Search Costs and Relational Contracting: The Impact of a Digital Phonebook on Small Business Supply Chains

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Abstract

Search frictions can be substantial in rural markets in developing countries and can raise the cost of learning market information. For small firms, search frictions interfere with learning about new suppliers in their upstream market, and raise the cost of meeting new customers in their downstream market. I experimentally investigate whether lowering upstream and downstream search costs for small firms in rural Tanzania improves firm outcomes and alters the incentive to engage in relational contracts with suppliers and customers. Using a randomized experiment of 507 small firms, I study the impact of a digital phonebook that lowers the cost of accessing new business and customer contacts. Participating firms are split into a control and treatment group with two variations: 1) a phonebook listing that is visible to upstream suppliers in urban areas, and 2) a phonebook listing that is visible to downstream customers in rural areas. I find that treated firms increase relational contracting with their suppliers and decrease it with their customers. Yet, there is no strong evidence that the number of new customers or suppliers increases. It suggests that being listed in the phonebook caused firms to update their valuation of relational contracts and respond by negotiating better terms with suppliers and customers.

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1 Introduction

High search costs along small firms' supply chains raise barriers to acquiring new information about prices, quality, and availability of goods. Small firms incur search costs when they source inputs from upstream suppliers located in urban centers. At the same time, they face search frictions to locate and communicate with downstream customers. Information frictions are a substantial share of total transaction costs for these businesses (Allen, 2014; Startz, 2018; Aggarwal et al., 2018). Lowering search costs along a supply chain can improve firm productivity (Bernard et al., 2019) and increase aggregate output (Oberfield, 2018). At a broad scale, these information frictions can constrain productivity for small firms in rural areas of developing countries in both their input and output markets, and prevent them from growing (Jensen and Miller, 2018).

The presence of search costs can increase the value of relational contracting where buyers leverage repeat transactions with sellers to access benefits. In rural markets, sellers may provide credit, or price discounts, or may arrange ordering and shipping of goods for buyers (Fafchamps, 2006). If it were costless to locate new sellers, buyers would have less incentive to repay deferred payments. Likewise, if it were costless to locate new buyers and if the pool of potential buyers was sufficiently large, sellers would have less incentive to sustain relational contracts with their customers. In practice, it is common for sellers to build-in incentives to ensure that trade relationships are sustained in agricultural and other settings with informal contracting (Sexton, 2013; Casaburi and Reed, 2019). Relational contracting helps resolve market failures that persist in developing country contexts - such as in the provision of credit. Yet, such contracts are also a side effect of high search costs and may be less important when firms' search costs are exogenously reduced.

In this paper, I ask if lowering search costs in input and output markets improves firm productivity and changes incentives to engage in relational contracting with suppliers and customers. Using a randomized experiment of 507 rural firms, I study the impact of a digital phonebook mobile application connecting mobile phone users to a platform that lists firm contact information from a variety of sectors in urban and rural areas in central Tanzania. The phonebook treatment affects firms in three ways. First, firms listed in the phonebook are *visible* to other users. Second, firms themselves can *search* within the platform. Third, firms know that they are listed, and update their expectations for engaging with business contacts.

Participating rural firms were split into a control group and two treatment groups. The first was an *Upstream Treatment:* a phonebook listing that is visible to upstream suppliers in urban areas. Upstream treated firms could also search the phonebook for these urban suppliers. The second treatment was a *Downstream Treatment:* a phonebook listing that was visible to downstream customers in rural areas. Firms in both treatment arms could view the other rural firms in their same treatment arm, and could view their own listing. The control group was not listed in the phonebook and could not search the phonebook for firms within the study area. The design allows me to compare the extent to which upstream or downstream search frictions constrain business performance, and to test whether lowering the cost of initial contact improves firm productivity. I use data from surveys with firms and usage data generated by the phonebook app to estimate treatment effects and explore underlying mechanisms.

Relational contracting includes benefits that firms provide to their customers and receive from their suppliers that are not readily provided through anonymous transactions in a spot market. Firms engage in relational contracting with their suppliers by receiving credit on input purchases, arranging shipping of inputs, and receiving price discounts. For their customers, firms provide credit on goods or services purchased, arrange sourcing of goods, and give price discounts to frequent customers. I document substantial use of relational contracting in input and output markets and show descriptive evidence that rural firms provide benefits of relational contracting to their customers more often than they receive them from their suppliers. To understand how rural firms value relational contracts with their suppliers, I present results from a discrete choice experiment that I conducted prior to treatment demonstrating that firms value their suppliers, credit, and delivery. These findings allow me to estimate how much firms are willing to pay in form of higher input prices to access these benefits.

Results fall into three categories of outcomes. First, upstream outcomes measure changes to relational contracting with suppliers, firm input search behavior, and whether firms contacted or purchased from new suppliers. Second, downstream outcomes measure changes to relational contracting with customers and contact with new customers. Finally, productivity outcomes examine changes to sales, input and output prices, and input sourcing efficiency.

Using an index of relational contracting activity, I find that being listed in the phonebook causes firms in the upstream treatment group to increase relational contracting with their suppliers by 0.10 standard deviations compared to the control group. These firms are 75% more likely to receive credit from their suppliers. Firms in both treatment arms decrease their overall search activities, and have fewer new suppliers compared to the control group. For customers, firms in both treatment arms decrease provision of relational contracting benefits by about 0.11 standard deviations compared to the control group. However, there is no strong evidence that the quantity of new customers increases compared to the control group. Empirical results do not provide evidence that sales revenue increased for treated firms. But, productivity improved through other channels: the upstream treatment arm increased output prices and downstream arm was also more likely to purchase inputs locally (saving travel time) and paid lower transport costs.

Although survey data revealed that firms' customer base did not increase, app usage data showed that 58% of downstream firms were found by a customer at least once throughout the 12-month treatment period. It is possible that firms communicated with new customers but that it was not frequent or substantial enough to show up in survey data. Further, 45% of upstream firms and 69% of downstream firms searched or were found by other rural firms (excluding instances where firms searched for their own listing). The upstream arm's engagement with urban firms was lower than their engagement with other rural firms – about 38% of upstream firms searched or were found by urban firms. Overall, this pattern shows that there was more pent-up demand to search in the app for information about other rural firms.

These findings are motivated by theoretical predictions about how changes in search costs change the firms' incentive to use relational contracting. A priori, whether lower search costs would lead to more or less relational contracting is ambiguous because it depends on how firms assess their bargaining power relative to suppliers and customers. On the supplier side, the value of existing relationships remains high because firms have already formed relationships and have a history of transactions. When treatment makes it less costly to locate new suppliers, firms can leverage the credible threat of divesting from relationships to gain new benefits from their existing suppliers. But, firms might also exercise the option to start new supplier relationships, decreasing the net provision of relational contracts from suppliers since they now transact with more new firms where there is no record of transactions to build on.

On the downstream side, if firms anticipate having more contact with new customers, they might reduce the relational benefits that they extend to existing customers. Conversely, if firms expect that other firms in the phonebook will compete for new or existing customers, they might increase their provision of relational contracts in order to retain customers. By examining the net effect on relational contracting in the short-run, empirical results resolve this ambiguity and suggest that it moves in opposite directions by increasing relational contracting with suppliers and decreasing them with customers. Further, usage data confirmed that 20-30% firms used the phonebook app to check their own listing. It affirms that one channel by which firms changed their sourcing behaviour was by updating their expectations about meeting new business contacts.

In a final set of analyses, I examine firm heterogeneity between firms in the retail and services sectors. An important aspect of search costs for rural firms is the cost of transportation that is paid each time they source inputs. I first show descriptively that retail firms source larger input orders and have lower per-unit transportation costs. The cost of maintaining supplier relationships in cities is less costly for these firms than for services firms, since input prices are lower in urban areas and transport costs can be spread over larger order sizes. After pooling both treatment arms, results show that the treatments cause service firms to engage in substantially *less* search activities, pay higher input prices, pay lower transport costs, and purchase inputs locally. This is consistent with the idea that firms' per-unit transaction costs drive much of their input search behavior. For service firms it is more worthwhile to pay higher input prices by searching locally than to incur higher time and transport costs by sourcing from urban suppliers. For these firms, access to other participating rural firms in the phonebook was as or more important than access to urban suppliers.

These findings contribute to the literature that seeks to understand constraints to small firm growth in developing countries by adding evidence about how search frictions relate to relational contracting and productivity. Policymakers and researchers have shown interest in investing in programs and policies that improve productivity for small firms and enable them to grow. Many small firms face barriers to expansion from both input and output sides of their supply chains. For inputs, incomplete markets for finance, labor, energy, and supplies create frictions that prevent enterprises from reliably meeting local demand for goods and services. For outputs, small firms in rural areas may have few avenues for reaching new customers or accessing new markets. Prior research has examined the role of relaxing input-related constraints to firm growth - such as access to capital and credit (De Mel et al., 2008), 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, 2016; Cai and Szeidl, 2018; Hardy and McCasland, 2018). Prior research has studied programs that relax input market constraints or output market constraints, but few studies have been able to experimentally relax both in a single setting (an exception is Anderson et al. (2018)). This research addresses this gap by exploring how search frictions in input and output markets constrain rural firms' trading relationships in Tanzania.

Much of the empirical evidence on relational contracting comes from international trade settings (Macchiavello and Morjaria, 2015; Startz, 2018), manufacturing (Mcmillan and Woodruff, 1999; Fafchamps and Quinn, 2016) or focuses on agricultural supply chains (Fafchamps and Minten, 2002; Macchiavello and Morjaria, 2020; Casaburi and Reed, 2019) where buyers and sellers only transact during harvest season. In contrast, this setting encompasses rural and urban areas in Tanzania to consider how upstream and downstream relational contracts are formed and sustained. Firms enrolled in this study are small or microenterprises with few employees - only 15% of firms have any paid employee - based in medium-sized rural towns in central Tanzania. Most firms source relatively homogeneous inputs from urban areas and re-sell them or process them into an value-added service in their rural communities. This includes basic food staples such as rice, beans, vegetables, and sugar, as well as household items like soap, and inputs for service providers such as thread, needles, bike tires, and cement. Despite operating in relatively competitive market conditions, I document substantial use of relational contracting by rural firms with upstream and downstream trading partners and compare how relational contracting norms respond to changes in search costs.

Other research offers examples of how firm productivity improves when new business contacts are introduced. Fafchamps and Quinn (2016) randomly link manufacturing firms in Kenya and find that business practices diffuse rapidly across new links. Cai and Szeidl (2018) find that firm productivity increases when managers in small and medium Chinese firms are randomly assigned to participate in business networking groups with managers from other firms. Brooks et al. (2018) study microenterprise mentors and showed that an important mechanism through which mentors influenced mentee outcomes was by introducing them to higher quality input suppliers.

A key difference in this setting is that contacts generated by this intervention intend to introduce buyers and sellers, rather than promote general dissemination of business knowledge or practices through exposure to knowledgeable peers. In that sense, this paper is closer to the work by Macchiavello and Morjaria and Ghani and Reed, who examine how changes in cost structure cause relational contracting to change. I build off work by Dillon et al. (2020), who study a paper version of the phonebook with particular attention on how households search for agricultural inputs. They document large impacts on firms and households using phones to source inputs and sell crops. Apart from studying a digital version of the phonebook, this research targets firms from a range of sectors with attention on urban-to-rural supply chains. Most firms in this study sell relatively homogeneous household commodities or providing common services. For these types of firms with modestly sized and irregular orders, we still know little about how the number and quality of business relationships affect operations.

The remainder of the paper is structured as follows: In Section 2, I provide background on information frictions and relational contracting in this setting. In Section 3, I use the background to motivate theoretical predictions that can be tested in data to understand how search costs affect relational contracting. Section 4 describes the experimental design and sampling frame. Section 5 provides details on the empirical strategy. I describe how willingness-to-pay for relational contracting was elicited through a discrete choice experiment and details on how treatment effects are measured. Section 6 describes results from the discrete choice experiment, phonebook usage, and field experiment survey data. Results from the field experiment highlight changes in 3 groups of outcomes: upstream outcomes, downstream outcomes, and productivity. I also provide results for the primary heterogeneous treatment effect of interest: differences between retail and service firms. Section 7 provides a discussion of results. Finally, in Section 8 I conclude by discussing the implications for firm productivity when a new technology facilitates a disruption to existing marketing norms.

2 Background: Urban-to-Rural Trade in Tanzania

2.1 Importance of Information Frictions

A firm's ability to mobilize resources and make adjustments that respond to changes in the market environment are important elements of its decision set. This includes the ability to choose among different goods and services offered by suppliers. Under excessive market fragmentation, which is more likely to occur in disconnected rural markets than in urban areas, excessive search costs limit firms' ability to engage in business transactions outside of their local market network. Jensen and Miller (2018) showed that mobile phone proliferation in southern India initially increased market integration in the fish market and subsequently lowered the cost of acquiring new information in complementary markets (boat-building) across geographically dispersed areas. It ultimately enabled high-productivity builders to grow and gain market share.

Search costs are a type of information friction that contribute to total transaction costs. In addition to physical travel costs, North's canonical 1991 paper described transaction costs as including search, bargaining, time, and contract enforcement costs associated with making market transactions, and well as social norms and institutional constraints. As mobile phone networks proliferated throughout the 2000s, the cost of communication decreased and lowered price dispersion in agricultural markets (Jensen, 2007; Aker, 2010). Yet, despite gains from cheaper communication, search and information frictions persist. Startz (2018) estimates that information costs, including those required to search for and maintain supplier relationships, explain a substantial portion of overall transaction costs in Nigerian wholesaler supply chains. Similarly, Allen (2014) estimates that nearly half of price dispersion is explained by information frictions in agricultural markets in the Philippines.

In the information frictions literature, it is common to point out that trade declines faster with distance than is explained by transportation costs alone. If this holds in the Tanzanian context, it implies that information frictions lower the total volume of trade in rural areas when substantial information costs are combined with remoteness and high travel costs. Aggarwal et al. (2018), in North-Central Tanzania, estimated that non-pecuniary costs of travel (including information frictions, opportunity costs, and concern of stock-outs) accounted for 57% of total travel costs.

In aggregate, information frictions and high search costs can lower productivity by increasing the likelihood of stock-outs, increasing transaction costs, and lowering firms' ability to adapt to changes in demand. For rural consumers that purchase from rural firms, welfare losses depend on whether there are many close substitutes in the market. In settings where consumers regularly purchase food staples from local markets, this can reduce food security through higher-than-necessary price variation, regular stock-outs in local firms, and high transportation costs to obtain preferred goods or services. Given that nearly half of rural household food budgets are spent in local markets, rural firms' supply chains are worth studying in detail to understand how local market institutions contribute to regional food security (Reardon et al., 2019). This research contributes to this literature by clarifying how input and output market business relationships contribute to small firms transaction costs and productivity.

2.2 Relational Contracting Norms

Once trading partners establish mutual trust, informal relational contracts are sustained by the value of future relationships (Baker et al., 2002). Relational contracting occurs both in markets where third parties have the capacity to enforce contracts and in settings where contract enforcement is weak. The key difference is that in settings with more contract enforcement, some part of the contract is binding and enforceable while additional benefits are contingent and result from a dynamic process where buyers and sellers transact over time to learn about each other (Michler and Wu, 2020; Sexton, 2013). Market transactions with contingency benefits can also arise in settings where little contract enforcement is provided by state institutions as long as the stream of future benefits is sufficiently high to compensate for costs of managing the relationship.

Instead of relying on externally enforced contracts, agents employ informal mechanisms to validate the quality of business partners or rely on repeat transactions as a commitment device 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. Using a survey of manufacturing firms in Vietnam, Mcmillan and Woodruff (1999) found that downstream firms were more likely to obtain credit from their upstream supplier if they have fewer options because the supplier benefits from the credible threat of holding-up shipments if the downstream customer does not pay their debt. This arrangement also reduces the downstream firms' bargaining power relative to their suppliers and it was not clear how this asymmetric power affected firms ability to grow their businesses. Similarly, Macchiavello and Morjaria (2020) found that higher competition among coffee mills in Rwanda lowers relational contracting with farmers by increasing incentives for farmers to default and decreasing coffee mills profit margins. In contrast, Ghani and Reed (2020) find that an increase in competition in input markets increased the provision of credit to repeat buyers in order to retain them as customers and deter entry of new firms.

The fact that high search costs and information frictions co-exist with relational contracting points to a central tension in this setting. If markets were perfectly competitive, all agents could engage in ad-hoc search in spot markets and obtain goods with the same price and quality attributes (Fafchamps, 2006). But, relational contracting, such as providing credit, arranging delivery, or ordering specialized goods, would not necessarily emerge because sellers must hold inventory and defer receipt of payment, or buyers must send payments and defer receipt of goods. If there is no recourse for unpaid debts, agents are forced to rely on cash payments at the moment of trade. To overcome these missing markets, agents build trust with their suppliers and customers in order to bear the risk of potential losses from allowing deferred payments.

In this context, some firms report repeat transactions with known suppliers, while others report engaging in ad-hoc search each time that they acquire inputs. I used baseline survey questions to characterize the typical 'contract' attributes between firms and their suppliers and customers. Table 1 documents common benefits at baseline of relational contracts for rural firms in their upstream (supplier) purchases and their downstream (customer) sales. When purchasing business inputs, only nine percent of firms report receiving any credit on goods purchased, 19% sent payments using mobile money, 29% reported receiving a price discount, and 17% had goods shipped to their storefront. Most of these benefits involve deferred payment and thus require buyers to build relationships with suppliers through repeat transactions. The exception is mobile money payments. Although mobile money payments are instantaneous and do not involve deferred payments, they represent a step toward formalizing a relationship because they require firms and their suppliers to exchange phone numbers, a pre-condition for repaying payments and arranging shipping. Not all firms rely on relational contracting with their suppliers and customers. Overall, only 40% of firms reported having preferred suppliers. The remaining 60% of firms may have suppliers that they recognize or are familiar with, but do not prioritize making purchases from them and are not consistently building the relationships required to obtain other benefits.

On the downstream side it is clear that, on average, rural firms *offer* benefits associated with relational contracting to their customers more often than they *receive* them from their suppliers. About 57% sold goods or services on credit, 53% gave a price discount to frequent customers, and 23% made special orders for their customers. Instead of asking about preferred or regular customers, the survey asked where most customers are from. The vast majority of firms (82%) report that most customers are from either their subvillage (similar to a neighborhood) or other areas in their village. Using mobile money with customers is equally infrequent as with suppliers - only 16% reported using it in the previous week.

2.3 Firm Heterogeneity: Retail and Service Firms

As detailed above, firms report a mix of purchasing inputs locally and travelling or having inputs shipped from another location. The experiment differentially lowers search costs for

Table 1: Upstream and Downstream Relational Contracting

	Mean	SD
Upstream Relational Contracting		
Receives Goods on Credit	0.09	0.29
Sends Mobile Money to Suppliers	0.19	0.39
Receives Price Discount	0.29	0.45
Has Preferred Suppliers	0.40	0.49
Input Acquisition Location		
Purchased Locally	0.33	0.47
Shipped from City	0.17	0.37
Travelled to City	0.50	0.50
Downstream Relational Contracting		
Sells Goods/Services on Credit	0.57	0.50
Receives Mobile Money from Customers	0.16	0.36
Gives Discount to Frequent Customers	0.53	0.50
Makes orders for Customers	0.23	0.42
Primary Customer Base		
Subvillage	0.30	0.46
Village	0.52	0.50
Other villages/cities	0.18	0.39

All variables are categorical (0/1).

rural firms to learn information about urban firms in one treatment arm. Therefore, to learn about how changes to search costs affects firms, it is worth considering which types of firms are more likely to transact in urban areas and which are more likely to search locally.

The natural division for examining firm heterogeneity is through firm sectors. The major sectoral demarcation is between retail firms and service firms. Retail firms are characterized by purchasing inputs and selling them at a mark-up to local customers. The most common retail firms are small dry-goods stores selling basic household commodities - rice, beans, sugar, tea, soap, etc. But the sample also include pharmacies, clothing retailers, and agro-input sellers. Service firms, on the other hand, purchase inputs and then engage in value-added production to provide a service to their customers. The most common service firms are tailors, bike mechanics, restaurants, and salon operators. All of these firms source inputs (thread, needles, bike tires, nails, raw food, shampoo, razors, etc.) that contribute to the service they provide.

Table 2: Baseline Input Acquisition by Firm Sector

	Service Firm	Retail Firm
Value of Inputs Purchased (Tsh)	73,187.11	369,618.30
Transport Costs on Inputs (Tsh)	4,140.72	12,349.11
Transport Costs Share of Inputs Purchased	0.10	0.05
Transport Costs Share, if Purchased in City	0.24	0.07
Inputs Acquisition		
Purchased Locally	0.56	0.20
Shipped from City	0.09	0.25
Travelled to City	0.35	0.56

Notes: T-tests of differences by sector reject a null of no difference with p-values<.01 for all variables.

Table 2 shows differences in input acquisition by firm sector. Over half of service firms purchased inputs locally, while only 20% of retail firms did. In contrast, 81% of retailers and 44% of service firms acquired inputs from a city, through travel or shipping. The average input purchase value was over four times as large for retail firms than services firms (about 370,000TSH for retailers compared to 73,000TSH for service firms, equivalent to approximately $30USD and $155USD). Yet, travel costs as a share of order size was twice as much for service firms than retailers, at 10% and 5%, respectively. The gap in share of transportation costs widens if the sample is constrained to include only those firms that purchased from a city. For service firms, the transport costs as a share of the order size jumps to 24%, while for retailers it only goes up to 7% of total order size.

3 Predictions: Search Costs with Relational Contracts

Thus far, I have described the importance of information frictions in rural areas and presented information about firms participation in relational contracting with their suppliers and customers. Table 1 showed descriptive evidence that firms provide relational contracting benefits to their customers more often than they receive them from their suppliers. This merits exploring in detail by asking what does economic theory predict will happen to relational contracting with suppliers and customers if search costs decrease?

3.1 Upstream and Downstream Relational Contracting

Suppliers have an incentive to offer relational contracts as long as they anticipate that the stream of future benefits from having a repeat customer is higher than the cost of maintaining the relationship. If it is too easy for customers to switch, sellers would have less incentive to offer relational contracts (Fafchamps, 2006). On the other hand, if search costs are so high that there are effectively no other sellers (they are a monopoly), then they also might not have a strong enough incentive to provide relational contracts to their customers. The presence of relational contracts for a given regime of search costs exists in between those two ends of the spectrum. When search costs are high and markets are imperfect, relational contracts can be a rational 'second best.' As recipients, relational contracts allow firms to access benefits that are not provided by other markets (credit, shipping) or lower input prices (discounts). As providers, relational contracting allows firms to build a loyal customer base. The question becomes how do relational contracts change when search costs decrease?

First, consider the upstream case where firms arrange relational contracting with their input suppliers. Under a regime of high search costs, rural firms have fewer incentives to search for new suppliers because the cost of doing so could quickly exceed the benefit of meeting a new supplier, including costs to confirm availability of goods, establish trading norms, and verify quality. When search costs decrease, the outside option becomes more valuable since it becomes less costly for firms to locate and initiate relationships with new suppliers.

If upstream relational contracting increases after search costs decrease, it suggests that suppliers have bandwidth to provide relational contracts after the bargaining position of their customers improves. In fact, in a survey of firms in urban centers conducted as a part of this study, 40% of urban firms indicated that they provided credit to their customers and 80% said they provided price discounts to frequent customers. Recall from Table 1 that only 10% of rural firms received credit from their suppliers and only 40% received a price discount. It shows that upstream suppliers in this setting provide relational contracting benefits, but rural firms were less likely to benefit from them.

Prediction 1: Decreasing search costs increases the value of an outside option for firms with respect to their suppliers. If firms initiate many new relationships, relational contracting would decrease because it requires repeat transactions. If, however, firms increase engagement with known suppliers, a decrease in search costs will lead rural firms to negotiate more favorable trades and increase the extent of relational contracting with known suppliers with whom they have a record of repeat transactions.

Next, consider the downstream case of rural firms relational contracting with their customers. Rural firms provide relational contracts to their customers as long as gains from a future stream of transactions is sufficiently high. From the rural customers' perspective, it is now cheaper to search among potential sellers. From rural firms perspective, they expect to interact with a pool of new potential customers. We could expect these rural customers to demand better terms from rural firms as observed by Ghani and Reed 2020). But from the rural firms' perspective, they are more likely to interact with new customers and change their offer of relational contracts. This could occur through two channels. First, if firms reach many new customers, they are less likely to provide relational contracting benefits to new customers with few transactions, bringing down their average provision of benefits. Second, even if firms customer base doesn't change, they may still anticipate new customers and withdraw relational contracting benefits from their pre-existing customer base. If that is the case, it provides evidence that the change in search costs increases firms bargaining power relative to their customers.

Prediction 2: Decreasing search costs increases the value of an outside option for firms *and* their customers. If firms access a new customer base, a decrease in search costs will lead rural firms to reduce the extent of relational contracting with their customers. Or, if firms have to compete to retain their existing customers, they will increase their provision of relational contracting.

3.2 Urban-to-Rural Trade with Heterogeneous Firms

Because relational contracting relies on repeat transactions, it is important to consider how transaction costs vary with firm type. Retail firms have larger input orders than service firms and purchase from cities more often, shown in Table 3.2. One important component of transaction costs are transport costs - a variable cost of production that must be paid each time a firm sources inputs. For firms with large input order sizes, it is relatively cheaper to search over a wider geographic area because they have lower transportation costs per unit of goods acquired.

In general, retail firms have larger orders, lower per-unit transaction costs, and are more likely to transact in cities. Paying transport costs to reach the city is worth it for some firms so that they can access lower input prices that are available in cities. This insight provides another prediction about how a networking technology that connects urban and rural firms will influence search behavior. Specifically, retail firms are more likely to search in cities compared to service firms because they have smaller transportation costs per unit of goods purchased.

> **Prediction 3:** If per unit transaction costs are high, firms will prefer to search in their local area. If per unit transaction costs are low, firms will prefer to search in urban areas because higher travel costs are attenuated by gains from lower input prices.

4 Experimental Design

This research is part of an ongoing program in central Tanzania to develop and market digital telephone directories that operate on all types of phones. *eKichabi* is the name for the digital phonebook based in Central Tanzania.[1] The digital phonebook is accessible through a USSD short code and is organized through a menu system similar to those used for mobile phone top ups and and mobile money transactions commonly seen in developing countries. The phonebook platform organizes participating firms by location and sector

[1] The word *eKichabi* is a portmanteau for "electronic Business Book", or *Kitabu cha Biashara* in Swahili.

and guides users through a set of menus to reach a screen that displays the firm's contact information, location, sector and product specialities.[2] Unlike a typical phonebook from a US setting, this phonebook app only lists firm contact information and does not list contact information for households or individuals that do not operate firms.

4.1 Description of Intervention

The program targets 3 types of participants linked through urban-to-rural supply chains: upstream urban suppliers, rural firms, and downstream rural consumers. The intervention focuses on the middle link of the supply chain: rural firms. Rural firms from small to medium sized commercial centers were invited to list their firm in the digital phonebook and then were randomly assigned to treatment and control groups. The first feature of the intervention is that all treated firms are listed in the digital phonebook and can search for other firms in the same treatment group. This means that they can search for their own business and search for other rural firms in their same treatment arm. Second, treated rural firms were split into two variations - 1) **Upstream Treatment:** a phonebook listing that targets upstream suppliers in urban areas, 2) **Downstream Treatment:** a phonebook listing that targets downstream consumers in rural areas.

Random assignment at the firm level generates exogenous variation in the likelihood that rural firms communicate with either upstream and downstream contacts. The objective of the upstream treatment is to lower the cost of contacting new potential suppliers in urban areas and the objective of the downstream treatment is to lower the cost of contacting new potential customers in rural areas. This variation effectively lowers the cost of making contacts along the supply chain and can be used to identify the impact of lowering search costs on business outcomes.

4.1.1 Search and Visibility by Treatment Group

The phonebook affects firms in two ways. First, firms listed in the phonebook are *visible* to other users. Second, firms themselves can *search* within the platform. The phonebook

[2] For an example of the phonebook menu system, see Figure 4 at the end of the paper and Dillon et al. (2020) and Weld et al. (2018) for more details.

permits constraining the visibility and search of specific users by assigning phone numbers to have viewing restrictions. Figure 1 summarizes the search and visibility restrictions for each group. Each treatment group has a 'search capacity,' which describes what treated firms can see when they search within the phonebook application. Each group also has a 'listing visibility', which describes which users can view each treatment group. The upstream treatment group can search for firms in urban areas and for other firms in their same treatment arm. The downstream treatment group can only search for other firms in their same treatment group and cannot search for urban firms. Their listing, however, is visible to customers in rural areas. Since customers are not listed in the phonebook, the downstream treatment arm cannot search for customers in the phonebook.

Since both upstream and downstream treatment groups can search for other firms in their treatment group, it is important to note that treatment effects capture search activity with nearby firms. Treatment assignment to the upstream group can be thought of as increasing the probability that the firm communicates with urban firms and assignment to the downstream treatment group increases the probability of communicating with customers. Treatment effects for the upstream group capture any additional effect that occurs due to having access to urban firms. And, treatment effects for the downstream group capture any additional effect due to being searchable by customers. When control firms dial into the phonebook, they are routed to see only firms that are located outside the relevant region and cannot search for any treated firms or urban firms.

4.1.2 Random Order of Listed Firms

The phonebook platform permits the research team to specify a listing order for firms based on string search queries, locations, and/or sectors. We assigned pre-specified phone numbers to view each list. Similar to searches in any online platform, we assume that search order corresponds to higher exposure for firms at the top of the search list (Varian, 2007; Athey and Ellison, 2011; de Cornière, 2016). Given that higher exposure could inadvertently prioritize some listed firms over others, the firm listing order was randomized for each new user that accessed the platform. In expectation, no firm in either arm will appear at the top of all searches within their assigned treatment arm, regardless of whether users search through menus or enter search terms.

4.1.3 Experimental Compliance

This dual nature of the platform (treated firms can both search and be found) has consequences for interpreting the average treatment effect (ATE). An intent-to-treat (ITT) causal estimate is equivalent to the ATE under perfect compliance. Here, the research team manages the firm listing on the application platform so that treatment compliance is guaranteed because all firms and consumers only access the version of the platform that is assigned to them. But, not all firms were found in searches by consumers nor did all firms choose to search within the platform itself. But, if firms changed their phone number and did not inform the research team, they could have inadvertently been assigned different application visibility and would not longer be experimentally compliant. Therefore, the treatment effect estimates are most consistent with an ITT interpretation.

4.1.4 Pre-Analysis Plan

This experiment was registered with the American Economic Association's Social Science Registry after completing the baseline survey in September 2019. A recent paper by Duflo et al. (2020) encourages researchers to be cautious in pre-specifying every possible outcome in order to remain open to unanticipated knowledge generation. The primary registered outcomes for this study includes most of the main outcomes presented here, did not include a relational contracting index as a primary outcome. The pre-analysis plan emphasized new relationships that firms could make as a result of treatment but did not directly anticipate the impact on prior relationships, which is why I provide a conceptual framework and motivate new findings using baseline outcomes. In the pre-analysis plan, I also noted implementing a discrete choice experiment to understand the value of exsiting relationships. In service of increasing transparency of how a pre-analysis plan morphs into a paper, I report pre-registered outcomes that are not highlighted in the main paper in an online appendix. This includes the other pre-registered heterogeneous treatment effects - gender of firm owner, remoteness of village, and firm preferences for either a downstream or upstream listing.

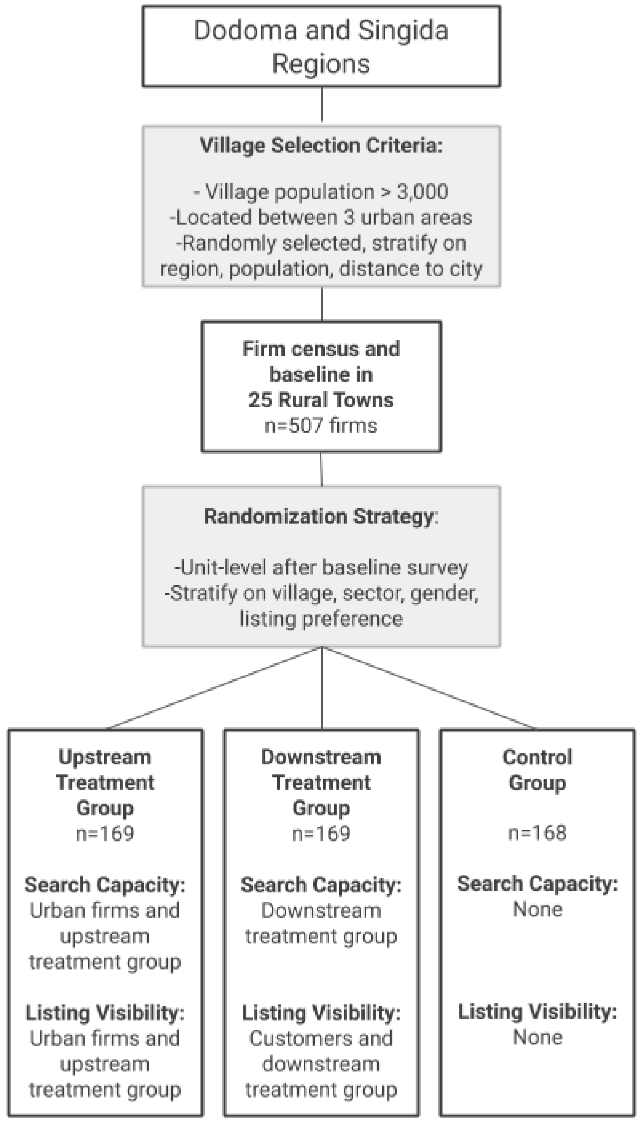

Figure 1: Experimental Design and Treatment Descriptions

4.2 Sampling Frame

Two regions in central Tanzania were identified for the research sample - Dodoma and Singida. Three urban centers- Singida City, Dodoma City, and Manyoni town- bound a trading area that encompasses the western half of Dodoma region and the southern half of Singida region. Villages located within wards connecting these three urban hubs were selected as the pool of sample villages. Focusing on geographically contiguous area increases the likelihood that firms in selected communities trade with the chosen urban areas and ensures that the phonebook lists firms that are relevant to their local commercial area.

Within this trading area, firms from villages with a population above 3,000 people were eligible to be drawn into the baseline sample of villages where the research team carried out phonebook enrollment. The population criteria ensures that there is sufficient density of potential businesses to invite for enrollment. There were 54 eligible villages that fit the population criteria within the study area. Of these eligible villages, 20 villages were randomly selected after stratifying on primary urban center, distance to urban center, and population. This stratification scheme ensures that villages are dispersed throughout the trading area such that there is variation in village remoteness and transportation costs. In addition, there were 5 pilot villages that were chosen for their relative proximity to Dodoma, where the research team was based. Although these villages were not randomly selected, enrolled firms were added to the pool of baseline firms in order to increase sample size and improve power for estimating effects. Firm-level random assignment followed the same procedure as that described below for baseline firms from randomly selected villages. Figure 1 shows the experimental design, sampling criteria, and strata variables.

4.2.1 Stratified Treatment Assignment

Firms were randomly allocated to experimental arms after the baseline survey was implemented. Unit-level randomization was chosen to maximize power and because firm-to-firm spillovers are expected to be minimal. As suggested in Athey and Imbens (2017), strata contained 6 firms (two times the number of intervention arms). Enrolled firms were grouped into strata based on village, sector, gender, and a self-reported measure of whether the firm places greater weight on accessing upstream contacts or downstream contacts, all of which were pre-specified in the pre-analysis plan. The measure of firm treatment preferences is used to ensure that firms who have a strong preference for either treatment are dispersed across arms.[3]

[3]Strata were assigned using the optimal greedy algorithm using R package `blockTools`, suggested by Moore (2012). This method is preferred in this setting because there is variation in the number and sector of firms per village. If strata were created by partitioning firms by village, sector, and gender, there would be too few firms per strata to optimally estimate sampling variance (Imbens and Rubin, 2015). The `blockTools` package assigns firms to strata by minimizing the maximum multivariate distance of firms within strata based on pre-selected variables.

4.2.2 Upstream Supplier and Downstream Customer Phone Numbers

Treatments intend to connect listed *rural firms* (the target of the intervention) that have their contact information in the phonebook platform with *platform users*, defined as other firms or consumers that dial into the phonebook platform to connect with listed firms. Figure 5 at the end of the paper shows the timing of treatments, surveys, and communication with urban firms and rural customers. After collecting baseline questionnaires with participating firms in the sample communities drawn from rural areas, the research team also visited three urban centers - Dodoma City, Singida City, and Manyoni Town to register urban firms. A total of 348 wholesale and retail firms consented to list their business contact information in the phonebook platform. This pool of firms is the 'urban' firm group. Their phone contact information is only searchable by firms in the upstream treatment arm. And, their phone numbers are constrained to only search for rural firms in the upstream treatment arm.

The last stage of fieldwork involved randomly selecting smaller communities in areas near to rural firms and requesting a community meeting to introduce the digital phonebook. These are communities with few local businesses and populations less than 3,000 people. Households in these small rural communities typically have to travel to neighboring towns to purchase goods and services. During community meetings, attendees were taught how to use the phonebook and provided with examples of use-cases. Our research team gathered 540 phone numbers from attendees that are used as the pool of 'downstream' consumers that can search for firms in the downstream treatment arm.

Finally, the digital phonebook was live and accessible to any mobile phone in Tanzania. Any new, unknown phone number was supposed to be randomly assigned to view either the upstream or downstream treatment arms. But, a programming error resulted in all unknown phone numbers being assigned to view the downstream treatment arm only. It means that downstream group had a higher exposure to unknown callers than the upstream arm.

4.3 Sample Characteristics

The sample area is located in the semi-arid central region of Tanzania. Table 10 at the end of the paper compares characteristics from the sample regions with the national average.

All three regions are less urban than the national average, have lower rates of non-farm employment and have lower mobile phone ownership rates. For a phone based study like this one, access to a mobile phone is required to participate and is part of the selection criteria. However, the first filter for participation is business ownership, which tends to overlap with phone ownership. No businesses declined to participate due to a lack of access to a phone.

Figure 2: Urban Firms, Rural Firms, and Rural Customers Locations in Tanzania

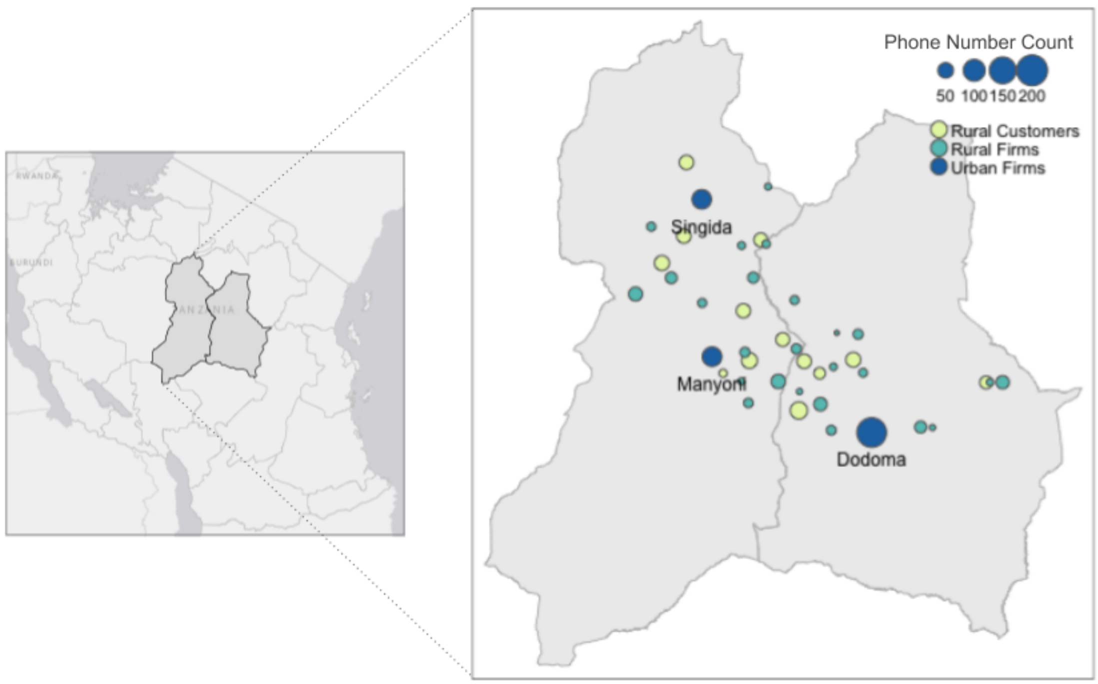

Figure 2 shows the geographic distribution of urban firms, rural firms in the treatment and control groups, and rural customers in Singida and Dodoma regions in central Tanzania. The size of the bubble indicates the number of phone numbers that were gathered from each location. Urban firm contact information 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 3: Baseline Characteristics for Rural Firms

Variable	N	Mean	St. Dev.
Age	507	35.45	11.06
Woman-owned	507	0.36	0.48
Yrs Education	507	7.41	3.43
Firm Age	506	5.46	6.80
Num. Paid Employees	503	0.21	0.59
Owns Smartphone (0/1)	457	0.24	0.43
Distance (km) to major market	507	65.26	31.32
Num. of competitors in village	435	4.77	3.84
Sector		**Share**	
Food/Crop Retail	204	0.40	
Non-Food Retail	60	0.12	
Ag Services	42	0.08	
Non-Ag Services	124	0.25	
Skilled Trades	77	0.15	

4.3.1 Rural Firm Characteristics

Table 3 presents descriptive statistics for firms that were enrolled into the phonebook platform during the baseline survey. The average firm owner is 35 years old and has 7 years of schooling. The average firm is just over 5 years old and has 0.21 paid employees - indicating that the vase majority of firms did not report any paid employees. About 36% of firms enrolled were owned by women. Firms reported an average of about 5 competitors from the same sector in their village. The majority of firm sectors relate to retail activities, split between 40% that sell food and crops and 12% that sell non-food items like clothing and medicine. The rest of firms are service firms that provide agricultural services (8%) like tractor rentals and milling, non-agricultural services (25%) like barber shops and restaurants, and skilled trades (15%), which includes tailors, welders, carpenters, and builders. The sample size varies slightly due to some instances of non-response and because some questions were dropped at different phases in piloting. As described below, regressions that measure treatment effects control for non-response in baseline outcomes.

4.3.2 Balance Checks

The balance table in Table 11 at the end of the paper compares the means for the treatment groups, control group, and t-tests for differences between groups. The balance table compares differences across groups among 22 covariates, including baseline demographic characteristics and baseline outcomes. Out of 22 covariates, 4 exhibit marginal imbalance at the 10% level - whether a firm was women-owned, owner age, customer calls, and the output price index. And, one covariate was imbalanced at the 5% level - whether the firm has access to electricity. But, an F-test of joint significance across all covariates fails to reject the null of no joint significance. Rather than add imbalanced covariates as controls in treatment effects regressions, I use a machine learning procedure to produce a unit-level prediction index following Ludwig et al. (2019) and Wager et al. (2016). 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.

5 Empirical Approach

5.1 Discrete Choice Experiment

To understand how firms value relational contracting, I administered a discrete choice experiment designed to elicit willingness to pay for benefits that are associated with relational contracting with suppliers following **?**. 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 previous section, 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.[4] After completing a series of comparisons, each participant will have generated binary choice data with information on which attributes were available for each choice.

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 (**?**).[5] 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:

$$Y_{ijk} = \alpha + \beta_1 Price_{ijk} + \beta_2 Supplier_{ijk} + \beta_3 Transport_{ijk} + \beta_3 Payment_{ijk} + \gamma_k + \epsilon_{ijk} \quad (1)$$

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.

[4]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.

[5]For further detail on assumptions, see Section C in the appendix.

5.2 Treatment Effects Estimation

Two sources of data were used to estimate treatment effects. First, administrative data from the phonebook application was used to understand what types of information firms searched for. Second, primary outcomes were measured using interviews from one baseline and three follow-up surveys collected over the treatment period. To estimate the causal effect of treatment on the outcome variables, I employ ANCOVA regressions.[6] Estimates of intent-to-treat (ITT) use the following ANCOVA specification:

$$Y_{it} = \alpha + \beta_1 Treat_i^{US} + \beta_2 Treat_i^{DS} + \gamma Y_{i,t=0} + \theta X_i + \lambda_t + \epsilon_{it} \tag{2}$$

Y_{it} represents the outcome variable of interest for firm i in survey round t. $Treat^{US}$ and $Treat^{DS}$ are the treatment indicator variables that represent whether firms were assigned to the upstream or downstream treatment groups. The intent to treat estimates are identified by $\hat{\beta}_1$ and $\hat{\beta}_2$, and are interpreted as the effect of being assigned to either upstream ($\hat{\beta}_1$) or downstream ($\hat{\beta}_2$) treatments on the outcome of interest. The subscript t indexes event time and is set to zero for the baseline value. $Y_{i,t=0}$ are the baseline values of the outcome variables. The vector X_i includes strata indicators, an indicator if the baseline outcome value was missing at baseline, and the machine learning prediction index, which does not vary with time.[7] The term λ_t captures any survey-specific time shocks. As in conventional in unit-level random assignment, standard errors were clustered at the firm level.

Multiple hypothesis testing follows **?** and Anderson (2008) by setting the false discovery rate to 5%. A FDR of 5% expects that at least one test out of twenty falsely rejects the null of no effect (a false positive or Type I error). Sharpened q-values are presented by each outcome grouping. Outcomes were grouped according to whether they pertain to primary upstream, downstream, or productivity outcomes.

[6] ANCOVA improves precision of estimates by including baseline values of outcome variables as controls in regressions. It is particularly useful in settings where outcome variables exhibit low and constant auto-correlation and are measured with noise. Presenting post-treatment data from numerous randomized evaluations with firms, McKenzie (2012) shows that auto-correlation of firm profits in Ghana and Sri Lanka are relatively constant, falling between 0.2 and 0.4. He finds that ANCOVA is preferred to differences-in-differences specifications for constant auto-correlation below 0.5.

[7] Including the 'missing at baseline' variable allows the ITT estimate to keep any firms which do not provide answers to specific questions during baseline rather than dropping them.

Section B in the appendix provides details on several robustness checks. Section B.2 shows that attrition was unrelated to treatment and baseline outcomes. Section B.3 provides p-values and multiple hypothesis testing on main outcomes using randomization inference. And, Section B.4 provides treatment effects estimates using an alternate index construction using inverse covariance matrix weighting.

5.2.1 Heterogeneous Treatment Effects

Heterogeneous treatment effects were estimated using the following model:

$$Y_{it} = \alpha + \beta_1 Treat_i + \beta_2 Service_i + \beta_3 Service_i \times Treat_i + \gamma Y_{i,t=0} + \theta X_i + \lambda_t + \epsilon_{it} \tag{3}$$

$Treat_i$ denotes the combined treatment groups. The variable $Service_i$ takes a value of 1 if a firm is in the services sector and takes a value of 0 if a firm is in the retail sector. β_1 is treatment effect for retail firms. $\beta_1 + \beta_3$ is treatment effect for service firms. β_3 is the difference between service and retail.

5.3 Outcome Variables

Outcomes are grouped into three categories - upstream, downstream, and productivity outcomes. Within the upstream and downstream categories, there are three analogous outcomes: Relational contracting index, engagement with new suppliers and customers, and phone communication. For the upstream outcomes, there is a supplier search index whose components include a series of variables indicative of search intensity, including number of suppliers called for information, number of suppliers that a firm transacted with, number of different locations searched, and whether suppliers were non-local. Since firms search at irregular intervals, these questions reference the most recent time that a firm purchased inputs.

On the downstream side, since it is not possible for firms to know the full search activities of their customers, the only variable that was asked is whether any customers came from outside the firms' village. This variable, called 'Non-local Customer', is a binary outcome that takes a value of 1 if the firm reported having a customer come from outside their village. As described in the set-up for this experiment, experimental firms are located in medium-sized towns that often serve as the primary purchasing locations for smaller, surrounding communities. It is common for firms to know whether one of their customers is from their same village or comes from nearby. This was a relevant outcome because the experiment provided information about how to dial into the digital phonebook to surrounding communities, knowing that they usually purchase goods from firms in participating villages.

Productivity outcomes include a sales revenue index, an output price index, an input price index, transport costs as a share of inputs purchased, and whether inputs were purchased locally. The sales revenue and output price indices provides information about whether treated firms experience a sustained increase in sales relative to control. The input price index, transport costs, and whether firms purchased inputs locally provide information about whether firms input sourcing costs decreased, providing evidence that they became more efficient. Further detail on index construction is provided in Section A in the appendix.

5.4 Empirical Tests

Table 4 summarizes empirical tests that can be used to inform the theorized relationships introduced in Section 3 using equation 2, and suppressing the treatment group counter so that $\beta_{\{1,2\}}$ collapses to β. The first panel summarizes how to interpret coefficients for upstream outcomes related to contact with new suppliers and changes in relational contracting, depending on the direction of treatment effects. The second panel summarizes how to interpret coefficients for downstream outcomes related to contact with new customers and changes in relational contracting depending on the direction of treatment effects. Part of the analysis compares whether the upstream treatment led to larger effects in upstream outcomes and whether the downstream treatment led to larger effects on downstream outcomes. The magnitude of treatment effects provides evidence about whether firms in either treatment group more readily increase their bargaining power with suppliers or with their customers.

Table 4: Summary of Empirical Tests

New Suppliers	Relational Contracting Response	Interpretation
Rural Firm Upstream Treatment Effects		
$\beta \leqslant 0$	$\beta > 0$	Increase relational contracting by increasing bargaining power with current suppliers
$\beta \leqslant 0$	$\beta < 0$	Decrease relational contracting by decreasing bargaining power with current suppliers
$\beta > 0$	$\beta < 0$	Adding new suppliers decreases average provision of relational contracting benefits
Rural Firm Downstream Treatment Effects		
New Customers	Relational Contracting Response	Interpretation
$\beta \leqslant 0$	$\beta > 0$	Increase relational contracting by decreasing bargaining power relative to current customers
$\beta \leqslant 0$	$\beta < 0$	Decrease relational contracting by increasing bargaining power with current customer base
$\beta > 0$	$\beta < 0$	Adding new customers decreases average provision of relational contracting benefits

6 Results

6.1 Willingness to Pay for Relational Contracting Attributes

Table 5 shows results from the discrete choice experiment. To make coefficients economically meaningful, they were converted into a measure of WTP by dividing the point estimate of the mean of an attribute level by the price coefficient.[8] The column 'WTP (Percent)' reports the willingness to pay and confidence interval for each contract level. 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 some contract attribute levels and consistently preferred those with different features.

[8]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.

Table 5: WTP for Contract Attribute Levels

	WTP (pct points) [CI]	Reference Category
Supplier Known	0.06	Supplier unknown
	[0.02, 0.10]	
Goods Delivered	0.33	Travel to city
	[0.25, 0.40]	
Mobile money payment	-0.01	Other payment options
	[-0.06, 0.05]	
50% cash now	0.18	Other payment options
	[0.12, 0.25]	
80% cash now	-0.01	Other payment options
	[-0.08, 0.06]	

Notes: The first column lists contract attribute levels from a discrete choice experiment. The second column shows the coefficients from a mixed logit specification converted. Coefficients represent the percentage point increase or decrease that participants were willing to pay on average for a contract attribute level. 95% confidence interval are in brackets. The reference category describes the other contract attribute level that participants compared against. 'Other payment options' includes cash, mobile money, and credit.

Firms expressed a WTP of a 6% premium for inputs from a known supplier relative to an unknown supplier, a 33% premium for goods to be delivered relative to travelling to a city, and 18% premium for provision of generous credit terms relative to paying cash at the time of purchase. This highlights the extent to which firms are willing to pay higher prices on inputs for contract attributes that benefit firms. Although a 6% price premium to purchase from known suppliers is small compared to having goods delivered and obtaining credit, it is notable because only 40% of firms in the baseline survey reported having preferred suppliers. And, in practice, obtaining these benefits requires forming relationships with known input suppliers.

6.2 Phonebook Usage

Before turning to treatment effects using data collected from surveys, this section reports results using data generated from the phonebook application. Data include user phone number, time and date of search, number of menu screens, and information about locations, sectors, and firms searched. Phone numbers collected by the research team can be matched back to identify whether it came from a known rural firm (firms with experimental conditions), rural customer, or urban firm. Table 6 reports results from regressions of phonebook usage outcomes on treatment. Outcome variables along the top row of each panel are binary variables, after collapsing all usage to an extensive margin measure of usage over the entire treatment period. Control firms were assigned to see firms that are outside of their geographic trading area. Panel A shows treated rural firms search behavior. Column 1, "Used Phonebook App" denotes whether a firm ever dialled into the application during the entire treatment period. The control mean in Column 1 shows that 50% of control firms dialed into the phonebook application at least once. But, both treatment arms were significantly more likely to dial into the platform, providing evidence that the firms available to them were more relevant than those visible to control firms.

Columns 2-5 denote whether a firm searched an urban area, rural area, retail firm, or service firm.[9] Column 2 reports whether firms searched in urban areas and confirms that control firms and the downstream treatment could not search urban firms in their region. It also shows there was relatively low uptake by the upstream treatment arm to search in urban areas – only 26% of the upstream arm ever searched for information from urban areas. Column 3 reports whether firms searched for other rural firms. Despite not having the capacity to search for rural firms, about 16% of control firms searched for rural firms. This variable is coded to include search queries and it is likely that control firms attempted to search by typing certain locations. Both upstream and downstream had the capacity to search for rural firms, and roughly 52% of downstream and 41% of upstream treatment arm searched for other rural firms (excluding instances where firms searched for their own listing).

Columns 2 and 3 provide information about whether firms were more interested in searching within urban areas or in rural areas. The upstream treatment arm is the only group that had the capacity to search for both, and they searched more in rural areas (41% searched rural areas compared to 26% that searched in urban areas). Columns 4 and 5 show whether there was more interest in searching for retail or service firms. After accounting for the

[9]Not all firms that dial into the phonebook app reach a final screen that lists a business phone number. Firms reported to the research team that sometimes they would use it to search for firm names, locations, and sectors, all of which can be found without going to the final screen that features a firm phone number. In other cases, the cell network may have failed or the USSD shortcode host could have timed out.

Table 6: Results: Rural Firm Phonebook Application Usage

Panel A: Firm Search Behavior in Phonebook Application

	(1) Used Phonebook App	(2) Searched Urban Areas	(3) Searched Rural Areas	(4) Searched Retail Firms	(5) Searched Service Firms
Upstream Treat	0.10*	0.26***	0.25***	0.18***	0.06
	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)
Downstream Treat	0.14**	0.02	0.36***	0.19***	0.16***
	(0.05)	(0.02)	(0.05)	(0.05)	(0.05)
Control Mean	0.50	0.01	0.16	0.15	0.26
Observations	507	507	507	507	507
Adj. R-squared	0.02	0.18	0.07	0.04	0.02

Panel B: Firm Found in Phonebook Application

	(1) Found by Any User	(2) Found by Rural Customer	(3) Found by Urban Firm	(4) Found by Rural Firm	(5) Found Own Listing
Upstream Treat	0.43***	-0.01	0.12***	0.37***	0.19***
	(0.04)	(0.02)	(0.03)	(0.04)	(0.03)
Downstream Treat	0.61***	0.58***	0.07***	0.61***	0.31***
	(0.04)	(0.04)	(0.02)	(0.04)	(0.04)
Control Mean	0.00	0.00	0.00	0.00	0.00
Observations	507	507	507	507	507
Adj. R-squared	0.32	0.49	0.04	0.31	0.12

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, strata fixed effects, and the prediction index. All dependent outcome variables are categorical (0/1) and denote any usage over the entire treatment period. Coefficients identify the effect of treatments on firm searches in phonebook (Panel A) and visibility (Panel B). All outcome variables exclude instances where firms searched for their own listing, except for Column 5 in Panel B "Found Own Listing."

control group search attempts, about 33-42% of treated firms searched for either retail or service firms.

Panel B reports whether treated firms were found by users. The control mean for all four specifications is zero since control firms are not listed in the phonebook app. Many downstream firms (61%) were found by any user and 43% of upstream firms were found by any user. As shown in columns 3, upstream treatment firms were more likely to be found by other rural firms than by urban firms. But, the downstream treatment arm was almost equally likely to be found by customers (58%) and other rural firms (61%). It is consistent with the finding from panel A where firms appear to search more for information from other rural areas. Finally, column 5 shows that firms also used the app to confirm that their listing was visible.

6.3 Upstream, Downstream, and Productivity Treatment Effects

Table 7 reports results for each group of outcomes over three rounds of follow-up surveys. Coefficients on indices can be interpreted as the number of standard deviations increase or decrease relative to the control group. First, Panel A reports treatment effects for the upstream outcome grouping. Firms in the upstream treatment arm increased relational contracting index with suppliers by 0.10 standard deviations (Column 1). Firms in both treatment arms decreased search activities by about 0.13 standard deviations compared to the control group (Column 2). Nearly 28% of firms in the control group reported buying inputs from a new supplier while both groups were about 4-5 percentage points less likely to have a new supplier, but the p-value on the upstream arms fails to reject the null of no effect (Column 3). Similarly, of all suppliers with whom control firms communicated, 12.6% were new, and both treatment groups marginally decreased their new suppliers share by 2.6-2.8 percentage points (Column 4). Finally, downstream firms also marginally decreased phone communication with suppliers. But, none of the marginally significant outcomes in columns 3-5 survive multiple testing corrections.

Earlier, I 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.

Second, Panel B reports treatment effects for the downstream outcomes grouping. Firms in both treatment arms decreased relational contracting with their customers at nearly the same magnitude - by about 0.10 standard deviations (Column 1). Firms in downstream treatment had small but positive coefficients on their likelihood of having any new customer and the share of new customers, but standard errors were too large to provide conclusive evidence that they had more new customers (Columns 3 and 4). These mixed results show that the phonebook increased the value of the outside option for rural firms, *without* substantially increasing their customer base. As highlighted in the conceptual framework, it provides evidence that firms increase their bargaining power relative to customers and the decrease in relational contracting comes from withdrawing contracting benefits from customers whom they previously knew.

Column 2 reports results for the variable 'Non-local Customer', a measure for whether firms reported having any customer come from outside their village. The point estimate on the downstream treatment arm is negative but not significant, failing to provide conclusive evidence on whether the downstream arm had fewer non-local customers. Phonebook usage data showed that downstream firms were looked-up nearly three times as much as those in the upstream treatment arm. Despite this, the downstream treatment arm had lower overall phone engagement with customers according to self-reported measures that were combined into the 'Customer Phone Activity Index'. Firms in the downstream treatment arm had -0.183 standard deviation decrease in communication with customers via phone.

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 6). 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.

Panel C displays the primary productivity outcomes. There are no significant changes in business revenue or input prices. But, firms in the upstream treatment arm had marginally higher output prices. This is consistent with evidence that firms pull back on downstream relational contracting by increasing their sales prices. Columns 4 and 5 in Panel C show that the downstream arm was more likely to purchase inputs locally in their village and paid lower per-unit transaction costs on their orders. Control firms paid on average 5% of the input order size on transport costs, and downstream firms paid 1.7% less.

The downstream treatment arm was also 9.5 percentage points more likely to purchase locally than the control group. These results reflect the fact that downstream treatment arm could search for other rural firms in their same arm but *were not able* to search for urban firms. This is also consistent with behavior that values relational contracting. It may be more difficult for firms to form relational contracting partnerships with input suppliers in cities for a number of reasons. Firms in urban centers supply hundreds of firms and it may be more difficult to keep track of relationships. In that sense, it is much more likely for firms to form trade relationships in their local area. And, it shows that they value saving transport costs and possibly save time by sourcing from areas that are near to where their business is located.

Table 7: Results: Upstream, Downstream, and Productivity Intent-to-Treat Effects

Panel A: Upstream Outcomes

	(1) Supplier Relational Contracting Index	(2) Input Search Activity Index	(3) Any New Supplier (0/1)	(4) New Supplier Share	(5) Supplier Phone Activity Index
Upstream Treat	0.101***	-0.134***	-0.046	-0.028*	-0.036
	(0.033)	(0.043)	(0.029)	(0.015)	(0.047)
Downstream Treat	0.045	-0.136***	-0.048*	-0.026*	-0.081*
	(0.032)	(0.041)	(0.029)	(0.016)	(0.044)
Control Mean	0.000	0.000	0.275	0.126	0.000
Upstream q-value	0.0066	0.0066	0.1483	0.1356	0.4400
Downstream q-value	0.1813	0.0066	0.1398	0.1398	0.1356
Obs	1229	1229	1188	1184	1252
Adj R-Squared	0.057	0.296	0.124	0.069	0.224

Panel B: Downstream Outcomes

	(1) Customer Relational Contracting Index	(2) Any Non-local Customer (0/1)	(3) Any New Customer (0/1)	(4) New Customer Share	(5) Customer Phone Activity Index
Upstream Treat	-0.119***	-0.013	0.002	-0.005	-0.038
	(0.034)	(0.035)	(0.032)	(0.015)	(0.053)
Downstream Treat	-0.109***	-0.053	0.011	0.005	-0.183***
	(0.034)	(0.034)	(0.033)	(0.014)	(0.051)
Control Mean	0.000	0.488	0.687	0.193	0.000
Upstream q-value	0.0028	0.8108	0.9391	0.8108	0.8108
Downstream q-value	0.0046	0.2857	0.8108	0.8108	0.0028
Obs	1252	1252	1203	1191	1252
Adj R-Squared	0.133	0.196	0.086	0.050	0.129

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table shows results from ANCOVA regressions of main outcomes on the upstream and downstream treatment groups. Controls include strata indicators, the prediction index, survey round indicators, baseline outcomes, and an indicator if baseline outcome was missing. Q-values are multiple hypothesis testing corrections for each outcome grouping (upstream, downstream, and productivity outcomes). Significance levels are marked for unadjusted p-values and q-value corrections are provided below each outcome.

Panel C: Productivity Outcomes

	(1) Sales Revenue Index	(2) Output Price Index	(3) Input Price Index	(4) Transport Costs Share of Inputs Purchased	(5) Inputs Purchased Locally (0/1)
Upstream Treat	-0.055	0.124**	0.070	-0.009	0.039
	(0.067)	(0.054)	(0.051)	(0.006)	(0.033)
Downstream Treat	0.022	0.088*	0.033	-0.017***	0.095***
	(0.070)	(0.053)	(0.053)	(0.006)	(0.033)
Control Mean	0.000	-0.092	-0.023	0.052	0.314
Upstream q-value	0.5146	0.0704	0.2838	0.2838	0.3513
Downstream q-value	0.7538	0.2428	0.5921	0.0217	0.0217
Obs	822	1081	1109	1197	1197
Adj R-Squared	0.279	0.063	0.196	0.107	0.354

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table shows results from ANCOVA regressions of main outcomes on the upstream and downstream treatment groups. Controls include strata indicators, the prediction index, survey round indicators, baseline outcomes, and an indicator if baseline outcome was missing. Q-values are multiple hypothesis testing corrections for each outcome grouping (upstream, downstream, and productivity outcomes). Significance levels are marked for unadjusted p-values and q-value corrections are provided below each outcome.

6.3.1 Relational Contracting Index Components

Table 8 shows results for components of the relational contracting indices. Results for index components are presented to show how each component contributes toward the total effect that is picked up once aggregated into an index. On the upstream side, firms substantially increase receiving any credit on goods purchased - 14.1% received credit compared to 8% in the control group. On average, upstream firms were also slightly more likely to know all of their suppliers and receive a price discount, but were less likely to have goods shipped or use mobile money. On the downstream side, firms in both treatment arms reduced discounting, special orders, and mobile money use with customers. But, provision of credit was unchanged.[10] Firms were also slightly less likely to report knowing all of their customers, but it was not statistically different from zero.

Not every component of the relational contracting indices moved in the expected direction. For example, despite an increase in total relational contracting compared to the control, upstream and downstream firms were less likely to have goods shipped from suppliers (although differences were not significant, standard errors are relatively narrow). In the discrete choice experiment, firms expressed a higher willingness to pay for having goods shipped over knowing their suppliers, receiving credit, and using mobile money. But, it is possible that having goods shipped is a more difficult benefit to arrange than negotiating for credit. Thus, when search costs decrease at the margin, firms gain a better bargaining position to ask for credit, but not quite enough to identify an average change in arranging delivery. And, as shown in Panel C in Table 7 above, downstream firms were more likely to purchase locally and have lower transportation costs, suggested that they forwent more transactions in the city compared to the control and upstream groups.

On the downstream side, firms reduced each component, but not significantly until aggregated into an index that picks up net changes. This suggests that index aggregation is a necessary tool to understand changes in outcomes that are often bundled together - such as capturing how terms of trade change when firms and customers transact.

[10]There are fewer observations for provision of credit and mobile money with customers because firms were not asked these questions in the first follow-up survey round.

Table 8: Relational Contracting Index Components

Panel A: Upstream Relational Contracting Index Components

	(1) Supplier Relational Contracting Index	(2) Receives Goods on Credit	(3) Knows All Suppliers	(4) Receives Price Discount	(5) Goods Shipped from Supplier	(6) Sends Mobile Money to Suppliers
Upstream Treat	0.101***	0.061**	0.046	0.004	-0.017	-0.036
	(0.033)	(0.024)	(0.029)	(0.033)	(0.027)	(0.040)
Downstream Treat	0.045	-0.004	0.048*	-0.008	-0.049*	-0.044
	(0.032)	(0.021)	(0.029)	(0.034)	(0.026)	(0.037)
Control Mean	0.000	0.080	0.725	0.547	0.181	0.348
Obs	1229	1186	1188	1248	1197	874
Adj R-Squared	0.057	0.076	0.124	0.120	0.065	0.138

Panel B: Downstream Relational Contracting Index Components

	(1) Customer Relational Contracting Index	(2) Provides Goods/Services on Credit	(3) Knows All Customers	(4) Gives Discount to Frequent Customers	(5) Makes Orders for Customers	(6) Receives Mobile Money from Customers
Upstream Treat	-0.119***	0.021	-0.002	-0.050	-0.033	-0.022
	(0.034)	(0.040)	(0.032)	(0.034)	(0.033)	(0.038)
Downstream Treat	-0.109***	0.000	-0.011	-0.045	-0.052	-0.062*
	(0.034)	(0.044)	(0.033)	(0.035)	(0.033)	(0.035)
Control Mean	0.000	0.480	0.313	0.642	0.341	0.255
Obs	1252	821	1203	1252	1251	873
Adj R-Squared	0.133	0.163	0.086	0.127	0.026	0.121

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table shows results from ANCOVA regressions of components of a upstream relational contracting index and downstream relational contracting index on the upstream and downstream treatment groups. Controls include strata indicators, the prediction index, survey round indicators, baseline outcomes, and an indicator if baseline outcome was missing.

6.4 Heterogeneity by Firm Sector

As described in Section 3.2, search behavior by retail and service firms is likely to differ because retail firms search and purchase more in cities and have lower per unit transportation costs which, in turn, lower search costs in urban areas and make relationships with suppliers based in cities more valuable.

Table 9 presents heterogeneous treatment effects for retail firms compared to service firms. Treatment arms are pooled to capture the net effect of being listed in the phonebook. The table highlights how retail and service firms have divergent search strategies that result in variation in their input acquisition costs and changes to relational contracting. Results confirm the prediction from the conceptual framework that service firms are more likely to search locally, pay higher input costs and pay lower transport costs. Panel A highlights search activities and price outcomes and Panel B compares relational contracting and new contacts for service and retail firms.

In Panel A, columns 1-2 are search activity outcomes, and show that service firms decreased total activity by 0.32 standard deviations compared to the control and searched 0.23 fewer locations. The consequences of these divergent search decisions show up in input prices and transportation costs. Columns 3-4 are the output and input price indices. There was no sector-specific treatment effect in the output price index. But, service firms paid 0.37 standard deviations higher input prices compared to retail firms. Service firms also decrease transport cost share by 2 percentage points and are 12.5 percentage points more likely to purchase locally. It provides evidence that service firms were willing to pay higher input costs to save on transport costs. At baseline, service firms paid nearly double the transport costs as a share of inputs purchased compared to retail firms, so this savings is potentially valuable for them.

Columns 1-3 of Panel B report heterogeneous treatment effects for supplier relational contracting index and two measures of transacting with new suppliers. Analogously, columns 4-6 report heterogeneous treatment effects for customer relational contracting index and measures of transacting with new customers. Retail firms increased relational contracting with suppliers by 0.07 standard deviations and service firms increased marginally more.

But, only service firms were significantly less likely to transact with a new supplier and had fewer new suppliers as a share of the number of suppliers. Both retail and service firms decrease relational contracting with customers, although service firms decreased by about 0.04 standard deviations more than retail firms. And, there were no differences in customer composition - neither sector experienced significantly more transactions with new customers, as measured through survey recall data.

Results from the discrete choice experiment suggest that firms were willing to pay slightly higher input prices to retain familiar suppliers, access credit, and arrange delivery. Service firms revealed behavior reflects this finding - they pay higher input prices, transact with known suppliers, pay lower transport costs, and increase relational contracting. It is consistent with a theoretical prediction that if per-unit transaction costs are high, firms will prefer to search in their local area - saving transport costs and lowering the variable cost of associated with establishing relational contracts.

One of the key differences between retail and service firms is that service firms purchase inputs and convert them into a value-added service, while retailers source goods and re-sell them at mark-up. While this distinction corresponded to different search patterns, both types of firms changed relational contracting in the same direction. For retail firms, the composition of suppliers and customers did not change. The customer composition did not change for service firms but they did decrease transactions with new suppliers. Returning to Table 4, these relationships confirm that being listed in the phonebook caused service and retail firms to change their valuation of relational contracts and increase bargaining power with pre-existing suppliers and customers. But, there is stronger evidence that service firms transacted with fewer new suppliers than retail firms.

Table 9: Heterogeneous Treatment Effects by Firm Sector

Panel A: Search Outcomes

	(1) Input Search Activity Index	(2) Number of Locations Searched	(3) Output Price Index	(4) Input Price Index	(5) Transport Costs Share of Inputs Purchased	(6) Inputs Purchased Locally (0/1)
Treat	0.016	0.046	0.201	-0.034	-0.004	0.012
	(0.046)	(0.047)	(0.150)	(0.072)	(0.006)	(0.034)
Service Firm	-0.127	0.295***	0.037	0.395***	0.015	0.314***
	(0.083)	(0.072)	(0.242)	(0.147)	(0.013)	(0.068)
Treat × Service	-0.324***	-0.225***	-0.234	0.366**	-0.020**	0.125**
	(0.073)	(0.070)	(0.221)	(0.161)	(0.010)	(0.054)
P-value $H_o : \beta_1 + \beta_3 = 0$	[0.0000]***	[0.0004]***	[0.8473]	[0.0325]**	[0.0057]***	[0.0011]***
Control Mean	0.001	1.268	-0.010	-0.019	0.052	0.314
Obs	1230	1194	903	995	1198	1198
Adj R-Squared	0.322	0.158	0.033	0.156	0.108	0.390

Panel B: Relational Contracting Outcomes

	(1) Supplier Relational Contracting Index	(2) Any New Supplier (0/1)	(3) New Suppliers Share	(4) Customer Relational Contracting Index	(5) Any New Customer (0/1)	(6) New Customer Share
Treat	0.070*	-0.015	-0.010	-0.097**	0.005	0.010
	(0.038)	(0.038)	(0.019)	(0.039)	(0.036)	(0.014)
Service Firm	-0.020	0.011	0.025	0.011	-0.212***	-0.027
	(0.074)	(0.056)	(0.029)	(0.073)	(0.060)	(0.025)
Treat × Service	0.005	-0.066	-0.037	-0.039	0.000	-0.020
	(0.055)	(0.051)	(0.027)	(0.060)	(0.054)	(0.025)
P-value $H_o : \beta_1 + \beta_3 = 0$	[0.0671]*	[0.0134]**	[0.0149]**	[0.0026]***	[0.9019]	[0.6124]
Control Mean	0.001	0.275	0.126	-0.000	0.687	0.193
Obs	1230	1189	1185	1253	1204	1192
Adj R-Squared	0.054	0.126	0.070	0.132	0.096	0.051

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table shows results from ANCOVA regressions of a subset of outcomes on pooled treatment groups interacted with a binary variable equalling 1 for service firms and 0 for retail firms. The treatment effect for retail firms is captured by the coefficient for Treat (β_1) and the treatment effect for service firms is Treat plus Treat × Service ($\beta_1 + \beta_3$). The p-value for a t-test on service firm treatment effect is in brackets with stars to denote significance levels. Controls include strata indicators, the prediction index, survey round indicators, baseline outcomes, and an indicator if baseline outcome was missing.

7 Anticipating General Equilibrium Effects

An important question to consider is what would happen to the search cost structure in this market once all firms have their firm listed in the phonebook and can search for all firms in their region. One consequence of unit-level experimental design over a relatively short period of time (14 months) is that it is not possible to measure medium-to-long-term changes to the general equilibrium of the market. Despite this, economic theory offers insights on what changes can be anticipated in this setting.

Previous research studying how search costs affect prices in commodity and labor markets found that price dispersion narrowed (Jensen 2007; Aker, 2010; Aker and Fafchamps, 2015; Jeong, 2019), but price levels did not change. This study found that output prices marginally *increased* after search costs decreased. I argued that this is consistent with a relational contracting framework where the rural firms increase the average price charged to their customers because they anticipate having more customers as a result of being listed in the digital phonebook. Once control firms are added to the phonebook, it is not clear that firms will have more new customers relative to their peer competitors and it is possible that price levels will return to their previous equilibrium if competition bids them downward.

Yet, it is also possible that prices remain at the higher level. Like many phone-based networking platforms, the digital phonebook studied here creates new opportunities for buyers and sellers to meet when they might not have met otherwise. These new contacts may cause buyers and sellers to decrease their reliance on ex-ante customer networks for sales and increase engagement with new customers. Since customers that benefit from relational contracting receive lower prices, an aggregate change in customer composition where all firms increase contact with new customers could cause the average price level to remain above the previous equilibrium. Evidence that firms with higher downstream relational contracting have lower prices is seen in Panel B of Table 7 in the appendix. A one standard deviation increase downstream relational contracting index is associated with a 0.16 standard deviation decrease in the output price index.

The upstream side could theoretically experience similar general equilibrium effects. Lowering search costs enables rural firms to locate and contact new potential suppliers. But, it does not change the costs required to invest in long-term relational contracting that unlocks access to credit, shipping, or price discounts. Again, as search costs lower for all firms, we would expect price dispersion in input markets to decrease. Unlike the downstream side, there was no significant change in average input price levels. But, service firms input prices increased and I showed that it is likely related to changing sourcing locations. But, firms in the upstream treatment arm were more likely to access credit. And, the discrete choice experiment showed that firms were willing to pay higher input prices if they were able to receive credit and purchase from familiar suppliers.

The fact that experimental results showed that firms searched less and were less likely to have a new supplier is further evidence that investing in supplier relationships is valuable to firms, particularly for firms in the services sector - who have smaller, less frequent input orders. Retail firms searched more and were more likely to transact in urban areas. As a result, search costs are a more important factor for sourcing inputs for retail firms compared to service firms and they stand to benefit more from technologies that increase connections between rural and urban areas.

8 Conclusion

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. I 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.

I find evidence that most changes in relational contracting were with existing suppliers and customers. On the customer side, firms did not report significant increases in the number of transactions with new customers. It is possible that firms anticipated that their customer base would increase but those increases did not translate into substantial changes to the number of transactions. This could be due to transactions being a relatively noisy measure. It is also possible that customers search was sporadic and did not translate into sustained increases in the number of customers.

Likewise for upstream outcomes, on average firms decreased transactions with new suppliers and searched less. Relational contracting relies on repeat transactions with both suppliers and customers to build trust. Increasing relational contracting with suppliers required firms to increase investment in their existing relationships. The digital phonebook only decreased search costs to locate initial market information but did not change costs for how long it takes to establish trust with suppliers. Yet, lowering search costs for firms increased the value of their outside option because it became easier to search for new trading partners if needed.

There is substantial variation by firm sector. Service firms significantly decrease input search activity compared to retail firms. I argue that this is driven by sectoral differences in the cost structure for input search. Service firms make less frequent, smaller purchases and it is not as valuable for them to travel to cities to obtain inputs. This is confirmed by the finding that service firms paid lower transportation costs and had a higher likelihood of purchasing inputs locally rather than travelling to urban areas.

In introducing a new technology that changes how users can search for information, this research project provided firms with an opportunity to learn about the market in their area on a completely new format - a digital phonebook platform. Firms significantly changed their search activities and their engagement with their ex-ante suppliers and customers. It shows that small changes to the search cost structure have the power to re-shape the way that firms transact along their supply chain.

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Additional Tables and Figures

Figure 3: Example of Feature Phone

Image from Weld et al., 2017

Figure 4: 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 5: Experimental Timeline

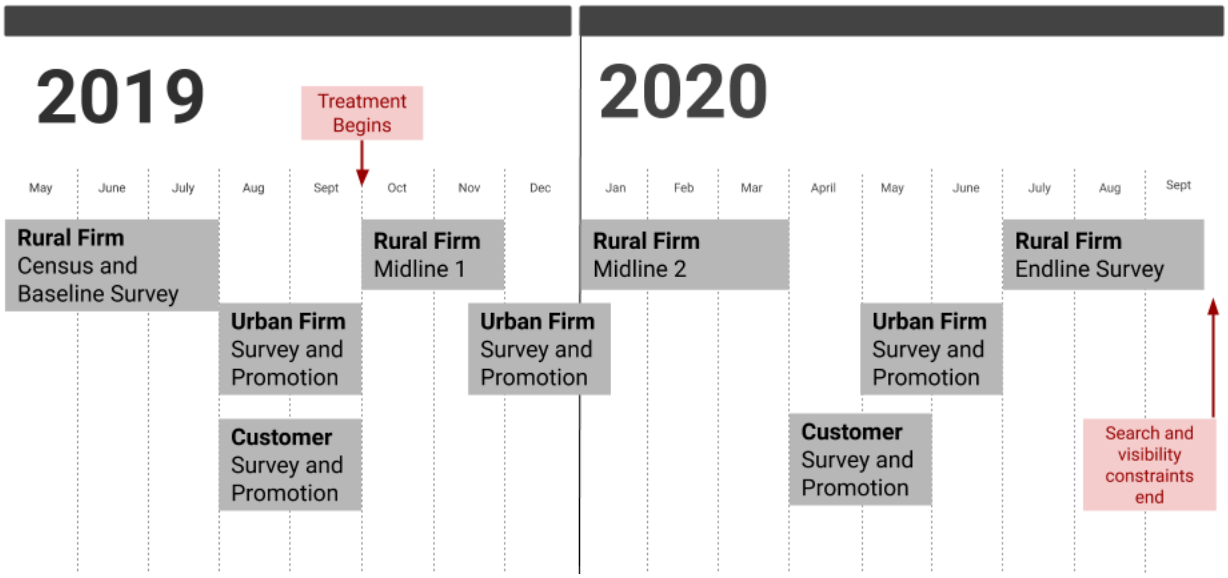


Table 10: Characteristics of Sample Regions and National Average

	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

Table 11: Balance Table

Variable	N	(1) Upstream Mean/SE	N	(2) Downstream Mean/SE	N	(3) Control Mean/SE	T-test Difference (3)-(1)	T-test Difference (3)-(2)
Woman-Owned (0/1)	169	0.38	168	0.36	170	0.35	-0.03*	-0.02
		(0.04)		(0.04)		(0.04)		
Owner Age	169	35.94	168	35.99	170	34.42	-1.52*	-1.56*
		(0.89)		(0.85)		(0.81)		
Years of Education	169	7.47	168	7.29	170	7.48	0.00	0.19
		(0.26)		(0.28)		(0.26)		
Firm Age (Yrs)	169	5.71	168	5.49	170	5.14	-0.57	-0.36
		(0.56)		(0.55)		(0.46)		
Firm Size (Incl. Owner)	169	1.33	168	1.36	170	1.37	0.04	0.01
		(0.04)		(0.05)		(0.06)		
Retail Sector (0/1)	169	0.54	168	0.52	170	0.52	-0.01	-0.00
		(0.04)		(0.04)		(0.04)		
No. Competitors	169	3.63	168	4.64	170	4.01	0.37	-0.64
		(0.26)		(0.34)		(0.30)		
Distance to City (km)	169	67.36	168	66.60	170	61.84	-5.51	-4.76
		(2.45)		(2.42)		(2.35)		
Firm has Electricity (0/1)	169	0.57	168	0.59	170	0.49	-0.07**	-0.10**
		(0.04)		(0.04)		(0.04)		
Owns Smart Phone (0/1)	169	0.22	168	0.21	170	0.21	-0.02	-0.00
		(0.03)		(0.03)		(0.03)		
Mobile Top-ups (Tsh)	169	1899.41	168	1791.67	170	1812.65	-86.76	20.98
		(150.70)		(131.98)		(127.19)		
Listing Priority Index	169	6.65	168	6.60	170	6.61	-0.05	0.01
		(0.12)		(0.12)		(0.13)		
Customer Calls	169	1.41	168	1.58	170	1.98	0.57*	0.40
		(0.16)		(0.20)		(0.26)		
Supplier Calls	169	0.29	168	0.30	170	0.49	0.20	0.19
		(0.09)		(0.10)		(0.13)		
Non-local Customer (0/1)	169	0.50	168	0.46	170	0.51	0.01	0.04
		(0.04)		(0.04)		(0.04)		
Non-local Supplier (0/1)	169	0.73	168	0.74	170	0.75	0.01	0.00
		(0.03)		(0.03)		(0.03)		
Output Price Index	169	-0.01	168	0.06	170	-0.08	-0.07	-0.14*
		(0.04)		(0.05)		(0.04)		
Input Price Index	169	0.03	168	0.02	170	-0.00	-0.04	-0.02
		(0.05)		(0.04)		(0.05)		
Sales Revenue Index	169	-0.11	168	-0.12	170	-0.00	0.11	0.12
		(0.05)		(0.05)		(0.06)		
Inventory Mgmt Score	169	0.47	168	0.45	170	0.50	0.03	0.05
		(0.03)		(0.03)		(0.02)		
Marketing Mgmt Score	169	0.33	168	0.29	170	0.32	-0.01	0.03
		(0.02)		(0.02)		(0.02)		
Inputs Purchased (Tsh)	169	240623.67	168	203242.26	170	225127.65	-15496.02	21885.39
		(41373.10)		(28973.69)		(39916.59)		
F-test of joint significance (F-stat)							1.21	0.91
F-test, number of observations							339	338

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.

Appendix

A Index Construction

Analysis of primary outcomes involves 8 indices: upstream relational contracting, downstream relational contracting, input search activities, upstream phone communication, downstream phone communication, sales revenue index, and input and output price indices. Index aggregation improves statistical power by testing fewer outcomes. Indices were constructed following Kling et al. (2007) which employs a procedure that sums equally-weighted z-scores computed for each component of an index. The z-scores are calculated at the unit-level by subtracting the control group mean and dividing by the control group standard deviation. The index captures the net change for a given set of related outcomes and are interpreted as the number of standard deviations increase or decrease compared to the control. The authors also suggest 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. Indices constructed by weighting by inverse covariance matrix of components following Anderson (2008) are provided as a robustness check in Section B.4.

- **Relational Contracting:** The components the upstream relational contracting index includes whether a firm receives goods on credit, knows all of their suppliers, receives a price discount, arranges shipping of inputs, and sends mobile money to suppliers. The components of the downstream relational contracting are analogous: whether a firm provides credit to customers, knows all of their customers, gives a price discount to frequent customers, places orders for customers, and receives mobile money payments.

- **Supplier Search:** The supplier search index includes the number of suppliers communicated with to ask information about inputs, number of suppliers transacted with, whether any supplier was new, the number of locations searched, and whether suppliers were local or from urban areas.

- **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 and 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.

- **Phone Activity:** For customer and supplier phone activity indices, the components of the each index are whether any calls were received over the previous week, 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 supplier and customer contacts.

- **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.

B Robustness Checks

B.1 Spillovers

Randomization at the unit-level requires that the stable unit treatment value assumption (SUTVA) holds, implying that there are no spillovers between units in different experimental conditions. Extensive margin spillovers (externalities) may occur between firms within the same village. A negative externality would occur if being listed in the phonebook drives treated firms to deprive non-treated firms of market share.[11] Table 7 showed results for changes in firm revenue (Column 1 in Panel C) and changes in customer composition (Columns 3 and 4 in Panel B). Neither treatment arm experienced significant changes in these outcomes, suggesting that firms did not gain market share or grow at the expense of control firms in their villages. Further, the attrition section below explains that differential attrition by treatment group did not occur, again providing evidence that treated firms did not gain at the expense of non-treated firms.

A positive externality on non-listed firms would occur if changes to the bargaining or demand structure of listed firms also improved bargaining or aggregate demand for non-listed firms. For example, if a firm's connection to upstream suppliers leads them to access lower prices, a positive spillover would occur if firms in their neighborhood also gain access to those lower prices or better market terms. Ruling out this type of spillover requires assuming

[11] After the study ended, all firms were listed in the platform so that any potential gains driven by exclusivity in the phonebook platform were temporary and would be bid away once the full sample was listed.

that firms internalize benefits of being listed in the phonebook. In other words, since firms operate in a competitive environment, their private gains are not shared with their neighbors. As a quick check, firms were asked if they source inputs in a group to provide evidence that firms do not engage in collective bargaining. In each survey round less than 1% of firms reported organizing with other firms in their village to source inputs. As another check, firms were asked in the endline survey if they discuss business activity with any other firm owners in their village. Only 10.5% of firms reported discussing any business activity with their neighbors, a relatively small share.

B.2 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, 2017).

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 1 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 1: 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 2 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., 2019). Here, the empirical strategy estimates an intent-to-treat (ITT), which equals the ATE under the assumption of perfect treatment compliance.

Table 2: Robustness: 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.

B.3 Randomization Inference

As a robustness check, p-values were computed by using randomization inference (Athey and Imbens, 2017). 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 (Young, 2019). Here, randomization inference is useful as a placebo test to check whether treatment-driven heteroskedasticity drives results. Similar to finite sample inference, only p-values below 0.10 percent threshold support rejecting a null of zero.

Table 3 reports randomization inference p-values for all of the primary outcomes using the Stata command `randcmd`. As suggested by Young (2019), I 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. I report them for groupings of upstream, downstream, and productivity outcomes, similar to how multiple hypothesis testing was conducted.

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 15 main outcomes, 7 were jointly significant - upstream relational contracting, downstream relational contracting, customer phone activity index, output price index, transport costs share, and whether firms purchased inputs from a local vendor rather than in a city. 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 of both treatments on all outcomes in a particular group. In other words, 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 three groupings - upstream, downstream, and productivity - 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 .01 level. These tests further indicate that search and visibility in the phonebook changed outcomes for firms in the treatment groups.

Table 3: 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	.0036	.1975	.0159	.0131	2000
Input Search Activity Index	.0019	.0011	.0018	.0131	2000
Any New Supplier	.1118	.0891	.1625	.0131	2000
New Supplier Share	.0644	.1028	.1203	.0131	2000
Supplier Phone Activity Index	.7654	.1856	.3830	.0131	2000
Downstream Outcomes Grouping					
Customer Relational Contracting Index	.0001	.0006	.0009	.0006	2000
Any Non-local Customer	.6940	.1180	.2527	.0006	2000
Any New Customer	.9324	.7318	.9381	.0006	2000
New Customer Share	.7340	.7270	.7370	.0006	2000
Customer Phone Activity Index	.3631	.0002	.0012	.0006	2000
Productivity Outcomes Grouping					
Sales Revenue Index	.4083	.7612	.5611	.0426	2000
Output Price Index	.0244	.0996	.0598	.0426	2000
Input Price Index	.1708	.5414	.3969	.0426	2000
Transport Costs Share Inputs Purchased	.2168	.0049	.0209	.0426	2000
Inputs Purchased Locally	.2871	.0077	.0237	.0426	2000
Joint Test - All Outcomes				.0062	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 Table 7. 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.

B.4 Inverse Covariance Weighted Index Construction

A second approach to index construction proposed in Anderson (2008) utilizes a standardization procedure similar to Kling et al. (2007), but weights components by the inverse of the covariance matrix of outcomes. 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.

All indices that were presented in the main outcomes were constructed following Anderson (2008) and results are shown in Table 4 in the Table Appendix. Inverse covariance matrix weighted indices are not centered about zero for the control group, making direct comparisons of effect sizes between the two indices difficult. But, in most cases standard errors are about twice as large as unweighted indices in the preferred specification. And, effect sizes tend to be larger. Overall, signs and effect sizes are relatively similar across both types of indices.

Table 4: Robustness: Inverse Covariance Matrix-Weighted Indices

	(1) Supplier Relational Contracting Index	(2) Customer Relational Contracting Index	(3) Input Search Activity Index	(4) Business Revenue Index	(5) Customer Phone Activity Index	(6) Supplier Phone Activity Index
Upstream Treat	0.187***	-0.209***	-0.183***	-0.019	-0.056	-0.099
	(0.069)	(0.069)	(0.066)	(0.063)	(0.073)	(0.062)
Downstream Treat	0.084	-0.215***	-0.201***	0.007	-0.271***	-0.168***
	(0.071)	(0.068)	(0.063)	(0.064)	(0.071)	(0.055)
Control Mean	0.429	0.356	0.705	0.153	0.255	0.114
Obs	1229	1252	1230	1252	1252	1252
Adj R-Squared	0.053	0.119	0.235	0.141	0.130	0.188

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls include strata indicators, the prediction index, survey round indicators, baseline outcomes, and an indicator if baseline outcome was missing. This table shows a robustness check for index construction using a procedure that down-weights index components that are highly correlated.

C Discrete Choice Experiment Detail

An discrete choice experiment was created for baseline firms. It was designed to elicit trade-offs on four attributes of a typical sourcing contract: price, preference for new versus old suppliers, delivery terms, and provision of credit. Firms examine different pairs of contracts each with four attributes and indicate which contract they prefer. Pilot data showed that some firms have stronger attachment to their suppliers relative to others, picking a contract in which they pay a higher price in order to keep their existing supplier.

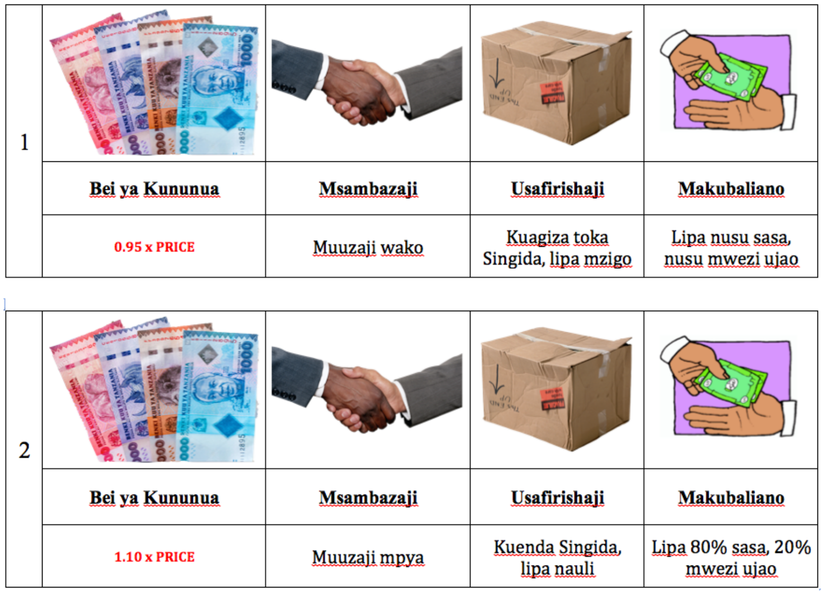
For each contract attribute, one option is associated with having built trust with a supplier. For example, suppliers must trust that credit will be repaid, or they must trust that payment for goods shipped will be received. Table 5 below shows each contract attribute and the different levels. Each column 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 each attribute - price, whether a supplier was known or unknown, delivery terms, and terms of credit (see example contract pairing in Figure A.5).

Table 5: 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 A.5 provides an example of a contract pairing).

Figure A.5: Example of Contract Pairing



Econometric analysis of discrete choice data draws from a random-utility model and uses a mixed logit (also called random parameters logit) model to estimate choice probabilities that represent group-level preferences for certain attributes (McFadden and Train, 2000). Coefficients on terms in the mixed logit are interpreted as the group-level preferences for an attributes. Econometric analysis uses the following model specification:

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

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. Unlike conditional logits, 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 attributes. DCE are useful to identify strength of preferences for specific contract attributes relative to other attributes, rather than a precise measure of willingness-to-pay for a market good.

Table 6 shows results from the discrete choice experiment.[12] The sample size comes from the 376 firms that completed the choice experiment multiplied by the 12 contracts they reviewed.[13] Coefficients are the mean and standard deviation of a distribution of tastes in the population that participated in the discrete choice experiment. 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

[12] For model specification and further detail on assumptions, see Appendix C.

[13] 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 $376 \times 12 - 2 = 4510$.

Table 6: Mixed Logit Results of Discrete Choice Experiment

	Dependent Var: Contract Choice		
	Mean (se)	SD (se)	WTP (Percent) [CI]
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

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

WTP by dividing the point estimate of the mean of an attribute level by the price coefficient. 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.

C.1 Baseline Relational Contracting

One question of interest is whether relational contracting makes a difference to firms. Here, I present evidence from the baseline survey on how relational contracting associates with key firm outcomes, such as revenues, employees, transportation costs, and input and output prices. Using baseline information on revealed behavior, I construct indices of firm participation in relational contracting with their upstream suppliers and downstream customers.

I also construct an index of WTP relational contracting with upstream suppliers using estimates from the discrete choice experiment. Individual level measures of WTP were estimated through simulation. Following **?**, this is only done for variables with significant coefficients on the estimated mean (e.g. Supplier known, Goods delivered, and payment of 50% cash now). The basic idea is that coefficient means and standard deviations of attribute preferences estimated in the mixed logit model are parameters that define an unconditional distribution of tastes in the population that can be used to estimate a conditional distribution of an individual by using their past choices. Since each firm compared six sets of two contracts, each participant provided six data points from which to estimate a conditional distribution of their individual preferences.

Results in Table 7 provide suggestive evidence on the importance of relational contracting, particularly with upstream input providers. Firms with higher index of upstream relational contracting tend to have higher sales revenue, more employees, lower output prices, lower transport costs and lower input prices (though the last two were not significantly different from zero). These results control for a suite of pre-determined firm-level controls, including firm age, years of education, gender of owner, firm sector, and village fixed effects. Despite adding controls, it is still likely that the relational contracting index is correlated with the error term and thus results are cautiously interpreted as correlations.

Downstream relational contracting does not exhibit as much correlation with firm productivity as the upstream relational contracting. It is not associated with any outcomes aside from having a lower output price index, which might occur as a result of known customers bargaining for lower prices. Similarly, when the results of the DCE are aggregated into an index, there is no relationship with firm productivity outcomes, except for paying higher input prices.

And finally, the bottom panel independent variable is constructed by taking the difference between firms' stated WTP for relational contracting and their observed upstream relational contracting index. Here, there are some suggestive correlations. Firms with greater differences between their stated and observed relational contracting are associated with lower sales revenue, fewer employees, higher transport costs, higher output prices, and higher input prices. This highlights the importance of unlocking firm networks so that firms that aspire to have relational contracts can more easily meet new firms and build relationships required to attain benefits from relational contracting.

Table 7: Baseline Outcomes Associated with Relational Contracting

	(1) Sales Revenue Index	(2) Total Employees	(3) Share Transport Costs	(4) Output Price Index	(5) Input Price Index
Supplier Relational Contracting Index					
Supplier Index	0.16**	0.18*	-0.02	-0.15*	-0.10
	(0.08)	(0.09)	(0.01)	(0.08)	(0.09)
Mean	-0.08	0.60	0.08	-0.01	0.02
Obs	506	501	418	393	343
Adj R-Squared	0.12	0.07	0.07	-0.01	0.11
Customer Relational Contracting Index					
Customer Index	0.04	0.02	-0.02	-0.16**	-0.04
	(0.06)	(0.06)	(0.02)	(0.07)	(0.07)
Mean	-0.08	0.60	0.08	-0.01	0.02
Obs	506	501	418	393	343
Adj R-Squared	0.11	0.06	0.08	-0.00	0.11
WTP Relational Contracting Index					
WTP Supplier Index	-0.09	-0.09	0.02	0.10	0.10*
	(0.06)	(0.08)	(0.02)	(0.07)	(0.06)
Mean	-0.08	0.60	0.08	-0.01	0.02
Obs	378	375	341	311	318
Adj R-Squared	0.17	0.04	0.03	-0.02	0.13
Difference - WTP and Supplier Relational Contracting Index					
Difference WTP	-0.09**	-0.11*	0.03**	0.17***	0.11**
	(0.05)	(0.06)	(0.01)	(0.06)	(0.05)
Mean	-0.08	0.60	0.08	-0.01	0.02
Obs	378	375	341	311	318
Adj R-Squared	0.17	0.05	0.04	0.01	0.13

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each regression controls include firm age, years of education of owner, gender of owner, firm sector, and village fixed effects.