Search Costs and Relational Contracting: The Impact of a Digital Phonebook on Small Businesses in Tanzania

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JOB MARKET PAPER

October 15, 2020

Abstract

Substantial information frictions raise the cost of searching for market information that firms use to operate their businesses. This includes search frictions associated with learning about goods and services offered by numerous suppliers dispersed along urban-to-rural supply chains. I investigate whether lowering search costs for small firms in rural Tanzania decreases information frictions and changes incentives to engage in relational contracting with suppliers and customers. Using a randomized experiment of 500 small firms, I study the impact of a digital phonebook that lowers the cost of accessing new business and customer networks. Participating small firms are split into a control and treatment group with two variations - 1) a business listing targeting input markets in urban areas, and 2) a business listing targeting customers in output markets in rural areas. I find that treated firms increase relational contracting with their suppliers and decrease it with their customers, suggesting that decreasing search costs improves the bargaining position of rural firms with their pre-existing networks.

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1 Introduction

High search costs along firms' supply chains raise barriers to acquiring new information about prices, quality, and availability of goods. 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. Small firms incur search costs when they source inputs from upstream suppliers located in urban centers. At the same time, downstream customers of rural firms in their output markets engage in search to locate goods and services from rural firms. Lowering search costs along a supply chain can improve firm productivity (Bernard et al., 2019) and increase aggregate output (Oberfield, 2018).

The presence of search costs can increase the value of relational contracting - where buyers leverage repeat transactions with sellers to access benefits that are not readily provided with one-off purchases in the spot market - such as when sellers provide credit, price discounts, and 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.

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 500 rural firms, I study the impact of a digital phonebook 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 experiment generates two sources of exogenous variation. First, rural firms are randomly listed in a digital phonebook that is searchable by mobile-phone users throughout Tanzania. Second, listed firms are split into two treatment groups - 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. The design allows for analysis comparing the extent to which input or output search costs constrain business performance and whether lowering the cost of initial contact improves firm productivity.

I define relational contracting to include benefits that firms provide to their customers and receive from their suppliers that are not readily provided through anonymous transactions in a spot market. Spot market purchases involve anonymous buyers and sellers that do not build trust over time. To show that rural firms prefer relational contracts with their suppliers, I present results from a discrete choice experiment demonstrating that firms value their suppliers, credit, and delivery, and are willing to pay higher input prices to access these benefits with known suppliers. 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 and show descriptive evidence that rural firms provide benefits of relational contracting to their customers more often than they receive them from their suppliers.

Using an index of relational contracting activity, I find that being listed in the phone directory causes firms in the upstream treatment group to increase relational contracting with their suppliers by 0.10 standard deviations compared to the control group. And they are 75% more likely to receive credit from their suppliers. Firms in both treatment arms also decrease their search activities and have fewer new suppliers compared to the control group. With respect to downstream relational contracting with customers, both treatment arms decrease provision of relational contracting benefits by between 0.11-0.12 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, the upstream treatment arm increased output prices and downstream arm was also more likely to purchase inputs locally (instead of travelling to cities) and paid lower transport costs.

These findings are motivated by theoretical predictions about how search costs change the information structure around how firms search and rely on relational contracting. Specifically, a change in search costs presents the possibility of an asymmetric response by firms with respect to upstream and downstream relational contracting. Since it becomes less costly to locate new suppliers, firms can leverage the credible threat of divesting from relationships with existing suppliers to gain new benefits since it becomes less costly to meet new suppliers. But, the value of existing relationships remains high because firms have already formed relationships and have a history of transactions. Therefore, firms can arrange better benefits from their existing suppliers. On the downstream side, if the firms have higher contact with new customers (or if they anticipate having more contact with customers), they will reduce their relational contracting benefits. This occurs if firms assess the cost of maintaining relational contracts with customers as too high and are willing to reduce it once it is easier to connect with new customers.

A final prediction examines firm heterogeneity - specifically whether a firm is in the retail or services sector. An important aspect of search costs for rural firms that source inputs from urban areas is the cost of transportation that are paid each time a firm sources inputs. I first show descriptively that retail firms source larger orders of inputs and have lower per-unit transportation costs. The cost of maintaining supplier relationships in cities is less costly for retail firms than for services firms, since input prices are lower in urban areas and transport costs can be spread over larger order sizes. Empirical results show that the treatments cause retail firms to engage in substantially *more* search activities, pay lower input prices, pay higher transport costs, and purchase inputs in urban areas compared to service firms. It supports the idea that firms' per-unit transaction costs drive much of their input search behavior and determines, in part, the extent to which it is worthwhile it to search for inputs in urban areas, or if it is more worthwhile to pay higher input prices by searching locally.

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 (an exception is Anderson et al. (2018)). Prior research has examined the role of in 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 no study has been able to experimentally relax both in a single setting. 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 having relatively competitive market conditions, I document substantial use of relational contracting by rural firms with upstream and downstream trading partners. I examine both input and output market constraints at the same time and compare how relational contracting norms respond to changes in search costs.

Other research offers examples of how firm welfare improves when new business contacts are introduced. Fafchamps and Quinn (2016) randomly link manufacturing firms in Kenya and find that new 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 mechanisms 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, it 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. Another difference is this research targets firms from a range of sectors with attention on urban-to-rural supply chains. Most firms in this study are small or microenterprises, selling 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 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 change 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 and field experiment. 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 pre-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. In a recent paper, 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 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 are more likely to obtain credit from their upstream supplier if they have fewer supplier 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. The subsequent sections describe these relational contracting norms.

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

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).

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.

3 Testable Predictions of Search Costs with Relational Contracting

Thus far, I have 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 clients 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.

The intervention described below increases contact between rural firms and rural customers by listing rural firms contact information in a digital phonebook. 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.

Table 2 summarizes empirical tests that can be used to inform these theorized relationships. The first panel summarizes how to interpret coefficients for upstream outcomes related to contact with new suppliers and changes in relational contracting. The second panel summarizes how to interpret coefficients for downstream outcomes related to contact with new customers and changes in relational contracting. As described in detail in Section 4, treated firms have two levels of treatment. First, all treated firms are listed in the digital phonebook and can search for their own treatment group. Second, firms were assigned to two arms designed to exogenously increase contact with *either* upstream suppliers *or* downstream customers. Therefore, an additional part in 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 more readily increase their bargaining power with suppliers or with their customers.

Table 2: Summary of Empirical Tests

Rural Firm Upstream Treatment Effects		
New Suppliers	Relational Contracting Response	Interpretation
$\beta \leqslant 0$	$\beta > 0$	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

3.2 Urban-to-Rural Trade with Heterogeneous 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 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 3: 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

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. 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.

Table 3 shows differences in transport costs 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.

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 and guides users through a set of menus to reach a screen that displays the firm's contact information, location, sector and product specialities (see Dillon et al. (2018) and Weld et al. (2018) for more details). Unlike a typical phonebook from a US setting, eKichabi 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

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

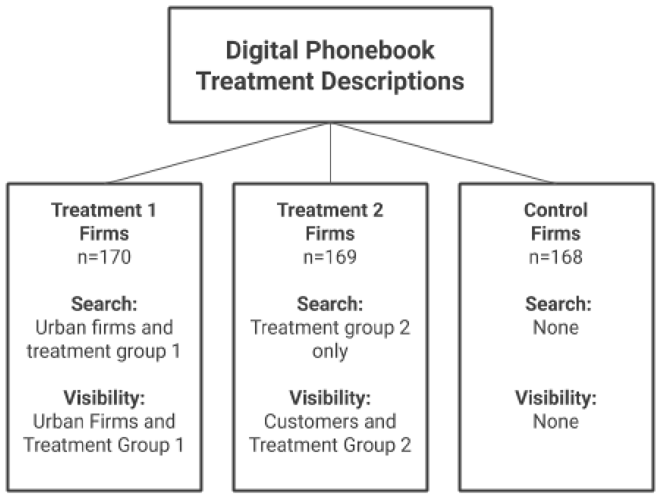
focuses on the middle link of the supply chain: rural firms. Rural firms from small to medium sized commercial centers are split into a control group and a treatment group with two variations - 1) a business listing that targets upstream wholesalers in the firms' input market, 1) a business listing that targets downstream consumers in the firms' output market. The "upstream" treatment addresses perceived shortcomings on the input supply-side of urban-to-rural supply chains. Enterprises in this group will be able to use the phonebook to see firms in the same treatment group and will have their business listing visible to wholesale urban firms that use the directory. The "downstream" treatment increases firms' exposure to the pool of potential new customers by promoting the firm's listing during searches by customers from surrounding communities. In addition, both treatment arms are able to search for other firms in their same treatment group.

The objective of treatment 1 is to lower the cost of contacting new potential suppliers and the objective of treatment 2 is to lower the cost of contacting new potential customers. Random assignment at the firm level generates variation in the likelihood that rural firms communicate with upstream and downstream contacts. This variation effectively lowers the cost of increasing business network size and can be used to identify the impact of lowering search costs on business outcomes. Further, the two separate treatment arms will differentially lower search costs for one side of the supply chain but not the other which permits comparing outcomes between upstream and downstream treatment groups.

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 permits constraining the visibility of specific users. The research design partitions firms into control plus two treatment groups. Treatment groups 1 and 2 were listed in the platform and control firms were not listed. Figure 1 summarizes these relationships. Treatment group 1 can view upstream firms in urban areas (the typical location of wholesale firms and input providers) but treatment group 2 cannot. Customers in rural areas can search only for firms in treatment group 2. But, customers are not listed in the phonebook (it only includes businesses) and therefore the downstream treatment arm cannot search for customers in the phonebook. The arrows in Figure 1 denote which groups can search for other groups within the phonebook platform. Firms in treatment group 2 can search other group 2 firms but cannot access to urban firms. Likewise, treatment group 1 can search other treatment group 1 firms *and* are visible and can search for upstream firms.

Figure 1: Description of Treatment



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. Therefore, treatment assignment to group 1 can be thought of as increasing the probability that the firm communicates with upstream firms and assignment to treatment group 2 increases the probability of communicating with downstream 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 and 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. The treatment assignments are designed to exogenously increase the probability that a firm engages with either their upstream input market or their downstream output market. Further, 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 December, 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, including input search activities, transactions with local and non-local customers and suppliers, phone activity with customers and suppliers, input and output prices, and transportation costs.

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. But, I did not pre-register a relational contracting index as a primary outcome. In service of increasing transparency of how a pre-analysis plan morphs into a paper, I report pre-registered outcomes in the appendix that are not highlighted in the main paper. 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.

4.2 Sampling Frame

Two regions in central Tanzania were identified for the digital directory - 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 2 shows the experimental design and sampling criteria.

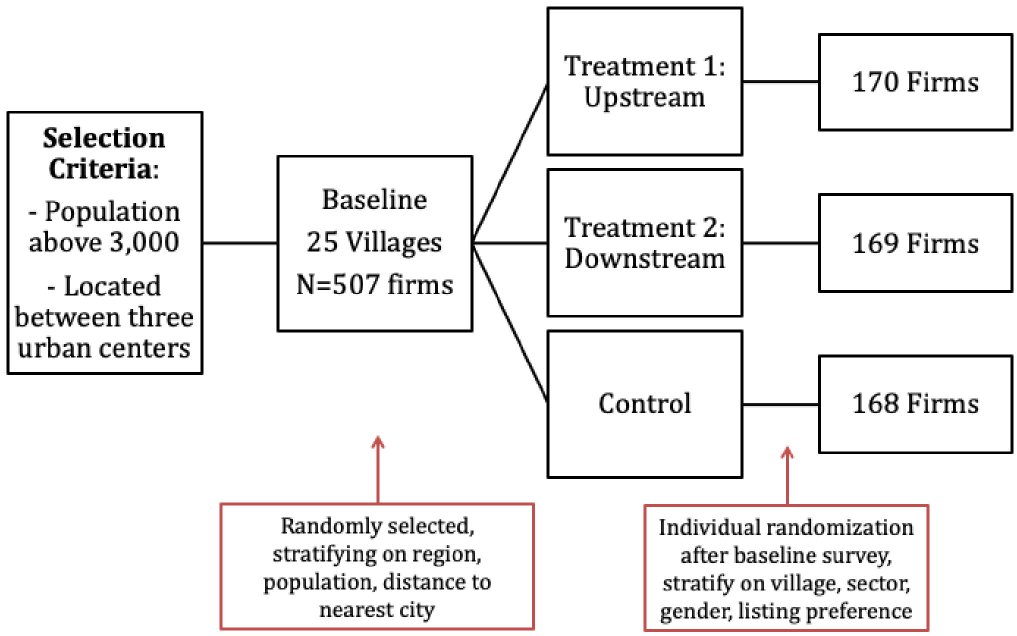


Figure 2: Experimental Design

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.[2]

[2]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. 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. 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.

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 second treatment arm.

Finally, the digital phonebook was live and accessible to any mobile phone in Tanzania. Therefore, new, unknown phone numbers were randomly assigned to view group 1 or group 2, which could potentially add noise to final outcomes.

4.3 Sample Characteristics

The sample area is located in the semi-arid central region of Tanzania. Table 10 in Appendix 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 3: Upstream Firms, Rural Firms, and Customers Locations

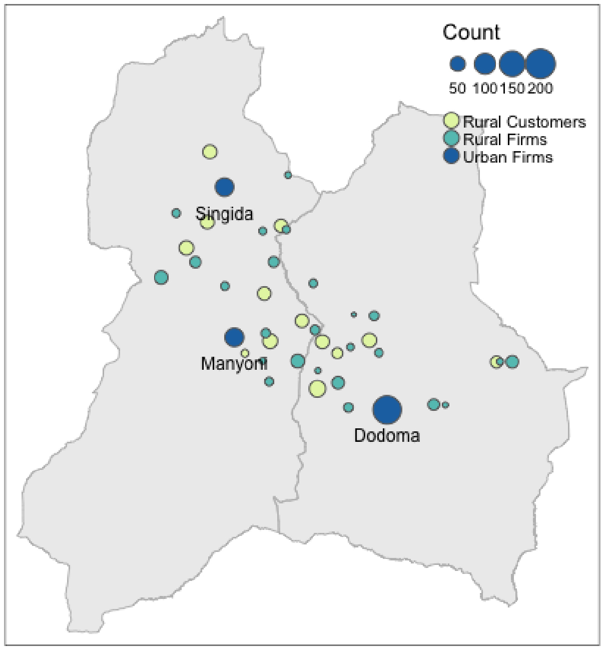


Figure 3 shows the geographic distribution of upstream firms, rural firms, and downstream customers in Singida and Dodoma regions in central Tanzania. The size of the bubble indicates the number of phone numbers that were gathered from each location. Upstream firm contact information was obtained from urban centers denoted with blue dots, rural firms that were assigned to treatment and control are located in villages denoted with green dots, and villages where the digital phonebook was promoted to potential customers are represented by yellow dots.

4.3.1 Rural Firm Characteristics

Table 4 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. 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

Table 4: 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	

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 in Appendix compares the means for the treatment groups, control group, and t-tests for differences between the groups. The balance table compares differences across groups among 22 covariates, including baseline demographic characteristics and baseline outcomes. Out of 22 covariates, 4 exhibit imbalance - owner age, whether the firm has access to electricity, customer calls, and the output price index. But, an F-test of joint significance across all covariates fails to reject the null of 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. The idea is to select variables that explain any arbitrary correlation between experimental groups and baseline outcomes and add them as a regression adjustment.

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 Train (2009). During the baseline survey, firms were asked to compare a series of 'contracts' with four different attributes:

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

As described in the 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.[3]

[3] 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.

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 (McFadden and Train, 2000).[4] 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:

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

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 attributes.

5.2 Treatment Effects Estimation

To estimate the causal effect of treatment on the outcome variables, I employ ANCOVA regressions.[5] Estimates of intent to treat (ITT) use the following ANCOVA specification:

$$Y_{it} = \alpha + \beta_1 T_i^{US} + \beta_2 T_i^{DS} + \gamma Y_{i,t=0} + \delta BLMiss_{i,t=0} + \theta X_i + \lambda_t + \epsilon_{it} \tag{1}$$

[4]For further detail on assumptions, see Section 2 in the appendix.

[5]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.

Y_{it} represents the outcome variable of interest for firm i in survey round t. T^{US} and T^{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 dependent variable and $BLMiss_{i,t=0}$ denotes values that are missing at baseline due to firm non-response.[6] The vector X_i includes strata dummies and the machine learning prediction index, which does not vary with time. 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 Benjamini and Hochberg (1995) 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.

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

[6] 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.

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 costs decreased, providing evidence that they became more efficient.

5.3.1 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.

This method was used to construct a sales revenue index, upstream and downstream phone communication indices, the upstream search activity index, and upstream and downstream relational contracting indices. The components the upstream relational contracting index is 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. 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.

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.

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.

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. Coefficients are interpreted as the standard deviation increase or decrease relative to the mean (instead of relative to the control group, as above). 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.

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.[7] 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.

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

[7] 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 (Percent) [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.

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 Upstream, Downstream, and Productivity Treatment Effects

Table 6 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 significantly increased relational contracting index with suppliers (Column 1). Firms in both treatment arms engaged in fewer search activities (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 significantly decreased their new suppliers share by 2.6-2.8 percentage points when using unadjusted p-values (Column 4). Finally, downstream firms also significantly decreased phone communication with suppliers.

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 (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 provide evidence 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 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, providing inconclusive 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 xx of the appendix). 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. 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 both arms had 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.[8]

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. Despite this, results in section 8 below show

[8]This is most likely due to purchasing locally and driving transport costs to zero. The transport cost share regression did not control for purchase location.

that search behavior in cities increases for retail firms, likely due to having larger order sizes and thus lower per-unit transportation costs.

Table 6: 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 p-value	0.0020	0.0018	0.1186	0.0639	0.4400
Upstream q-value	0.0066	0.0066	0.1483	0.1356	0.4400
Downstream p-value	0.1631	0.0010	0.0979	0.0975	0.0678
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 p-value	0.0006	0.7041	0.9391	0.7288	0.4683
Upstream q-value	0.0028	0.8108	0.9391	0.8108	0.8108
Downstream p-value	0.0014	0.1143	0.7297	0.7277	0.0004
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).

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 p-value	0.4117	0.0211	0.1703	0.1424	0.2459
Upstream q-value	0.5146	0.0704	0.2838	0.2838	0.3513
Downstream p-value	0.7538	0.0971	0.5329	0.0023	0.0043
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).

6.2.1 Relational Contracting Index Components

Table 7 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.[9] 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 Table **??** 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.

[9] 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 7: 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.

6.3 Firm Heterogeneity

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 8 presents heterogeneous treatment effects for retail firms compared to service firms. It highlights how retail and service firms have divergent search strategies that result in variation in their input acquisition costs. Results confirm the prediction from the conceptual framework that retail firms are more likely to increase search activity in urban areas, access lower input costs and pay higher transport costs. Columns 1-3 highlight search activities and columns 4-6 highlight changes in costs that result from differences in search. Column 1 is the combined search activity index and shows that retail firms increased search activities by 0.28-0.37 standard deviations compared to service firms, who decreased search by between 0.28-0.34 standard deviations compared to the control group. Columns 2 and 3 show that service firms were less likely to communicate with new suppliers and less likely to search outside of their community compared to retail firms.

The consequences of these divergent search decisions show up in input prices and transportation costs. Column 4 shows that service firms in the downstream treatment arm increased input prices by 0.28 standard deviations compared to control and that retail firms in the downstream arm decreased input prices by 0.40 standard deviations compared to service firms. It is surprising that this occurs in the downstream treatment arm as opposed to the upstream treatment arm, who had access to phonebook listings for urban firms. But, retail firms in downstream treatment were slightly less likely than upstream retail firms to communicate and purchase from suppliers outside their local area. Service firms in both treatment arms were more likely to purchase inputs locally and paid lower transportation costs as a result (Columns 5 and 6). Since both treatment arms had access to other rural firms in their same arm, it demonstrates that retail firms were more likely to uptake opportunities to search - both locally and in urban areas. And yet, the larger coefficients on the upstream arm suggests that when they had the option to search for firms in urban areas, retail firms increased input search activities to a greater degree than those that could only search for other rural firms (the downstream treatment arm).

Table 8: Retail Firms Supplier Search

	(1) Input Search Activity Index	(2) Any New Information Supplier (0/1)	(3) Non-local Information Supplier (0/1)	(4) Input Price Index	(5) Transport Costs Share of Inputs Purchased	(6) Inputs Purchased Locally (0/1)
Upstream Treat	-0.341***	-0.067*	-0.228***	0.172	-0.017*	0.122**
	(0.065)	(0.038)	(0.049)	(0.111)	(0.010)	(0.050)
Downstream Treat	-0.275***	-0.096***	-0.184***	0.281**	-0.031***	0.152***
	(0.060)	(0.035)	(0.047)	(0.110)	(0.009)	(0.048)
Retail Sector=1	0.128	-0.011	0.248***	-0.448***	-0.016	-0.310***
	(0.083)	(0.056)	(0.062)	(0.123)	(0.013)	(0.068)
Upstream × Retail=1	0.369***	0.040	0.238***	-0.155	0.015	-0.134**
	(0.084)	(0.059)	(0.055)	(0.136)	(0.011)	(0.064)
Downstream × Retail=1	0.278***	0.094*	0.172***	-0.397***	0.025**	-0.114*
	(0.082)	(0.057)	(0.054)	(0.135)	(0.011)	(0.062)
Control Mean	0.001	0.275	0.802	-0.019	0.052	0.314
Obs	1230	1189	1194	995	1198	1198
Adj R-Squared	0.322	0.125	0.439	0.185	0.109	0.390

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table shows results from heterogeneous treatment effects ANCOVA regressions of a subset of outcomes on the upstream and downstream treatment groups interacted with a binary variable equalling 1 for retail firms and 0 for service firms. Controls include strata indicators, the prediction index, survey round indicators, baseline outcomes, and an indicator if baseline outcome was missing.

6.4 Platform Engagement

Platform usage data includes phone number of callers, search activity within the platform, time and day of search, number of menu screens, and which firm was ultimately found. Phone numbers collected by the research team can be matched back to identify whether it came from a rural firm, rural customer, or urban firm. Table 9 reports results from an ANCOVA regression where all firms baseline outcome is zero, since no firm appeared in the phonebook platform during the baseline survey.

Panel A shows the rural firms search behavior. Three types of firms are listed in the platform: urban firms, rural firms from this research project, and rural firms in a nearby region. Control firms could only access rural firms from the adjacent region. We could not assign a phone number to have zero access to the platform. Instead we assigned them to see firms that are outside of their geographic trading area.

Outcome variables along the top row of each panel are binary variables. Column 1, "Used eKichabi Platform" denotes whether a firm ever dialled into the application during the survey period. The control mean in Column 1 shows that 29% of control firms dialed into the phonebook application at least once. 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 2-4 denote whether a firm searched an urban firm, rural firm in the same region, or the other non-experimental region. Not all firms that dial eKichabi 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.[10] Columns 2 and 3 confirm that control firms could not search either urban or rural firms in their region. Likewise, the downstream treatment arm could not search urban firms. Both upstream and downstream could search for rural firms in the same region and the other region. Again,

[10]The drop in control mean from Column 1 to Column 4 reflects this tendency for users to stop searching before reaching a final screen. The way to interpret the difference is that 19% of control users dialled eKichabi and 5% reach a final screen that featured a firm name and phone number.

the treatment assignments constrained the upstream arm to reach upstream suppliers and downstream firms to be reachable by rural customers, who are not listed in the application.

Panel B shows whether the treated firms were found by users. The control mean for all four specifications is zero since control firms are not listed in the eKichabi platform. Nearly all of the downstream firms (92%) were found by a user and 23% of upstream firms were found.[11] In both cases, search among rural firms in the same region accounts for a higher share of the search than by wholesalers and rural customers. However, downstream firms were far more likely to be found by a rural customer (27% were found each round) compared to the upstream arm, of which 4% were found by urban suppliers each round. It indicates that overall, the downstream treatment arm was more active on the application, both in terms of searching nearby rural firms and in terms of being found by customers.

6.5 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.[12] Table 6 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

[11] Since regressions include strata fixed effects, survey round indicators, and the prediction index, the coefficients are not precisely equivalent to the unconditional group means, but they are close.

[12] 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.

Table 9: eKichabi Phonebook Platform Usage

Panel A: Firms Search Behavior

	(1) Used eKichabi (0/1)	(2) Searched Urban Firm	(3) Searched Rural Firm	(4) Searched Firms Other Region
Upstream Treat	0.10***	0.04***	0.11***	-0.04***
	(0.03)	(0.01)	(0.02)	(0.01)
Downstream Treat	0.15***	-0.00	0.20***	-0.04***
	(0.03)	(0.00)	(0.02)	(0.01)
Control Mean	0.19	0.00	0.02	0.05
Observations	1521	1521	1521	1521
Adj. R-squared	0.15	0.09	0.14	0.03

Panel B: Firms Found in Application

	(1) Found by Any User	(2) Found by Rural Customer	(3) Found by Urban Firm	(4) Found by Rural Firm
Upstream Treat	0.23***	-0.00	0.04***	0.20***
	(0.02)	(0.01)	(0.01)	(0.02)
Downstream Treat	0.92***	0.27***	0.02***	0.36***
	(0.02)	(0.02)	(0.01)	(0.02)
Control Mean	0.00	0.00	0.00	0.00
Observations	1521	1521	1521	1521
Adj. R-squared	0.68	0.25	0.01	0.28

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table shows treatment effects regressions using application usage data. Each column has an outcome variable regressed on the treatment group indicators. Controls include strata fixed effects, the prediction index, and survey round dummies.

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 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.

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 *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 input price levels. 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 networking technologies have shifted how agents engage with their networks. Digital phonebooks that are accessible on any type of phone are a bridge technology that allows users in rural areas that do not own smartphones to access new contacts from outside their typical networks. 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 perceived their customer base to 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 - sectors, locations, and contact details of upstream firms - 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.

There is substantial variation by firm sector. Retail firms significantly increase input search activity compared to service 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. Since the downstream treatment arm could only observe other rural firms in the same treatment arm, it suggests that learning information about other neighboring firms can encourage agents to thicken their local networking engagement. This is confirmed by the downstream treatment arm's lower transportation costs and higher likelihood of purchasing inputs locally rather than travelling to urban areas.

In introducing a new technology that changes firm networks, 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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Tables

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	(1) Upstream N	(1) Upstream Mean/SE	(2) Downstream N	(2) Downstream Mean/SE	(3) Control 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.

1 Robustness Checks

1.1 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: 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.

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 difference by treatment group. Columns 3-5 report the attrition rates for each survey round, also finding no differences by treatment group.

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 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 defintions of attrition described above - ever attrit, and permanent attrit. 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 ever attrit 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.

1.2 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 6. 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.

1.3 Alternate 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.

2 Discrete Choice Experiment

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.

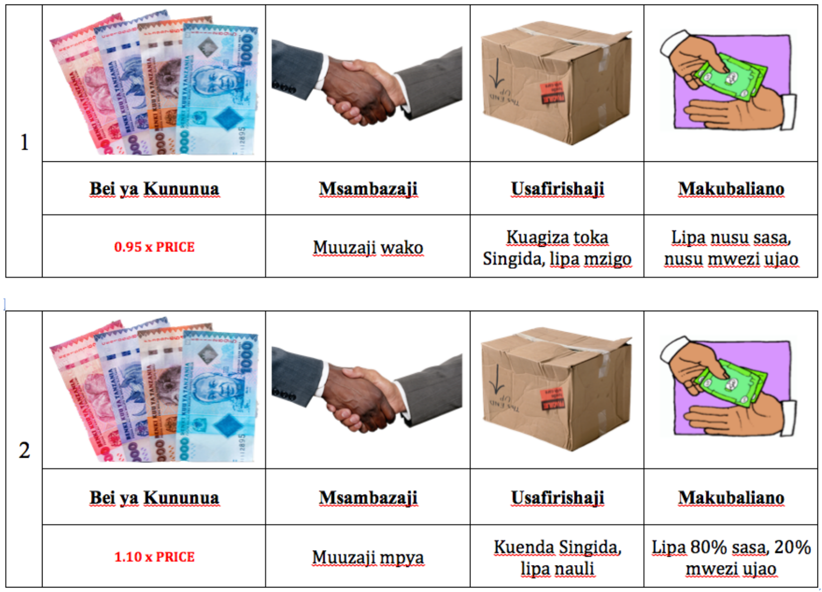
For each contract attribute, one option is associated with having built trust with a supplier. For example, suppliers must trust that credit will be repaid, or they must trust that payment for goods shipped will be received. Table 5 below shows each contract attribute and the different levels. Each column 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.[13] The sample size comes from the 376 firms that completed the choice experiment multiplied by the 12 contracts they reviewed.[14] 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

[13]For model specification and further detail on assumptions, see Appendix 2.

[14]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.

2.1 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 Train (2009), 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.

3 Reporting from Pre-Analysis Plan

Not every outcome that was described in the pre-analysis plan is presented in the main paper. This section discusses variable construction for other outcomes that were discuss in the pre-analysis plan but not incorporated in the main paper.

3.1 Customer and Supplier Search

A few survey questions asked firms whether they had customers ask for a product they did not have in stock. Table 8 shows firm outcomes based on questions about demand from customers. The first column is the number of sales transactions during the previous two days. It provides information about whether treated firms enjoyed sustained increases in business activity as a result of treatment. The variable "Item Stock-out" was assigned 1 if the firm indicated that they did not have an item in stock with two conditions: 1. it is an item that they normally have in stock, and 2., a customer asked for it during the period when it was not available. The treatment effects were negative but not significant. Notably, the control group mean for a stock-out was 47%, demonstrating that there is a lot of room for firms to improve on this margin. Lastly, column 3 shows that treated firms did not add any new products at a different rate than the control group.

Table 8: Customer Search Outcomes

	(1) No. Sales Transactions	(2) Item Stock-Out (0/1)	(3) Added New Product (0/1)
Upstream Treat	0.34	-0.01	-0.02
	(1.11)	(0.04)	(0.03)
Downstream Treat	-1.06	-0.03	-0.03
	(1.04)	(0.04)	(0.03)
Survey Round	0.78	-0.06*	0.03
	(0.78)	(0.03)	(0.02)
Control Mean	15.35	0.47	0.10
Obs	792	841	842
Adj R-Squared	0.29	0.16	0.05

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

On the supplier side, firms were asked to provide information about how many suppliers they called for information ("information suppliers") compared with how many suppliers they transacted with during the most recent input supply purchase ("transaction suppliers"). Table 9 reports these changes. The upstream treatment arm has negative, yet not significant, decrease in communication with information and transaction suppliers. And the downstream treatment significantly decreased the number of suppliers that they communicated with during their last purchase.

The "Transaction/Information Share" variable can be interpreted as the share of total suppliers from whom a purchase was made. As shown in column 3, both treatment arms were significantly more likely to purchase from suppliers that they communicated with. The control group mean is 88%, showing that the vast majority of communication results in a transaction. For the upstream and downstream treatment, this ratio increased to 91% and 92%, respectively. Columns 4 and 5 document the share of transaction and information suppliers that were new to the responding firm. The control group means for columns 4 and 5 signify that 11% of transaction suppliers and 14% information suppliers were new to the firm. For the upstream treatment, this decreased significantly and only 7% of total transaction suppliers were new. It suggests that on average, firms preferred to communicate with fewer and more familiar suppliers.

Table 9: Supplier Search Outcomes

	(1) No. Information Suppliers	(2) No. Transaction Suppliers	(3) Transaction/ Information Share	(4) Share of New Transaction Suppliers	(5) Share of New Information Suppliers
Upstream Treat	-0.16	-0.05	0.03**	-0.04**	-0.03
	(0.10)	(0.08)	(0.01)	(0.02)	(0.02)
Downstream Treat	-0.25***	-0.12	0.04***	-0.01	-0.01
	(0.09)	(0.07)	(0.01)	(0.02)	(0.02)
Survey Round	0.41***	0.34***	-0.01	-0.02	-0.01
	(0.08)	(0.06)	(0.01)	(0.02)	(0.02)
Control Mean	2.25	1.85	0.88	0.11	0.14
Obs	818	820	802	802	804
Adj R-Squared	0.27	0.24	0.04	0.05	0.06

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.2 Business Activity Outside the Local Market

Variables measuring the extent to which firms conduct business activity outside their local market are designed to pick up changes in the geographic area over which the firm conducts business. Firms were asked to list locations of suppliers and customers. Column 1 in Table 10 is a binary variable that takes a value of 1 if the firm reported having any customer from outside their village. Although many firms do not perfectly know where their customers come from, they generally know whether a customer is from their local village or from another town nearby. Fifty-two percent of control group firms reported a non-local customer. The downstream treatment was 8 percentage points less likely to report a customer from outside their own village, despite having their phone number available to a range of users in nearby communities.

Table 10 also provides evidence that the upstream treatment arm decreased their search radius as a response to treatment. Columns 2 and 3 show that they were 6 percentage points less likely to communicate with a non-local supplier to gain information, and 8 percentage points less likely to transact with a non-local supplier. The treatment was designed with the idea to increase connectivity between urban and rural areas. It could be that once firms take into account their travel costs and the price differential, they strictly prefer to source from local sources.

Table 10: Business Activity Outside the Local Market

	(1) Non-local Customer	(2) Non-local Information Supplier	(3) Non-local Transaction Supplier
Upstream Treat	-0.03	-0.06*	-0.08**
	(0.04)	(0.04)	(0.03)
Downstream Treat	-0.08**	-0.04	-0.05
	(0.04)	(0.04)	(0.03)
Survey Round	-0.05	-0.02	-0.02
	(0.03)	(0.02)	(0.02)
Control Mean	0.52	0.71	0.74
Obs	843	797	799
Adj R-Squared	0.18	0.40	0.41

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.3 Heterogeneous Treatment Effects

There are four groups of interest for heterogeneous treatment effects - retail and service-oriented firms, gender of the firm owner, firm remoteness, and the firm's self-reported listing preference, elicited through a series of location preference questions detailed below. All of these variables were included as strata variables are were balanced at baseline.

3.3.1 Women-Owned Businesses

Women-owned businesses constitute an important sub-population of businesses since women are less likely to access capital and more likely to face legal and labor market discrimination (Campos and Gassier, 2017) and may crowd into less profitable sectors (Hardy and Kagy 2018). About 36% of the sample in this study are owned by women. Part of the reason that a gender-based profit gap may exist is because women are less likely to access new business networks. In the previous sample, women are over-represented among small street vendors and underrepresented among large wholesalers. Examining differences in treatment outcomes based on gender will provide information about the extent to which women-owned businesses are more or less likely to engage in search behavior or build new business partnerships.

Table 11: Woman-Owned Businesses - Phone Communication and Supply Chain

	(1) Customer Calls	(2) Supplier Calls	(3) Non-local Customer	(4) Non-local Information Supplier	(5) Non-local Transaction Supplier
Upstream Treat	-0.12	0.14	-0.04	-0.04	-0.07*
	(0.40)	(0.11)	(0.05)	(0.05)	(0.04)
Downstream Treat	-1.10***	-0.04	-0.09**	-0.04	-0.06
	(0.39)	(0.11)	(0.05)	(0.04)	(0.04)
Woman-Owned Bus (WOB) = 1	0.40	0.31	-0.05	-0.18*	-0.23**
	(0.87)	(0.19)	(0.11)	(0.11)	(0.10)
Upstream × WOB=1	-0.06	-0.29	0.03	-0.04	-0.00
	(0.62)	(0.18)	(0.09)	(0.08)	(0.07)
Downstream × WOB=1	0.06	-0.02	0.04	0.00	0.03
	(0.59)	(0.17)	(0.08)	(0.07)	(0.07)
Survey Round	-0.07	0.05	-0.05	-0.02	-0.02
	(0.23)	(0.07)	(0.03)	(0.02)	(0.02)
Obs	839	837	843	797	799
Adj R-Squared	.11	.15	.18	.41	.41

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.3.2 Remoteness

Firms located in rural areas face higher transaction costs and are less likely to access new technology. Comparing firms based on their location will provide information about how these transaction costs attenuate potential gains from new technology. For example, in a similar setting, Aggarwal et al. (2018) used structural estimation techniques to find that a one standard deviation increase in travel time corresponds to a 20-25% lower input adoption rate and output sales among farmers in remote areas. The main hypothesis for this setting is that increasing access to contact information could improve rural firms' ability to source and sell goods and services. However, as distance from the main goods-exporting urban centers increases, gains to new information could remain lower than the costs of acquiring those goods. For this subgroup analysis, the baseline sampled was partitioned based on whether they belong to a community that is above the median distance to an urban center.

Table 12: Village Remoteness - Phone Communication and Supply Chain

	(1) Customer Calls	(2) Supplier Calls	(3) Non-local Customer	(4) Non-local Information Supplier	(5) Non-local Transaction Supplier
Upstream Treat	-0.50	0.09	-0.06	-0.07	-0.12**
	(0.40)	(0.10)	(0.05)	(0.05)	(0.05)
Downstream Treat	-1.11***	0.03	-0.15***	-0.04	-0.08*
	(0.40)	(0.11)	(0.05)	(0.05)	(0.05)
Remote=1	-0.59	0.16	-0.05	0.01	-0.04
	(0.51)	(0.14)	(0.06)	(0.05)	(0.05)
Upstream × Remote=1	0.98	-0.15	0.07	0.03	0.11
	(0.63)	(0.18)	(0.08)	(0.07)	(0.07)
Downstream × Remote=1	0.16	-0.19	0.16**	-0.00	0.07
	(0.62)	(0.18)	(0.08)	(0.07)	(0.07)
Survey Round	-0.08	0.05	-0.05	-0.02	-0.02
	(0.23)	(0.07)	(0.03)	(0.02)	(0.02)
Obs	839	837	843	797	799
Adj R-Squared	.12	.15	.18	.4	.41

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.3.3 Listing Priorities Index

Since the eKichabi platform is a tool that connects firms with customers and other firms located outside the local market, the baseline survey included a set of questions designed to elicit firm preferences on where to expand their network geographically. The goal is to to differentiate firms based on their listing priorities - that is, whether a firm prefers a listing that connects them to rural communities (their downstream market) or to urban firms located in cities (their upstream market). The set of questions will ask firms to compare two geographies - one relatively near and the other relatively distant - and allocate 10 tokens between them. For example, if comparing a nearby village (relatively near) to a city (relatively far) a firm may choose 8 tokens for the nearby village and 2 tokens for the city, while another firm may prefer 4 for the nearby village and 6 for the city. The question repeated for a set of six geographic comparisons. These comparisons were aggregated into an index by taking the average of the number of tokens after orienting comparisons by nearest-furthest. Piloting this set of questions affirmed that there is variation in responses that is arguably correlated with firms' desire to expand their geographic network, an important dimension of heterogeneity relevant to this setting.

Table 13: Listing Priorities Index - Phone Communication and Supply Chain

	(1) Customer Calls	(2) Supplier Calls	(3) Non-local Customer	(4) Non-local Information Supplier	(5) Non-local Transaction Supplier
Upstream Treat	0.31	0.10	0.02	-0.01	-0.03
	(1.30)	(0.37)	(0.19)	(0.17)	(0.16)
Downstream Treat	0.68	-0.01	-0.09	0.33**	0.38**
	(1.38)	(0.34)	(0.17)	(0.15)	(0.15)
Listing Priority Index	0.02	-0.03	-0.03	0.00	0.01
	(0.20)	(0.04)	(0.02)	(0.02)	(0.02)
Upstream × Listing Index	-0.07	-0.01	-0.01	-0.01	-0.01
	(0.19)	(0.05)	(0.03)	(0.03)	(0.02)
Downstream × Listing Index	-0.27	-0.00	0.00	-0.06**	-0.07***
	(0.21)	(0.05)	(0.03)	(0.02)	(0.02)
Survey Round	-0.08	0.05	-0.05	-0.02	-0.02
	(0.23)	(0.07)	(0.03)	(0.02)	(0.02)
Obs	839	837	843	797	799
Adj R-Squared	.12	.15	.18	.41	.42

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$