output Price Index	(7) Sales Revenue Index
Treat×Woman-owned	0.055	-0.201**	0.017*	0.002	0.058	-0.054	0.002
	(0.058)	(0.098)	(0.009)	(0.056)	(0.063)	(0.089)	(0.093)
Treat	0.049	0.103**	-0.016**	0.047	-0.137***	0.133**	0.006
	(0.034)	(0.049)	(0.006)	(0.030)	(0.033)	(0.066)	(0.072)
Woman-owned	0.138	0.260	-0.031	0.204**	0.188*	0.014	0.034
	(0.094)	(0.166)	(0.020)	(0.091)	(0.106)	(0.150)	(0.154)
Treat+Interaction=0	0.0257	0.2544	0.8545	0.3029	0.1404	0.1855	0.8904
Control Mean	-0.002	-0.180	0.061	0.183	0.009	-0.105	0.087
Observations	1230	1110	1198	1190	1253	1055	1253
Adj R-Squared	0.065	0.188	0.105	0.424	0.136	0.066	0.126

Robust standard errors in parenthesis clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table reports ANCOVA regressions main outcomes using heterogeneity by the gender of the firm owner. Controls include strata indicators, survey round indicators, baseline outcomes, and an indicator if baseline outcome was missing. Control mean is for male-owned firms in the control group.

Table 7: Heterogeneous Treatment Effects by Remoteness

	Supplier Outcomes				Customer Outcomes		
	(1) Supplier Relational Contracting Index	(2) Input Price Index	(3) Transport Cost Share	(4) Purchased Inputs Locally	(5) Customer Relational Contracting Index	(6) Output Price Index	(7) Sales Revenue Index
Treat×Remote Market	0.052	-0.130	0.021**	-0.111**	-0.183***	0.013	0.177*
	(0.059)	(0.097)	(0.010)	(0.052)	(0.058)	(0.098)	(0.102)
Treat	0.049	0.081	-0.018***	0.094***	-0.043	0.108*	-0.059
	(0.037)	(0.057)	(0.006)	(0.036)	(0.040)	(0.064)	(0.072)
Remote Market	0.023	0.099	-0.008	0.061	0.119**	-0.047	-0.135
	(0.051)	(0.087)	(0.008)	(0.044)	(0.047)	(0.078)	(0.089)
Treat+Interaction=0	0.0245	0.5226	0.7110	0.6394	0.0000	0.0804	0.0801
Control Mean	-0.013	-0.044	0.056	0.261	-0.056	-0.079	0.057
Obs	1230	1110	1198	1190	1253	1055	1253
Adj R-Squared	0.063	0.184	0.105	0.422	0.137	0.066	0.128

Robust standard errors in parenthesis clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table reports ANCOVA regressions main outcomes using heterogeneity by whether a firm is located in a market that is above median road distance to the urban market. Controls include strata indicators, imbalance prediction index, survey round indicators, baseline outcomes, and an indicator if baseline outcome was missing. Control mean is for control group near urban centers.

Table 8: Heterogeneous Treatment Effects by Firm Sector

	Supplier Outcomes				**Customer Outcomes**		
	(1) Supplier Relational Contracting Index	(2) Input Price Index	(3) Transport Cost Share	(4) Purchased Inputs Locally	(5) Customer Relational Contracting Index	(6) Output Price Index	(7) Sales Revenue Index
Treat×Service Firm	-0.002	-0.034	-0.019*	0.103**	-0.034	-0.081	0.060
	(0.055)	(0.088)	(0.010)	(0.048)	(0.059)	(0.094)	(0.099)
Treat	0.072*	0.041	-0.001	0.006	-0.096**	0.148**	-0.021
	(0.038)	(0.054)	(0.005)	(0.028)	(0.039)	(0.060)	(0.076)
Service Firm	-0.027	0.500***	0.015	0.312***	0.018	0.035	-0.152
	(0.074)	(0.110)	(0.013)	(0.062)	(0.074)	(0.101)	(0.103)
Treat+Interaction=0	0.0805	0.9144	0.0156	0.0047	0.0031	0.3504	0.5374
Control Mean	0.021	-0.278	0.041	0.111	0.046	-0.118	0.185
Obs	1230	1110	1198	1190	1253	1055	1253
Adj R-Squared	0.060	0.206	0.104	0.456	0.131	0.066	0.127

Robust standard errors in parenthesis clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table reports ANCOVA regressions main outcomes using heterogeneity by whether a firm is in the retail or service sector. Controls include strata indicators, survey round indicators, baseline outcomes, and an indicator if baseline outcome was missing. Control mean is for retail firms in the control group.

Appendices – For Online Publication Only

Figure A1: Example of Feature Phone

Image from Weld et al., 2017

Figure A2: Phonebook Application Menus

```
Select an option:
1.Browse by Location
2.Browse by Sector
3.Search
4.Help
```

A) User input : 1

```
Select District
1.Babati Mjini
2.Chamwino
3.Chemba
4.Dodoma Urban
5.Kiteto
0.Next
99.Back
```

B) User input : 5

```
Select Village
1.Busi
2.Keikei
3.Kinyasi
4.Kiteo
5.Kwadelo
0.Next
99.Back
```

C) User input : 4

```
1.All Businesses (24)
or Select Subvillage
2.Kiteo - Marumba
3.Kiteo - Matinga
4.Kiteo - Muya
5.Kiteo - Nkundusi

99.Back
```

D) User input : 1

```
Select Business
1.Ally Kiosk
2.Amiri Shop
3.Chavai Kiosk
4.Fundi Baiskeli
5.Genge la Mama Mtaa
0.Next
99.Back
```

E) User input : 1

```
 Ally Kiosk
-----------------
 Location:
 Kiteo - Matinga
 Phone:  T653965711
```

F) Business found

Image from Weld et al., 2017

Figure A3: Experimental Timeline

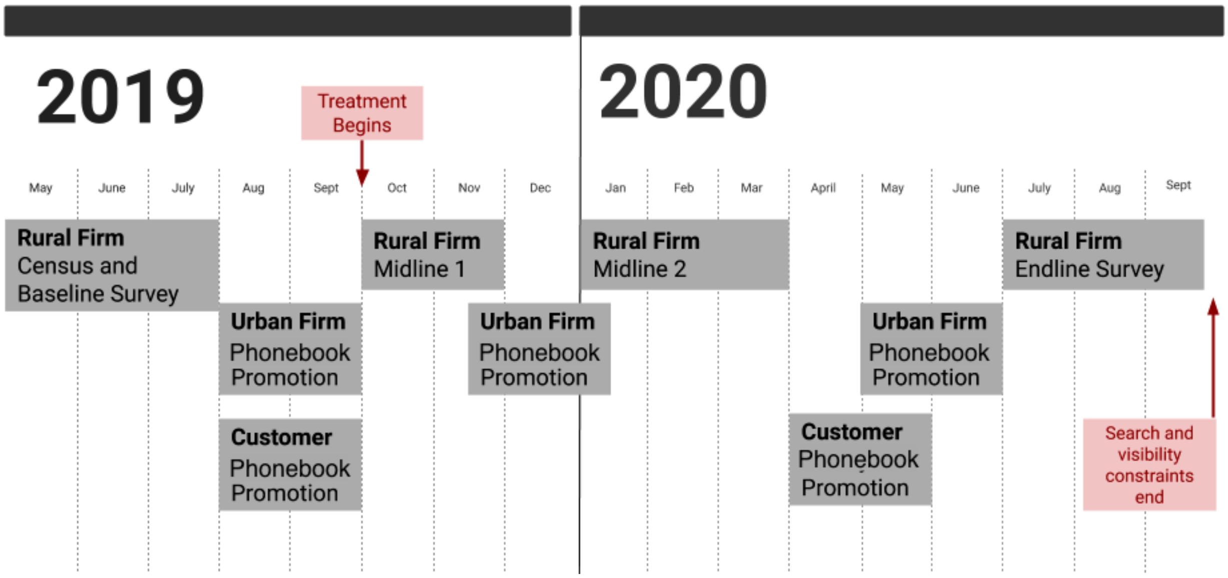
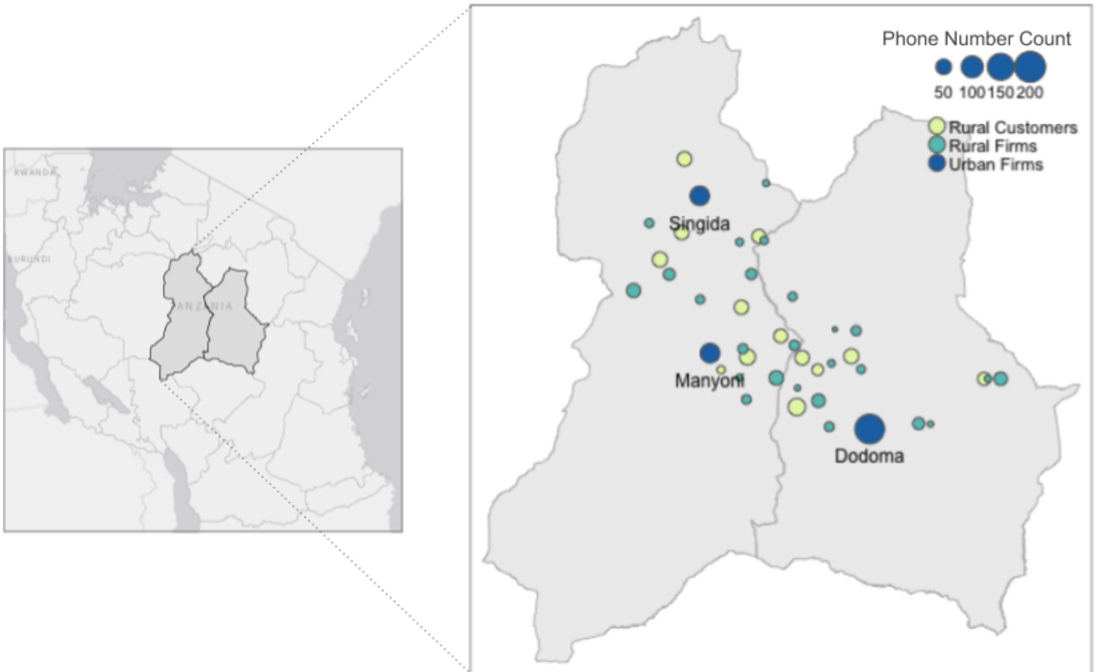


Figure A4: Urban Firms, Rural Firms, and Rural Customers Locations in Tanzania



Notes: Map of the geographic distribution of urban firms, rural firms in the treatment and control groups, and rural customers in Singida and Dodoma regions in central Tanzania. The size of the bubble indicates the number of phone numbers that were gathered from each location. Urban firm contact information was obtained from urban centers denoted with blue dots, rural firms that were assigned to an experimental condition are located in villages denoted with green dots, and villages where the digital phonebook was promoted to rural customers are represented by yellow dots.

Table A1: Firm Baseline Characteristics by Groupings of Heterogeneity

	Gender		Remote Markets		Firm Sector	
	(1)	(2)	(3)	(4)	(5)	(6)
	Men-owned Mean	Women-owned Mean	Near Urban Mean	More Rural Mean	Service Sector Mean	Retail Sector Mean
Panel A: General Characteristics						
Woman-Owned Firm	0.00	1.00	0.39	0.33	0.42	0.31
Owner Age	36.08	34.34	34.65	36.63	34.60	36.20
Owner Years of Education	7.44	7.36	7.56	7.19	7.09	7.70
Age of Firm	5.72	5.00	4.89	6.31	5.93	5.04
Number of Workers (including owner)	1.34	1.39	1.35	1.36	1.38	1.34
Owner has Smartphone	0.29	0.15	0.26	0.21	0.21	0.26
Has Electricity	0.61	0.61	0.64	0.57	0.58	0.63
Daily Average Number of Sales	13.71	18.42	16.88	13.06	11.13	19.58
Daily Average Sales (Tzs)	64885.98	26355.11	47302.47	55334.13	26432.13	71726.10
Distance to City (km)	66.92	62.35	43.90	96.99	66.34	64.30
Retail Sector (0=Services Sector)	0.57	0.45	0.52	0.54	0.00	1.00
Number of Competitors	4.37	5.47	4.70	4.85	5.01	4.55
Panel B: Receives Supplier Relationship Benefits						
Receives Goods on Credit	0.05	0.16	0.11	0.06	0.11	0.07
Receives Price Discount	0.27	0.31	0.31	0.26	0.18	0.37
Sends Mobile Money to Suppliers	0.21	0.15	0.21	0.16	0.11	0.26
Panel C: Inventory Sourcing						
Number of Suppliers Contacted	1.74	1.63	1.58	1.89	1.50	1.86
Transport Costs - None (0/1)	0.26	0.45	0.36	0.30	0.54	0.17
Inventory Shipped from City	0.20	0.11	0.17	0.15	0.09	0.22
Transport Costs - Travel (0/1)	0.55	0.43	0.47	0.55	0.37	0.61
Inventory Expenditure (Tzs)	309040.35	142887.43	264764.52	216643.65	78120.30	377137.60
Transport Costs Share of Inventory Expenditure	0.08	0.07	0.07	0.09	0.10	0.05
Panel D: Offers Customer Relationship Benefits						
Offers Goods/Services on Credit	0.55	0.60	0.60	0.53	0.47	0.66
Offers Frequent Customer Discount	0.54	0.50	0.53	0.52	0.50	0.55
Receives Mobile Money from Customers	0.17	0.12	0.18	0.13	0.14	0.17
Makes Special Orders for Customers	0.24	0.21	0.28	0.17	0.22	0.24
Panel E: Customer Sources (does not sum to 100)						
Customers from same village	0.90	0.95	0.92	0.91	0.93	0.91
Customers from neighboring villages	0.60	0.54	0.56	0.60	0.62	0.55
Customers from distant villages or city	0.16	0.09	0.13	0.14	0.17	0.10

A1 Sample characteristics and balance

Table A2 reports population means of each region included in the study (Dodoma and Singida) compared to Tanzania as a whole. Means are authors' calculations using the World Bank's 2014 Living Standards and Measurement Survey for Tanzania. Dodoma and Singida regions have lower share of the population living in urban areas, have lower mobile phone ownership rates, less rainfall, lower literacy rates, and lower rate of non-farm employment. Dodoma city is the largest urban center in the region.

Table A2: Characteristics of Sample Regions and National Average

	Dodoma Region	Singida Region	Tanzania
Population (millions)	2.3	1.5	50.1
Urban Population Share	16.2	14.7	29.6
Average HH Size	4.6	5.3	4.9
Literacy Rate	67.5	67.1	71.8
Mobile Phone Ownership Rate	49.5	54.7	63.9
Non-Farm Primary Employment	28.2	31.4	37.2
Land Area (Sq. km)	41,000	49,300	883,300
Population density (/sq km)	55.12	30.4	56.7
Average Rainfall (mm/year)	495.7	732	1100

The balance table in Table A3 compares the means for the treatment groups, control group, and t-tests for differences between groups. The balance table compares differences across groups among 23 covariates, including baseline demographic characteristics and baseline outcomes. Out of 23 covariates, 5 exhibit imbalance in one of the comparisons - owner age, whether the firm has access to electricity, the number of competitors, the supplier relationship index, and the output price index. The two outcomes (supplier relationships and output prices) are controlled for via the ANCOVA specification. The F-test of joint significance across all covariates fails to reject the null of no joint significance for 2 out of 3 groups and marginally rejects differences for the upstream arm compared to control. Rather than add imbalanced covariates as controls in treatment effects regressions, as a robustness check, we used a machine learning procedure to produce a unit-level prediction index following Wager et al. (2016) and Ludwig et al. (2019). The prediction index was constructed by regressing treatment on baseline outcomes and their interactions and selecting variables through random forest and lasso selection procedures to build an index. The idea is to select variables that explain any arbitrary correlation between experimental groups and baseline outcomes and add them as a regression adjustment to improve precision. In practice, the index had little explanatory power and is excluded from analysis but is available upon request from the authors.

Table A3: Balance Table

Variable	(1) Upstream Mean/SD	(2) Downstream Mean/SD	(3) Control Mean/SD	T-test P-value (1)-(2)	(1)-(3)	(2)-(3)
Woman-Owned Firm	0.379	0.363	0.347	0.526	0.101	0.569
	(0.487)	(0.482)	(0.477)			
Owner Age	35.941	35.988	34.424	0.925	0.076*	0.151
	(11.559)	(10.998)	(10.596)			
Owner Years of Education	7.473	7.286	7.476	0.698	0.863	0.675
	(3.361)	(3.600)	(3.336)			
Owner has Smartphone	0.225	0.208	0.206	0.726	0.322	0.613
	(0.419)	(0.407)	(0.406)			
Age of Firm	5.710	5.494	5.138	0.870	0.229	0.307
	(7.220)	(7.145)	(5.988)			
Number of Workers	1.331	1.357	1.371	0.793	0.494	0.528
	(0.574)	(0.622)	(0.728)			
Has Electricity	0.568	0.589	0.494	0.880	0.030**	0.026**
	(0.497)	(0.493)	(0.501)			
Daily Number of Sales	14.213	12.173	12.506	0.215	0.108	0.949
	(23.985)	(19.571)	(16.323)			
Daily Average Sales (Tzs)	43513.905	41967.262	55531.765	0.800	0.172	0.168
	(85503.915)	(87198.553)	(111960.207)			
Distance to City (km)	67.359	66.602	61.844	0.556	0.166	0.283
	(31.832)	(31.334)	(30.696)			
Retail Sector	0.538	0.524	0.524	0.620	0.502	0.730
	(0.500)	(0.501)	(0.501)			
Number of Competitors	3.633	4.643	4.006	0.031**	0.454	0.189
	(3.382)	(4.429)	(3.871)			
Supplier Relationship Index	0.043	-0.049	-0.000	0.034**	0.337	0.234
	(0.447)	(0.459)	(0.439)			
Supplier Search Index	-0.062	-0.016	0.000	0.421	0.240	0.865
	(0.466)	(0.535)	(0.610)			
Input Price Index	0.104	0.022	0.027	0.279	0.220	0.786
	(0.664)	(0.601)	(0.616)			
Purchased Inputs within Village	0.337	0.363	0.341	0.683	0.743	0.972
	(0.474)	(0.482)	(0.476)			
Purchased Inputs Outside Village	0.592	0.625	0.565	0.549	0.843	0.318
	(0.493)	(0.486)	(0.497)			
Transport Costs Share	0.072	0.062	0.058	0.506	0.549	0.883
	(0.185)	(0.138)	(0.149)			
Customer Relationship Index	-0.010	-0.076	-0.000	0.289	0.883	0.197
	(0.543)	(0.529)	(0.533)			
Customer Communication Index	-0.099	-0.082	0.000	0.884	0.164	0.221
	(0.576)	(0.600)	(0.784)			
Non-local Customer	0.497	0.464	0.506	0.293	0.726	0.317
	(0.501)	(0.500)	(0.501)			
Output Price Index	0.133	0.260	-0.032	0.187	0.017**	0.001***
	(0.750)	(0.889)	(0.557)			
Revenue Index	-0.099	-0.124	0.000	0.576	0.147	0.088*
	(0.506)	(0.500)	(0.766)			
N	169	168	170			
F-test of joint significance (p-value)				0.443	0.078*	0.268

Notes: The value displayed for t-tests are the differences in the means across the groups. The value displayed for F-tests are the F-statistics. F-stat regression includes strata dummies and dummies for any missing variables, as specified in the primary treatment effects specification. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

A2 Index Construction

Analysis of primary outcomes involves 7 indices: supplier relational contracting, customer relational contracting, supplier search, customer communication, sales revenue index, and input and output price indices. We prioritize index aggregation to reduce the number of hypothesis tests. All indices were constructed using inverse covariance weighting following Anderson (2008). It has the effect of down-weighting components with little variation across units, and increasing weight on components that are relatively less correlated with other components. This index construction would penalize indices whose components are highly correlated. If between-component correlation were driving results, this index would result in larger standard errors. And if between-component correlation does not drive results, the weighting procedure is equivalent to efficient generalized least squares and can result in smaller standard errors.

The first step for index construction is to orient all the variables in the same direction and create z-scores. The z-scores are calculated at the unit-level by subtracting the control group mean and dividing by the control group standard deviation. All indices except the price indices were oriented relative to the control group so that the coefficients can be interpreted as the standard deviation difference from the control group. We follow Kling et al. (2007) and others to use an imputation procedure for outcomes with missing information. It fills in missing data with the experimental group mean (e.g. the treatment group 1 is assigned the mean of the rest of treatment group 1). Non-response for sensitive outcomes (anything relating to revenues and costs) is common by small business owners in Tanzania. Price indices used the mean of the item instead of the control group because there were cases where there were too few items in the control group to construct a mean and standard deviation.

- **Relational Contracting:** The components the supplier relational contracting index includes whether a firm receives goods on credit, receives a price discount, arranges shipping of inputs, and sends mobile money to suppliers. The components of the customer relational contracting are analogous: whether a firm provides credit to customers, gives a price discount to frequent customers, places orders for customers, and receives mobile money payments. The recall window is over the previous three months.

- **Supplier Search:** The supplier search index includes the number of locations searched, the number of suppliers communicated with in-person, whether the respondent had any incoming and/or outgoing phone communication with suppliers by phone in the week prior to each survey.

- **Customer Communication:** The customer communication index includes the exact number of calls received over the previous two days, calls made over the previous two days, and whether contacts were new. It captures the net change in phone activity and provides information about whether treatments increase phone engagement with customer contacts.

- **Sales Revenue:** The components of the sales revenue index included four survey questions that asked for daily sales revenue at four different time points in the previous month: The best sales day, the worst sales day, an average sales day, and the most recent full day. Extensive piloting revealed that firms were willing to report daily revenue figures but were more likely to refuse questions that asked about profits and weekly revenues. Differences in sales revenue represent shifts in a firms' revenue distribution and reveals whether treatment reliably increases firm revenue at multiple points throughout the prior month.

- **Input and Output Prices:** To construct input and output price indices, firms were asked 4 input and 4 output prices on a common set of items according to their sector. For retail firms, input and output prices are the same good since they sell goods at a mark-up. For service firms, input prices were asked for typical inputs that a firm would need to operate and output prices were asked for common items that are manufactured or services performed. For example, all bicycle mechanics were asked the price of 4 inputs: tires, tubes, spokes, and chain grease, and asked the output price for typical services rendered: changing a spoke, changing a tire, changing a tube, and greasing a chain. This was done to build a set of item prices that could be compared across firms. Item prices were winsorized at the top and bottom 1% of the distribution to reduce the influence of outliers. Z-scores were constructed at the item-survey round level by subtracting the control group mean price and standard deviation. Unlike the other indices, there were sometimes too few items in the control group to subtract the control group mean. Price z-scores were averaged to create an index. Changes in sample sizes on regressions with input and output price indices as the dependent variable reflect the fact that some firms did not source or sell the same items as other firms and therefore a comparison could not be constructed.

A3 Heterogeneity by Competition

The extent of local competition facing treated firms shapes both how they respond to the treatment and how their suppliers adjust to their newfound exposure. We defined competition using two variables - first, a measure based on the number of competitors in the market and second based on the number of firms in the same sector that a treated firm can view on the platform. The second measure captures whether a firm would encounter more or fewer same-sector firms when searching the platform.

Table A4 Panel A reports results for competition defined using the number of firms in the market. We see that the increase in relationship benefits received from suppliers is substantially larger in magnitude and more statistically precise for firms with fewer competitors (column 1; the effect for High Competition is smaller and not statistically different from zero). There is no similar difference for customer-facing relationship services, although the positive sign of the interaction effect is consistent with firms that face more competition reducing customers' benefits by less (column 5). We see opposite effects for supplier relational contracting in Table A4 Panel B where competition is defined using the number of competitors listed in the directory. High competition firms appear to attain more supplier relational contracts and fewer customer relational contracts, although differences between groups are not precisely measured.

For both definitions, the other important difference between treatment effects in Low and High Competition environments is in regard to input and output prices. Firms in Low Competition environments see an *increase* in the input prices they pay; firms in more competitive environments do not (column 2 in both tables). A possible reason for that difference is that firms in Low Competition environments can more readily pass on those costs. Low Competition firms see a statistically different increase in Output prices in Panel A and increase the total effect in Panel B.

Collectively these findings suggest that firms and their suppliers are aware of the variation in competition facing each firm, and take that into account when renegotiating their relationships. This finding aligns closely with a key finding in (Ghani and Reed, 2022), who study the consequences of an increase in upstream competitors on the relationship benefits enjoyed by firms. Of course, the observed variation in the number of competitors may itself be a consequence of deeper differences between firms (e.g. more productive firms may have driven out the local competition), so we cannot be sure that differences in treatment effects are entirely due to variation in the competitive environment.

Table A4: Heterogeneous Treatment Effects by Number of Competitors in Market

	Supplier Outcomes				Customer Outcomes		
	Panel A: Competition defined as number of same-sector firms in the market						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Supplier Relational Contracting Index	Input Price Index	Transport Cost Share	Purchased Inputs Locally	Customer Relational Contracting Index	Output Price Index	Sales Revenue Index
Treat×High Comp	-0.088	-0.237**	0.002	0.043	0.034	-0.017	-0.021
	(0.058)	(0.099)	(0.011)	(0.057)	(0.058)	(0.097)	(0.104)
Treat	0.104***	0.112**	-0.010	0.034	-0.128***	0.114*	0.008
	(0.035)	(0.056)	(0.007)	(0.035)	(0.038)	(0.061)	(0.068)
High Competition	0.035	0.247***	-0.012	-0.001	0.036	0.055	0.114
	(0.049)	(0.085)	(0.008)	(0.048)	(0.053)	(0.082)	(0.085)
Treat+Interaction=0	0.7314	0.1157	0.2420	0.0648	0.0309	0.1827	0.8563
Control Mean	-0.016	-0.094	0.057	0.254	-0.018	-0.107	-0.003
Obs	1230	1110	1198	1190	1253	1055	1253
Adj R-Squared	0.062	0.191	0.104	0.420	0.133	0.066	0.128
	Panel B: Competition defined as same-sector firms listed in phonebook						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treat×High Comp	0.032	-0.294***	-0.015	-0.091*	0.032	0.050	-0.071
	(0.057)	(0.094)	(0.011)	(0.055)	(0.062)	(0.114)	(0.105)
Treat	0.054	0.207***	-0.001	0.102**	-0.130***	0.080	0.047
	(0.042)	(0.072)	(0.008)	(0.043)	(0.047)	(0.098)	(0.084)
High Competition	0.070	0.244***	-0.001	0.146***	0.081	0.015	0.164*
	(0.052)	(0.085)	(0.010)	(0.048)	(0.052)	(0.103)	(0.095)
Treat+Interaction=0	0.0185	0.1378	0.0079	0.7260	0.0085	0.0103	0.6892
Control Mean	-0.019	-0.137	0.052	0.201	-0.052	-0.127	-0.001
Obs	1230	1110	1198	1190	1253	1055	1253
Adj R-Squared	0.067	0.191	0.106	0.427	0.137	0.066	0.129

Robust standard errors in parenthesis clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table reports ANCOVA regressions main outcomes using heterogeneity by whether a firm has above median number of competitors in their market at baseline. Controls include strata indicators, survey round indicators, baseline outcomes, and an indicator if baseline outcome was missing. Control mean is for low competition firms in the control group.

A4 Results for Index Components

Table A5: Treatment Effects for Index Components

Panel A: Suppler Relational Contracting Index Components

	(1) Receives Goods or Services on Credit	(2) Receives Price Discount	(3) Sends Mobile Money to Suppliers	(4) Shipped Inventory from Suppliers
Upstream Treat	0.057**	0.004	-0.023	-0.019
	(0.023)	(0.032)	(0.040)	(0.027)
Downstream Treat	-0.007	-0.007	-0.036	-0.045*
	(0.020)	(0.032)	(0.038)	(0.025)
Control Mean	0.080	0.547	0.354	0.181
Obs	1210	1249	822	1198
Adj R-Squared	0.079	0.123	0.142	0.067

Panel B: Customer Relational Contracting Index Components

	(1) Sells Goods or Services on Credit	(2) Offers Frequency Discount	(3) Receives Mobile Money from Customers	(4) Makes Orders for Customers
Upstream Treat	0.025	-0.036	-0.015	-0.018
	(0.039)	(0.032)	(0.036)	(0.031)
Downstream Treat	-0.013	-0.040	-0.056	-0.042
	(0.041)	(0.034)	(0.034)	(0.032)
Control Mean	0.480	0.642	0.255	0.341
Obs	822	1253	874	1252
Adj R-Squared	0.162	0.126	0.124	0.027

Standard errors in parenthesis clustered at firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table reports ANCOVA regressions for components of supplier and customer relational contracting indices. Controls include strata indicators, survey round indicators, baseline outcomes, and an indicator if baseline outcome was missing.

A5 Attrition

Two types of attrition rates are assessed, 1) by assigned groups, and 2) by baseline covariates. The first compares differential attrition by treatment status and tests whether the difference is statistically different. If treatment groups have higher attrition rates, some foreseeable reasons might be if participants change their businesses in response to treatment, or perhaps learn new opportunities and migrate to another community. A related concern is if treatment-related attrition increases firm exit. For example, firms may increase their network and learn information that discourages them from investing further in their business and decide to close. Seasonal firm closures is common in this setting as some firms pop-up to take advantage of the busy agricultural season and temporarily close during periods that require a lot of agricultural labor. For better or worse, small firm entry and exit is a common element of small enterprise environment in developing countries (McKenzie and Paffhausen, 2019).

For the purposes of measuring attrition, firm closure and firm non-response are measured the same way. The research team conducted all follow-up surveys via phone. In cases where firms did not answer the phone after a few attempts, the team reached out to village leaders and asked to connect with firm owners. In cases where the owner was not found, village leaders were able to confirm whether the firm closed or connect the research team with the new firm operators. In cases where firms had new operators, we conducted the survey with the new operator and updated the phonebook to include the new phone number. It is worth noting that this rarely occurred - in most cases if a firm operator left a community, they shut down their business and the firm would be classified as 'closed' and 'attrited.'

Table A6 shows the differential attrition rate by two definitions of attrition. First, columns 1 and 2 show results for the variable 'Periodic non-response', which takes a value of 1 in cases where a firm did not respond to at least one survey. About 35.3% of control firms did not respond to at least one survey round, but there were no differences by treatment group. Second, the outcome variable 'permanent attrition' takes a value of 1 in cases where there was no response after the baseline survey. The permanent attrition rate is much lower - only about 5.3% of control firms attrited after the baseline survey and there were no differences by treatment group. Columns 3-5 report the attrition rates for each survey round, also finding no differences by treatment group.

Table A6: Differential Attrition by Treatment Group

	(1) Periodic Non-Response	(2) Permanent Attrition	(3) Arrit Follow-up 1	(4) Attrit Follow-up 2	(5) Attrit Follow-up 3
Upstream Treat	-0.058	0.006	-0.024	0.006	-0.046
	(0.051)	(0.024)	(0.038)	(0.041)	(0.043)
Downstream Treat	0.011	-0.005	-0.017	0.004	0.009
	(0.051)	(0.024)	(0.038)	(0.041)	(0.043)
Control Mean	0.353	0.053	0.165	0.182	0.206
Obs	507	507	507	507	507
Adj R-Squared	0.004	0.004	0.051	0.040	0.000

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports results for a set of regressions where an attrition indicator is regressed on treatment status and strata indicators.

To get a sense for drivers of firm closures and attrition, the third survey round asked firms why they closed and whether they planed to reopen. Nearly 40% of temporarily closed/attrited firms closed their business to work on agricultural activities and 20% reported moving to another city or village to look for wage work. The remainder closed due to household shocks (fire, flood, and theft), childcare and family healthcare responsibilities, a lack of customers, lack of capital, or due to faulty equipment in need of repair. 75% of firms that closed stated that they planned to reopen their firm in the near future.

The second type of attrition rate based on baseline covariates serves to rule out selective attrition on observables. Table A7 in the Table appendix reports two tests of selective attrition based on two definitions of attrition described above - periodic non-response, and permanent attrition. A regression with the attrition status as the independent variable and the baseline balance covariates interacted with treatment status on the right-hand side was run along with an F-test of joint significance of regressors. The F-stat for the periodic attrition regression was 1.63, too low to reject a null hypothesis of zero joint significance at the 10% level (p-value is 0.1143). And the F-stat for permanent attrition group was 0.83, with a p-value of 0.5762, also failing to reject the null of a joint effect. Given that differential attrition by assigned groups and selective attrition on observables do not appear problematic, making the additional assumption that unobservables do not drive differences preserves identification of the average treatment effect (ATE) for the study population (Ghanem et al., 2023). Here, the empirical strategy estimates an intent-to-treat (ITT), which equals the ATE under the assumption of perfect treatment compliance.

Table A7: Selective Attrition Test

	(1) Ever Attrit	(2) Permanent Attrit
Upstream Treat × Supplier Relational Contracting Index	-0.013	0.050
	(0.106)	(0.051)
Downstream Treat × Supplier Relational Contracting Index	0.186*	0.049
	(0.108)	(0.052)
Upstream Treat × Input Search Activity Index	-0.064	-0.090*
	(0.106)	(0.051)
Downstream Treat × Input Search Activity Index	-0.210**	0.010
	(0.094)	(0.045)
Upstream Treat × Number of Suppliers	-0.047	0.015
	(0.058)	(0.028)
Downstream Treat × Number of Suppliers	0.142***	-0.007
	(0.054)	(0.026)
Upstream Treat × Supplier Phone Activity Index	0.101	-0.047
	(0.087)	(0.042)
Downstream Treat × Supplier Phone Activity Index	-0.047	-0.030
	(0.093)	(0.045)
Upstream Treat × Customer Relational Contracting Index	0.076	0.043
	(0.087)	(0.042)
Downstream Treat × Customer Relational Contracting Index	-0.208**	-0.024
	(0.087)	(0.042)
Upstream Treat × Non-local Customer=1	-0.159	-0.084
	(0.143)	(0.069)
Downstream Treat × Non-local Customer=1	-0.349**	-0.081
	(0.148)	(0.071)
Upstream Treat × Number of Customers	0.001	0.001
	(0.002)	(0.001)
Downstream Treat × Number of Customers	-0.003	-0.000
	(0.002)	(0.001)
Upstream Treat × Customer Phone Activity Index	-0.118	-0.060
	(0.089)	(0.043)
Downstream Treat × Customer Phone Activity Index	-0.025	-0.018
	(0.077)	(0.037)
Upstream Treat × Sales Revenue Index	-0.014	0.007
	(0.080)	(0.038)
Downstream Treat × Sales Revenue Index	-0.088	0.010
	(0.084)	(0.040)
Upstream Treat × Output Price Index	0.019	0.026
	(0.075)	(0.036)
Downstream Treat × Output Price Index	0.081	0.031
	(0.060)	(0.029)
Upstream Treat × Input Price Index	0.042	0.066*
	(0.075)	(0.036)
Downstream Treat × Input Price Index	-0.060	0.013
	(0.073)	(0.035)
Upstream Treat × Transport Costs Share	0.253	0.151
	(0.242)	(0.117)
Downstream Treat × Transport Costs Share	-0.556*	0.180
	(0.330)	(0.159)
Upstream Treat × Purchased Locally=1	0.144	0.059
	(0.120)	(0.058)
Downstream Treat × Purchased Locally=1	-0.134	0.005
	(0.114)	(0.055)
F-Stat	1.6314	0.8305
p-value	0.1143	0.5762
Control Mean	0.353	0.053
Obs	507	507
Adj R-Squared	.041	.011

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls include strata indicators and an indicator if variable was missing at baseline. F-stat reports the test statistic for an F-test of all the outcome by treatment interactions. The p-value the for both models fails to reject the null that coefficients on the outcome by treatment interactions are zero.

A6 Randomization Inference

As a robustness check, p-values were computed by using randomization inference (Athey and Imbens, 2017, Young, 2019. Randomization inference re-assigns treatment and re-estimates treatment effects under the placebo assignment. The simplest version of randomization inference iterates through different placebo treatment assignments to generate a distribution of treatment estimates. The probability that a value as large as the actual treatment effect is computed and becomes the p-value for that hypothesis. Randomization inference is especially useful to limit the presence of large outliers that may be present within treated groups. If however, data do not exhibit substantial outliers, then randomization p-values should be roughly similar to conventional asymptotic inference

Table A8 reports randomization inference p-values for all of the primary outcomes using the Stata command `randcmd`. As suggested by Young (2019), we report randomization-t p-values which are based on re-sampling from a distribution of t-statistics and is more valid in cases with multiple treatment arms. The first two columns report the individual randomization p-value for the upstream and downstream treatments, respectively. The third column reports randomization p-value of joint significance testing a sharp null of whether both treatments had any effect. Finally, Young (2019) also offers a test of joint significance based on outcome groupings. we report them for groupings of supplier and customer outcomes.

Individual treatment p-values in columns 1 and 2 roughly mirror those estimated using standard asymptotic inference reported in the main body of the paper. This provides evidence that treatment driven heteroskedasticity or outliers did not bias treatment effects estimates.

Columns 3 and 4 provide new information not presented in the results sections of the main paper. Column 3 lists p-values for a joint test of whether both treatments combined outcomes were statistically different than control. Out of 10 main outcomes, 6 were jointly significant for treatment arms. It suggests that access to the directory and being listed in the directory significantly changed outcomes in similar ways despite being sorted into treatment arms meant to 'boost' either upstream or downstream contact.

Finally, column 4 presents results from Westfall-Young joint significance based the effect

Table A8: Robustness: Randomization Inference

Outcome	(1) Upstream Treatment Individual p-value	(2) Downstream Treatment Individual p-value	(3) Joint Test Both Treatments p-value	(4) Joint Test Outcome Grouping p-value	(5) Iterations
Upstream Outcomes Grouping					
Supplier Relational Contracting Index	.0171	.3881	.0586	.0505	2000
Supplier Search Index	.0198	.0058	.0104	.0505	2000
Transact with Suppliers Outside Village	.0211	.0065	.0168	.0505	2000
Input Price Index	.2431	.9893	.4113	.0505	2000
Transport Cost Share	.2484	.0107	.0436	.0505	2000
Downstream Outcomes Grouping					
Customer Relational Contracting Index	.0943	.0774	.1795	.0138	2000
Customer Communication Index	.3656	.0013	.0039	.0138	2000
Transact with Customers Outside Village	.5118	.0655	.1792	.0138	2000
Output Price Index	.0102	.1472	.034	.0138	2000
Sales Revenue Index	.9635	.7623	.9266	.0138	2000
Joint Test - All Outcomes				.0247	2000

Notes: This table compares p-values for main outcomes using randomization inference. The first two columns show individual p-values for each treatment for main outcomes that can be directly compared to asymptotic p-values and multiple hypothesis testing p-values presented in Tables 4 and 5. Column 3 is a joint test of significance for both treatments combined for each outcome. Column 4 is a joint test of significance for both treatments for each group of outcomes. The last row reports the p-value of a joint test of significance on all outcomes.

of both treatments on all outcomes in a particular group. It tests whether the experiment had any effect whatsoever on groups of treatment outcomes. This test also embeds multiple hypothesis test corrections within each group, but not across groups. For all both groupings, p-values are below .05, thereby rejecting the null hypothesis of no effect whatsoever. And the last row of the table reports a p-value for a test of joint significance on all outcomes and rejects the null of no experimental effects across all main outcomes below a .05 level. These tests further indicate that search and visibility in the phonebook changed outcomes for firms in the treatment groups.

A7 Discrete Choice Experiment

To understand how firms value relational contracting, we administered a discrete choice experiment designed to elicit willingness to pay for benefits that are associated with relational contracting with suppliers following Train (2009). During the baseline survey, firms were asked to compare a series of 'contracts' with four different attributes:

- **Input Price:** The price of a recently-purchased input, varied by 5%, 10%, and 15% discount or cost increase.
- **Known Supplier:** Preference for whether a supplier was known to them or completely new.
- **Transportation:** Preference to pay for travel to purchase goods in an urban area, or pay shipping to have goods delivered.
- **Payment Terms:** Preferences for using mobile money payments or being offered credit to defer payment on some of their balance.

As described in the main text, in practice these attributes are available to some firms but are not formalized in written contracts. For each contract attribute, one option is associated with building trust with a supplier. For example, suppliers must trust that credit will be repaid, or they must trust that payment for goods shipped will be received.

Discrete choice experiments are effective for identifying which components of trading with suppliers are relatively more valuable to firms. They require participants to compare sets of contracts with variation in attribute levels and to state which contract they would prefer.[17] After completing a series of comparisons, each participant will have generated binary choice data with information on which attributes were available for each choice.

For each contract attribute, one option is associated with having built trust with a supplier. For example, suppliers must trust that credit will be repaid, or they must trust that payment for goods shipped will be received. Table A9 below shows each contract attribute and the different levels. Each column heading represents a contract *attribute*, and rows denote the *levels* for each attribute. In the course of the DCE, firms were shown 6 pairs of contracts and asked to specify which was preferred. Each contract listed one level from

[17] Consistent with the literature on discrete choice experiments, the term *attribute* refers to components of informal trading contracts - in this case, price, known supplier, transportation, and payment terms. The term *levels* refers to variation within each attribute - such as the different prices shown to participants.

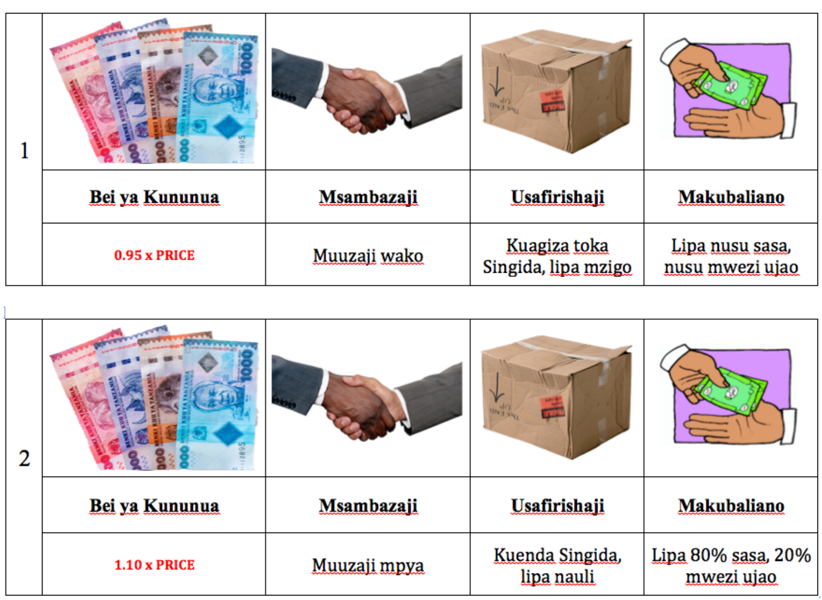
each attribute - price, whether a supplier was known or unknown, delivery terms, and terms of credit (see example contract pairing in Figure A5).

Table A9: Discrete Choice Experiment Contract Attributes and Levels

Price	Supplier	Transport	Payment
.85 x Price	Known	Deliver, pay shipping	Cash now
.90 x Price	Unknown	Travel, pay bus fare	M-Pesa Now
.95 x Price			50% now,
1.00 x Price			50% in one month
1.05 x Price			80% now,
1.10 x Price			20% in one month
1.15 x Price			

DCE require participants to compare sets of contracts with variation in attribute levels. Attribute levels were randomly determined through an orthogonal array algorithm After completing a series of comparisons, a mixed logit model is used to estimate the relative importance of each level. Firms were shown 6 pairs of contracts and asked to specify which was preferred. Each contract listed one level from each attribute - price, whether a supplier was known or unknown, delivery terms, and terms of credit (Figure A5 provides an example of a contract pairing).

Figure A5: Example of Contract Pairing



Econometric analysis of discrete choice data draws from a random-utility model and uses a mixed logit model to estimate choice probabilities that represent the relative importance of each attribute level (**?**). Coefficients on terms in the mixed logit are interpreted as the group-level preferences for an attributes. Point estimates can also be converted into measures of willingness-to-pay (WTP) for certain attribute levels. While these WTP measures are not incentivized, we used the most recent per unit price for an input as the base price in the experiment. Econometric analysis uses the following model specification:

$$Y_{ijk} = \alpha + \beta_1 Price_{ijk} + \beta_2 Supplier_{ijk} + \beta_3 Transport_{ijk} + \beta_3 Payment_{ijk} + \gamma_k + \epsilon_{ijk} \quad (2)$$

Firm i selects alternative j among choice sets k. Y_{ijk} is a binary variable which takes a value of 1 if the firm owner chose a certain contract. Mixed logit specifications are robust to arbitrary correlation within alternatives and heterogeneous preferences of agents. In other words, each agent is assumed to have their own preference distribution of the various options. Coefficients on terms in the mixed logit are interpreted as the group-level preferences for an attribute level. Price is treated as fixed coefficient, meaning that only a mean is estimated and assumed to be fixed for the population.

To make coefficients economically meaningful, they can be converted into a measure of WTP by dividing the point estimate of the mean of an attribute level by the price coefficient.[18] The column 'WTP (Percent)' reports the willingness to pay and confidence interval for each contract level. The coefficient on price is negative - meaning that participants were less likely to choose a contract as the price went up. The fact that the price coefficient is negative and statistically significant provides a check that the experiment was understood and taken seriously by participants since it suggests adherence to downward sloping demand. Likewise, not all attribute levels were meaningful to participants (paying with Mpesa and paying 80% of their balance at once). It indicates that firms were indifferent about these contract attributes and consistently preferred those with better terms.

[18] For example, the coefficient on price is -6.11 and the coefficient on purchasing from a known supplier is 0.33, so the WTP is obtained by computing 0.33/-6.11. Confidence intervals were constructing following Hole, 2007.