Three Essays in Development Economics on Rural Firms and Markets

By

JESSICA RUDDER

DISSERTATION

Submitted in partial satisfaction of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

Agricultural and Resource Economics

in the

OFFICE OF GRADUATE STUDIES

of the

UNIVERSITY OF CALIFORNIA

DAVIS

Approved:

____

Travis Lybbert, Chair

____

Brian Dillon

____

Arman Rezaee

____

Rachael Goodhue

Committee in Charge

2021

Abstract

Drawing on theory from development economics and industrial organization, I study the economics of rural firms and markets to understand how different types of shocks affect firm operations. I examine three types of shocks: technology, weather, and prices. I use a combination of randomized experimental variation and quasi-experimental variation to identify the effect of each type of shock on small firm outcomes. The primary outcomes are relational contracting with suppliers and customers, firm performance (sales, profits, hiring of workers), number of competitors, and changes to input and output prices.

In the first essay, I evaluate how a technology shock designed to lower search costs affects how firms interact with their suppliers and customers. For small firms, search frictions interfere with learning about new suppliers in their upstream market, and raise the cost of meeting new customers in their downstream market. Using a randomized experiment of 507 small firms, I study the impact of a digital phonebook that lowers the cost of accessing new business and customer contacts. Participating firms are split into a control and treatment group with two variations: 1) a phonebook listing that is visible to upstream suppliers in urban areas, and 2) a phonebook listing that is visible to downstream customers in rural areas. I find that treated firms increase relational contracting with their suppliers and decrease it with their customers. Yet, there is no strong evidence that the number of new customers or suppliers increases. This pattern suggests that being listed in the phonebook caused firms to update their valuation of relational contracts and respond by negotiating better terms with suppliers and customers.

In the second essay, I study how a weather shock that lowers agricultural production affects rural firms whose customer base experiences crop losses. In the absence of insurance and credit markets, the effect of adverse weather shocks on rural firms is ambiguous because drought shifts both demand and supply curves. I use spatial and temporal variation in the 2016-2017 drought in Kenya to characterize the direct and indirect effects of drought-induced food insecurity on local firm outcomes. Firms in areas directly affected by drought

have lower sales, profits, and hire fewer workers than firms in non-drought areas. Firm entry also increases in drought areas compared to non-drought areas, consistent with prior evidence that farming households form new businesses as a coping strategy following shocks. Subsector analysis reveals substantial heterogeneity. Service firms fare better than retail firms. But examining retail sub-sectors shows that firms selling higher-value food products (meat/fish and fruits/vegetables) experience greater declines than staple grain sellers in markets directly affected by drought, while firms selling high-value foods increase sales in non-drought areas. This is consistent with consumers in drought regions decreasing consumption of non-necessities.

In the third essay, I explore how input price shocks passthrough to consumer prices for rural and urban firms. Price variation is a typical feature of markets in developing countries. Rural firms face substantial price variation when purchasing goods (inputs) that they re-sell as outputs. How much of this input variation passes through to prices for rural customers? Rural households rely on local businesses to purchase household food staples and other essential commodities. Yet, relatively little economic literature examines retail passthrough rates of these essential food staples to clarify how it affects local food security. I use a panel of input and output prices for 230 urban firms and 240 rural firms to evaluate passthrough from idiosyncratic input price shocks on key commodities sold through urban-to-rural supply chains. I find that rural firms smooth both negative and positive input price shocks more than urban firms. By exploring possible mechanisms, I find suggestive evidence that smaller community size is associated with lower output prices, suggesting that social ties may play a role. At the same time, competitive pressure matters as well - rural firms who face new entrants and have higher absolute number of competitors have higher passthrough rates, consistent with a competitive market framework.

Acknowledgments

I am grateful to the Department of Agricultural and Resource Economics at the University of California, Davis for the training in economics. My dissertation committee members Travis Lybbert, Rachael Goodhue, Arman Rezaee, and Brian Dillon provided invaluable advice throughout my PhD years and helped me to refine unpolished observations about international development into full-formed ideas rooted in economic theory.

This dissertation is the culmination of a re-educational journey that started sometime in 2014 when I decided that I was capable of pursuing a PhD. My initial inspiration came after I joined the Evans Policy Analysis and Research Group at the Evans School of Public Policy and Governance at the University of Washington. Leigh Anderson, Mary Kay Gugerty, and Brian Dillon were critical guides in training me to prepare for a PhD. I am guessing that when Brian Dillon hired me as a research assist for the summer of 2014, he did not anticipate that he would continue to mentor me and I am grateful for his willingness to share knowledge, advice, folksy sayings, and encouraging me to explore new ideas.

I am grateful to our collaborators on the Phonebooks project in Tanzania. I thank the leadership at the Institute for Rural Development Planning in Tanzania for their collaboration, especially Emmanuel Mwang'onda, Stanslaus Msuya, and Adalbertus Kamanzi. Editha Kokushubira, Adili Michael, Eden Luvinga, Neema Mkuna, and Felix Mbakile provided excellent research assistance. The project was supported by the Cornell Institute for Social Science at Cornell University and a Jastro Shields grant from the University of California Davis. Galen Weld and Richard Anderson at the University of Washington provided computer programming support that made this research possible. I thank the 850 firms that we surveyed from 2019-2020 for their enthusiasm and participation. I heard stories of how a simple phonebook was useful for their business and I hope it continues to be a technology that facilitates access to information. Adili, Editha, and I have worked together since 2014 and have formed a friendship that has provided a constant source of joy whenever I visit Tanzania. Keep the supu nyama warm for me - I hope to be back soon!

My thinking on how small firms fit into the rural economy started when I was a Peace Corps Volunteer in the Comarca Ngäbe-Buglé in Panama. I am grateful to the families in Chichica, Munä who welcomed me to their community and shared food and stories with me. I also learned from watching my parents Bruce and Jane Rudder operate a small business in my hometown in Northern Arizona. It always seemed to me that one of the biggest differences between my parent's small business and small businesses in Panama and Tanzania is that my parents could access credit to smooth consumption during months when business was down. All small business owners deserve to have access to tools that enable them endure shocks and become stable resources for their families and communities.

I am grateful to my dog co-caretaker, co-homeowner, and partner Derek Rury. I am proud of the support we have provided each other while pursuing our PhDs. Our time in California was highlighted with trips to the mountains and time spent with our dear friends in the Bay and Sacramento - Brett Rudder, Irene Chung, Andrea Kraus, Moiz Kapadia, Scott Mortensen, Helen Walker, Charles Walker, Jodgy/Jeege Kingsley, Becca Robinson, and Lauren Asprooth. I am thankful for my oldest friendships with Jessica Holst, Kathryn Bryant, Alyssa Maheu, Aynsley Muller, and Candice Goodrich. UC Davis ARE students are a supportive, welcoming, and chill bunch of friends and collaborators. I am grateful to the other students in my cohort, especially Karen Oritz, Laura Meiznen-Dick, Shri Kiruba, Pierce Donavon, Ed Whitney, and Tor Tolhurst for helping me make it through our first year. I am grateful to my adoptive cohort, especially Joakim Weill, Armando Rangel, Miki Doan, Ashley Spalding, Caitlin Kieran, and Charlotte Ambrozek and my office mates Maxime Depalle, Matthieu Stigler, and Sarah Smith. I am so grateful that I could count on friendship with the 'regular' econ students - Kiki Siregar, Monica Rodriguez, John Blanchette, Justin Wiltshire, Peppe Ippedico, Iulia Iuras - thank you for the dinners and adventures.

This dissertation was composed while listening Burna Boy, Sauti Sol, Bad Bunny, J Balvin, Karol G, Tinariwen, Tems, Amaarae, Lido Pimienta, Torreblanca, and Gepe. I am grateful for how this music supported me through data cleaning, analysis, and writing.

Contents

Introduction

In addition to growing food for own consumption, agricultural households supplement their consumption with food acquired in local markets. A substantial portion of household budgets are spent purchasing food staples, household goods, and services from small firms in their local market. These small firms constitute a large and under-studied market for goods and services that are pervasive throughout rural areas in developing countries. A large literature contemplates supply chains where crops produced in rural areas are procured from smallholder farmers, stored, shipped, and re-sold to urban areas or in other markets. The reverse supply chain of goods that initiate in urban centers and are transported to rural areas also merits attention from researchers and policy-makers. After all, rural firms' capacity to efficiently deliver goods and services directly affects household budgets in terms of prices paid, time spent searching for and acquiring goods and services, and ensuring inventories are stocked so that food is consistently available for purchase.

I draw on theory from development economics and industrial organization to study rural firms and markets following three types of changes to their supply chains: 1.) the introduction of a digital technology that lowers search costs, 2.) a macro-economic weather shock that affects firm performance and new firm entry, and 3.) how idiosyncratic input price shocks are passed through to output prices faced by households.

The first essay uses a randomized experiment of 500 firms in Tanzania and asks if lowering search costs via a new digital technology that connects buyers and sellers improves firm productivity and changes incentives to engage in relational contracting with suppliers and customers. The digital technology is a mobile-based phonebook application (app) that is accessible on feature phones that are common in rural areas in Tanzania, making the phonebook app an ideal technology for rural firm owners in the 'last-mile' supply chain. The phonebook app lists firms' sector, location, and contact information for a range of retail and service sectors in both urban and rural areas. Relational contracting is a term that characterizes how sellers provide additional benefits (trade credit, shipping services, price discounts, and special orders) for buyers with whom they have a history of repeat transactions. Rural firms engage in relational contracting in both their upstream supply chain with suppliers in urban centers and in their downstream supply chain with their customers in rural areas. The phonebook app makes it easier to meet new suppliers and customers, which increases bargaining power for rural firms because they have a credible threat to discontinue existing relationships.

Participating firms are split into a control and treatment group with two variations: 1) a phonebook listing that is visible to upstream suppliers in urban areas, and 2) a phonebook listing that is visible to downstream customers in rural areas. Using an index of relational contracting activity, I find that being listed in the phonebook causes firms in the upstream treatment group to increase relational contracting with their suppliers by 0.10 standard deviations compared to the control group. With respect to customer relational contracting, treatment effects go in the opposite direction - both treatment arms decrease provision of relational contracting benefits by about 0.11 standard deviations compared to the control group. However, there is no strong evidence that the quantity of new customers or new suppliers increases compared to the control group. The fact that both treatment arms decreased customer relational contracting suggests that all treated firms anticipated reaching new customers. It is consistent with the idea that being listed in the phonebook caused firms to update their valuation of relational contracts and respond by negotiating better terms with known suppliers and customers.

The second essay explores the consequences for rural firms from an economy-wide negative shock that lowers agricultural productivity. A drought in Kenya in 2016-2017 caused maize production to decrease primarily in southeastern and northern Kenya which preceded nation-wide increase in maize prices. Rural firms are affected through both supply and demand channels. In areas directly affected by drought, rural firms' customer base of agricultural households experienced crop losses that lowered their income, affecting local aggregate demand for retail goods and services sold by rural firms. In non-drought areas, agricultural production was stable, implying that local farmers that sell to markets may have benefited from maize price increases, also affecting aggregate demand in non-drought markets. Maize price increases affected firms in both drought and non-drought areas by raising input costs, especially among staple grain sellers or other food retailers whose supply was affected by the drought shock.

Using differences-in-differences and two-way fixed effects identification strategies, empirical results show that firms in areas directly affected by drought have worse performance in terms of sales, profits, and hiring of workers than firms in non-drought areas but that firm entry increases. Sales decrease by 12-23%, profits by 13-27%, and hiring decreases by 50%, but number of competitors increases by 23%. By contrast, in non-drought areas, the number of competitors decreases and firm performance improves - sales increase by 18%, profits by 32%, and hiring increases two-fold while the number of competitors declines by 18%. Low revenue and more competitors means that local aggregate demand is distributed across more firms that enter after the shock occurs, meaning that the market as a whole could have grown but revenues are distributed across more firms resulting in a net decline in firm profitability. Among a sub-sample of women-owned firms, those in drought-areas are more likely to remain open than those in non-drought areas. Higher entry and a higher likelihood of remaining open, despite low revenues is consistent with having lower opportunity cost of labor and fewer opportunities to earn income.

Prior research established that the own-price elasticity of demand for staple grains is less elastic than demand for non-necessity foods, such as fruits, vegetables, meat, and fish. As income decreases and maize prices rise, rural household demand for staple grains like maize would be less elastic than for other foods, as households substitute to high-calorie staple grains. To infer how consumers allocate demand among food retailers, I disaggregate the retail sector into different categories based on types of goods sold - staple grains, vegetables/fruit, and meat/fish, and non-food retail. Consistent with prior work on elasticities, I observe that firms that sell food products with more elastic demand (vegetables/fruit and meat/fish) fare worse than staple grain sellers. This is consistent with households meeting their basic food needs by purchasing staple foods and lacking additional resources after the drought to purchase non-necessities. The opposite occurs in non-drought areas. Meat/fish sellers sales and profits increase substantially more than the other food and non-food retail categories. This increase for meat/fish retailers suggests that consumers in the local area benefited from higher staple grain prices and increased purchases of luxury foods.

In the third essay, I use data on input (wholesale) and output (retail) prices collected from retail firms in urban and rural areas in Tanzania to estimate passthrough rates following changes in input prices for three types of goods – staple foods, perishable foods, and differentiated products. Information frictions and search costs raise price uncertainty for retail firms when they purchase goods for re-sale. And seasonal price variation means that month-to-month changes in input prices are common. Due to seasonal price variation, rural households' ability to pay for foods that meet their dietary needs varies throughout the year. For rural firms, price uncertainty and seasonal variation means that input prices go up and down throughout the year. The extent to which these changes passthrough to output prices paid by customers affects the purchasing power of rural households.

I show that retail passthrough rate elasticities are larger for input price decreases than for input price increases. Across urban and rural firms, a one percent increase in input prices is associated with a 0.30-0.62% increase in output prices and a one percent decrease in input prices is associated with a 0.33-0.85% decrease in output prices, depending on the types of goods included in the sample. I then show that rural firms have 55% lower passthrough rates than urban firms for staples goods and 23-32% lower passthrough for perishable and differentiated products. Following input price decreases, rural firms have 23% lower passthrough rates than urban firms for perishable and differentiated products, and similar passthrough rates as urban firms for staple foods. A one percent increase in input prices relates to a 0.53% increase in output prices and a one percent decrease in input prices is associated with a 0.83% decrease in output prices. It shows that for staples, rural firms passthrough more cost savings and less cost increases, suggesting that rural firms bear some price risk by smoothing output prices despite experiencing higher input prices. Output price smoothing helps households bear seasonal price variation and improves households' ability to afford nutritional diets.

Taken together, these essays show that rural firms are an integral part of the food market system and provision a reliable source of food and non-food products in rural areas. From one perspective, they are intermediaries that negotiate between rural consumers and urban wholesalers, which is a potential source of market power. From another perspective, much like agricultural households, rural firms are themselves constrained from making optimal investments and lack access to formal insurance and credit markets. After the drought in Kenya, new firms were created and other firms remained open despite worsening economic conditions, suggesting that firm owners had few other options to generate income. Rural firms are also responsive to their customers, engaging in relational contracting to provide additional benefits in exchange for accessing a reliable customer base. This means that customers have bargaining power and can withdraw purchases if they feel like a local firm has unfair practices. Rural firms also passthrough savings from input price decreases to a greater degree than they passthrough higher costs from input price increases, suggestive of favorable terms for their customers.

New digital technologies have the potential to increase access to information for rural firm owners and connect them with urban supplier networks, sources of credit, training, and insurance. New networking opportunities generate opportunities for ideas exchange, productivity-enhancing investments, and other innovations designed to benefit rural people. Yet, researchers and policymakers should be cognizant of how bargaining power and the distribution of welfare could change as new supply chain technologies are developed. Firms provide relational contracting benefits to their customers because they value the long-term potential of a sustained business relationship. Mobile technologies tend to increase the viability of anonymous transactions, which means that prices may be lower but reliance on social networks could decrease. In rural economies, social networks in small communities are an important source of partial insurance. In monitoring food system performance following environmental shocks such as drought, flood, pest pressure, or other system-wide shocks, rural firms can provide essential information about how local markets function and whether food or cash assistance programs need to be mobilized.

Essay 1.

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

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

The presence of search costs can increase the value of relational contracting where buyers leverage repeat transactions with sellers to access benefits. In rural markets, sellers may provide credit, or price discounts, or may arrange ordering and shipping of goods for buyers (Fafchamps, 2006). If it were costless to locate new sellers, buyers would have less incentive to repay deferred payments. Likewise, if it were costless to locate new buyers and if the pool of potential buyers was sufficiently large, sellers would have less incentive to sustain relational contracts with their customers. In practice, it is common for sellers to build-in incentives to ensure that trade relationships are sustained in agricultural and other settings with informal contracting (Sexton, 2013; Casaburi and Reed, 2021). Relational contracting helps resolve market failures that persist in developing country contexts - such as in the provision of credit. Yet, such contracts are also a side effect of high search costs and may be less important when firms' search costs are exogenously reduced.

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

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

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

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

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

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

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

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

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

These findings contribute to the literature that seeks to understand constraints to small firm growth in developing countries by adding evidence about how search frictions relate to relational contracting and productivity. Policymakers and researchers have shown interest in investing in programs and policies that improve productivity for small firms and enable them to grow. Many small firms face barriers to expansion from both input and output sides of their supply chains. For inputs, incomplete markets for finance, labor, energy, and supplies create frictions that prevent enterprises from reliably meeting local demand for goods and services. For outputs, small firms in rural areas may have few avenues for reaching new customers or accessing new markets. Prior research has examined the role of relaxing input-related constraints to firm growth - such as access to capital and credit (De Mel et al., 2008), management and business training (Bloom et al., 2013; McKenzie and Woodruff, 2014; Anderson et al., 2018), and has begun unpacking the role of networks to disseminate knowledge and improve business practices (Fafchamps and Quinn, 2016; Cai and Szeidl, 2018; Hardy and McCasland, 2018). Prior research has studied programs that relax input market constraints or output market constraints, but few studies have been able to experimentally relax both in a single setting (an exception is Anderson et al. (2018)). This research addresses this gap by exploring how search frictions in input and output markets constrain rural firms' trading relationships in Tanzania.

Much of the empirical evidence on relational contracting comes from international trade settings (Macchiavello and Morjaria, 2015; Startz, 2018), manufacturing (Mcmillan and Woodruff, 1999; Fafchamps and Quinn, 2016) or focuses on agricultural supply chains (Fafchamps and Minten, 2002; Macchiavello and Morjaria, 2020; Casaburi and Reed, 2021) where buyers and sellers only transact during harvest season. In contrast, this setting encompasses rural and urban areas in Tanzania to consider how upstream and downstream relational contracts are formed and sustained. Firms enrolled in this study are small or microenterprises with few employees - only 15% of firms have any paid employee - based in medium-sized rural towns in central Tanzania. Most firms source relatively homogeneous inputs from urban areas and re-sell them or process them into an value-added service in their rural communities. This includes basic food staples such as rice, beans, vegetables, and sugar, as well as household items like soap, and inputs for service providers such as thread, needles, bike tires, and cement. Despite operating in relatively competitive market conditions, I document substantial use of relational contracting by rural firms with upstream and downstream trading partners and compare how relational contracting norms respond to changes in search costs.

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

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

The remainder of the paper is structured as follows: In Section 1, I provide background on information frictions and relational contracting in this setting. In Section 2, I use the background to motivate theoretical predictions that can be tested in data to understand how search costs affect relational contracting. Section 3 describes the experimental design and sampling frame. Section 4 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 5 describes results from the discrete choice experiment, phonebook usage, and field experiment survey data. Results from the field experiment highlight changes in 3 groups of outcomes: upstream outcomes, downstream outcomes, and productivity. I also provide results for the primary heterogeneous treatment effect of interest: differences between retail and service firms. Section 6 provides a discussion of results. Finally, in Section 7 I conclude by discussing the implications for firm productivity when a new technology facilitates a disruption to existing marketing norms.

1 Background: Urban-to-Rural Trade in Tanzania

1.1 Importance of Information Frictions

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

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

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

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

1.2 Relational Contracting Norms

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

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

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

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

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).

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.

1.3 Firm Heterogeneity: Retail and Service Firms

As detailed above, firms report a mix of purchasing inputs locally and travelling or having inputs shipped from another location. The experiment differentially lowers search costs for rural firms to learn information about urban firms in one treatment arm. Therefore, to learn about how changes to search costs affects firms, it is worth considering which types of firms are more likely to transact in urban areas and which are more likely to search locally.

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

Table 2: Baseline Input Acquisition by Firm Sector

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

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

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

2 Predictions: Search Costs with Relational Contracts

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

2.1 Upstream and Downstream Relational Contracting

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

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

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

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

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

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

2.2 Urban-to-Rural Trade with Heterogeneous Firms

Because relational contracting relies on repeat transactions, it is important to consider how transaction costs vary with firm type. Retail firms have larger input orders than service firms and purchase from cities more often, shown in Table 2.2. One important component of transaction costs are transport costs - a variable cost of production that must be paid each time a firm sources inputs. For firms with large input order sizes, it is relatively cheaper to search over a wider geographic area because they have lower transportation costs per unit of goods acquired.

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

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

3 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.[2] Unlike a typical phonebook from a US setting, this phonebook app only lists firm contact information and does not list contact

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

[2] For an example of the phonebook menu system, see Figure 8.2 at the end of the paper and Dillon et al. (2020) and Weld et al. (2018) for more details.

information for households or individuals that do not operate firms.

3.1 Description of Intervention

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

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

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

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

3.1.2 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.

3.1.3 Experimental Compliance

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

3.1.4 Pre-Analysis Plan

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

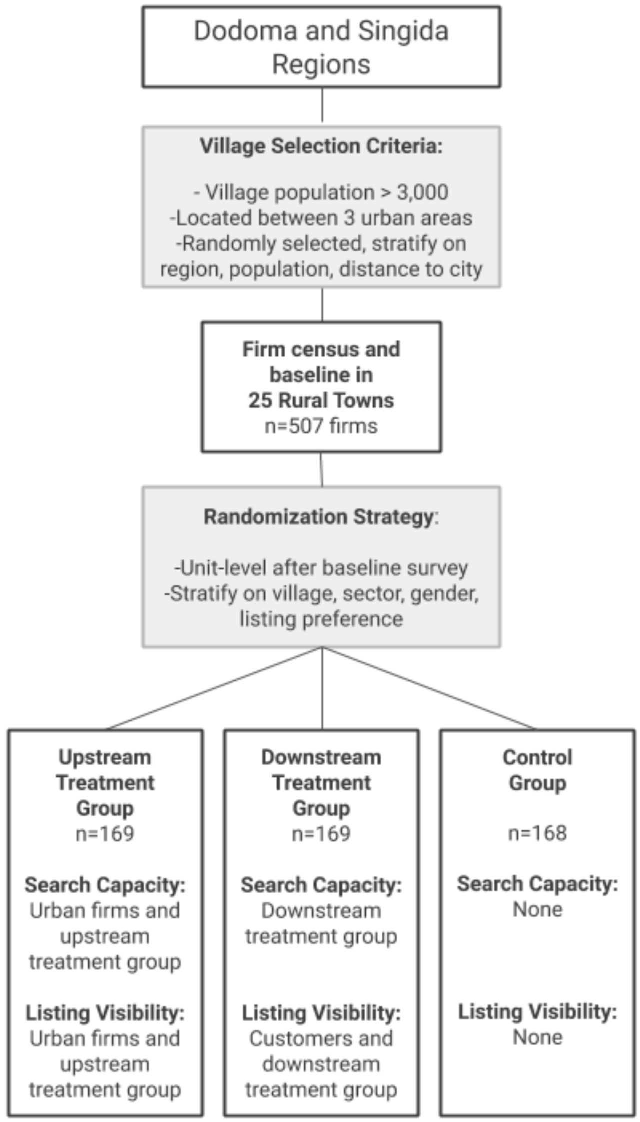


Figure 1: Experimental Design and Treatment Descriptions

3.2 Sampling Frame

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

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

3.2.1 Stratified Treatment Assignment

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

3.2.2 Upstream Supplier and Downstream Customer Phone Numbers

Treatments intend to connect listed *rural firms* (the target of the intervention) that have their contact information in the phonebook platform with *platform users*, defined as other firms or consumers that dial into the phonebook platform to connect with listed firms. Figure 8.3 at the end of the paper shows the timing of treatments, surveys, and communication with urban firms and rural customers. After collecting baseline questionnaires with participating firms in the sample communities drawn from rural areas, the research team also visited three urban centers - Dodoma City, Singida City, and Manyoni Town to register urban firms. A total of 348 wholesale and retail firms consented to list their business contact information in the phonebook platform. This pool of firms is the 'urban' firm group. Their phone contact information is only searchable by firms in the upstream treatment arm. And, their phone numbers are constrained to only search for rural firms in the upstream treatment arm.

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

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

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

3.3 Sample Characteristics

The sample area is located in the semi-arid central region of Tanzania. Table 8.1 at the end of the paper compares characteristics from the sample regions with the national average. All three regions are less urban than the national average, have lower rates of non-farm employment and have lower mobile phone ownership rates. For a phone based study like this one, access to a mobile phone is required to participate and is part of the selection criteria. However, the first filter for participation is business ownership, which tends to overlap with phone ownership. No businesses declined to participate due to a lack of access to a phone.

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

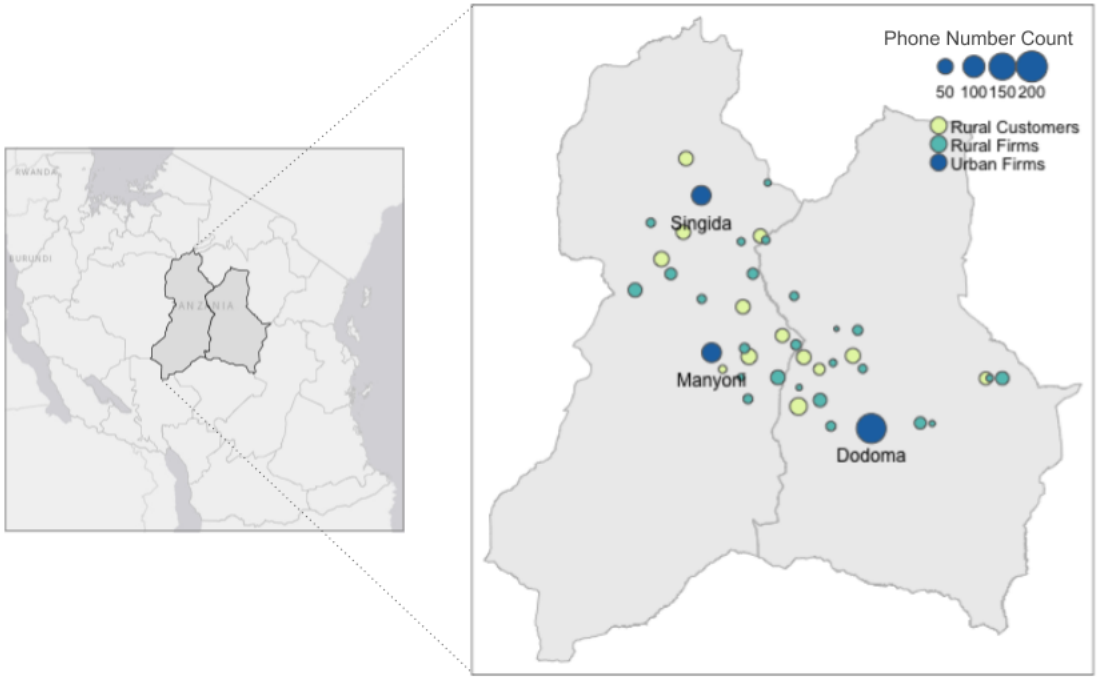


Figure 23.1 shows the geographic distribution of urban firms, rural firms in the treatment and control groups, and rural customers in Singida and Dodoma regions in central Tanzania. The size of the bubble indicates the number of phone numbers that were gathered from each location. Urban firm contact information was obtained from urban centers denoted with blue dots, rural firms that were assigned to an experimental condition are located in villages denoted with green dots, and villages where the digital phonebook was promoted to rural customers are represented by yellow dots.

3.3.1 Rural Firm Characteristics

Table 3 presents descriptive statistics for firms that were enrolled into the phonebook platform during the baseline survey. The average firm owner is 35 years old and has 7 years of schooling. The average firm is just over 5 years old and has 0.21 paid employees - indicating that the vase majority of firms did not report any paid employees. About 36% of firms enrolled were owned by women. Firms reported an average of about 5 competitors from

Table 3: Baseline Characteristics for Rural Firms

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

the same sector in their village. The majority of firm sectors relate to retail activities, split between 40% that sell food and crops and 12% that sell non-food items like clothing and medicine. The rest of firms are service firms that provide agricultural services (8%) like tractor rentals and milling, non-agricultural services (25%) like barber shops and restaurants, and skilled trades (15%), which includes tailors, welders, carpenters, and builders. The sample size varies slightly due to some instances of non-response and because some questions were dropped at different phases in piloting. As described below, regressions that measure treatment effects control for non-response in baseline outcomes.

3.3.2 Balance Checks

The balance table in Table 8.2 at the end of the paper compares the means for the treatment groups, control group, and t-tests for differences between groups. The balance table compares differences across groups among 22 covariates, including baseline demographic characteristics and baseline outcomes. Out of 22 covariates, 4 exhibit marginal imbalance at the 10% level - whether a firm was women-owned, owner age, customer calls, and the output price index. And, one covariate was imbalanced at the 5% level - whether the firm has access to electricity. But, an F-test of joint significance across all covariates fails to reject the null of no joint significance. Rather than add imbalanced covariates as controls in treatment effects regressions, I use a machine learning procedure to produce a unit-level prediction index following Ludwig et al. (2019) and Wager et al. (2016). The prediction index was constructed by regressing treatment on baseline outcomes and their interactions and selecting variables through random forest and lasso selection procedures to build an index. The idea is to select variables that explain any arbitrary correlation between experimental groups and baseline outcomes and add them as a regression adjustment to improve precision.

4 Empirical Approach

4.1 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.[4] After completing a series of comparisons, each participant will have generated binary choice data with information on which attributes were available for each choice.

Econometric analysis of discrete choice data draws from a random-utility model and uses a mixed logit model to estimate choice probabilities that represent the relative importance of each attribute level (McFadden and Train, 2000).[5] Coefficients on terms in the mixed logit are interpreted as the group-level preferences for an attributes. Point estimates can also be converted into measures of willingness-to-pay (WTP) for certain attribute levels. While these WTP measures are not incentivized, we used the most recent per unit price for an input as the base price in the experiment. Econometric analysis uses the following model specification:

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

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

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

[5]For further detail on assumptions, see Section 11 in the appendix.

4.2 Treatment Effects Estimation

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

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

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

Multiple hypothesis testing follows 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

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

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

q-values are presented by each outcome grouping. Outcomes were grouped according to whether they pertain to primary upstream, downstream, or productivity outcomes.

Section 10 in the appendix provides details on several robustness checks. Section 10.B shows that attrition was unrelated to treatment and baseline outcomes. Section 10.C provides p-values and multiple hypothesis testing on main outcomes using randomization inference. And, Section 10.D provides treatment effects estimates using an alternate index construction using inverse covariance matrix weighting.

4.2.1 Heterogeneous Treatment Effects

Heterogeneous treatment effects were estimated using the following model:

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

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

4.3 Outcome Variables

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

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

Productivity outcomes include a sales revenue index, an output price index, an input price index, transport costs as a share of inputs purchased, and whether inputs were purchased locally. The sales revenue and output price indices provides information about whether treated firms experience a sustained increase in sales relative to control. The input price index, transport costs, and whether firms purchased inputs locally provide information about whether firms input sourcing costs decreased, providing evidence that they became more efficient. Further detail on index construction is provided in Section 9 in the appendix.

4.4 Empirical Tests

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

Table 4: Summary of Empirical Tests

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

5 Results

5.1 Willingness to Pay for Relational Contracting Attributes

Table 5 shows results from the discrete choice experiment. To make coefficients economically meaningful, they were converted into a measure of WTP by dividing the point estimate of the mean of an attribute level by the price coefficient.[8] The column 'WTP (Percent)' reports the willingness to pay and confidence interval for each contract level. Not all attribute levels were meaningful to participants (paying with Mpesa and paying 80% of their balance at once). It indicates that firms were indifferent about some contract attribute levels and consistently preferred those with different features.

Table 5: WTP for Contract Attribute Levels

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

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

Firms expressed a WTP of a 6% premium for inputs from a known supplier relative to an unknown supplier, a 33% premium for goods to be delivered relative to travelling to a city, and 18% premium for provision of generous credit terms relative to paying cash at the time

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

of purchase. This highlights the extent to which firms are willing to pay higher prices on inputs for contract attributes that benefit firms. Although a 6% price premium to purchase from known suppliers is small compared to having goods delivered and obtaining credit, it is notable because only 40% of firms in the baseline survey reported having preferred suppliers. And, in practice, obtaining these benefits requires forming relationships with known input suppliers.

5.2 Phonebook Usage

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

Columns 2-5 denote whether a firm searched an urban area, rural area, retail firm, or service firm.[9] Column 2 reports whether firms searched in urban areas and confirms that

[9]Not all firms that dial into the phonebook app reach a final screen that lists a business phone number. Firms reported to the research team that sometimes they would use it to search for firm names, locations, and sectors, all of which can be found without going to the final screen that features a firm phone number.

Table 6: Results: Rural Firm Phonebook Application Usage

Panel A: Firm Search Behavior in Phonebook Application

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

Panel B: Firm Found in Phonebook Application

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

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table reports results from treatment effects regressions of a phonebook usage outcomes on a treatment indicator, strata fixed effects, and the prediction index. All dependent outcome variables are categorical (0/1) and denote any usage over the entire treatment period. Coefficients identify the effect of treatments on firm searches in phonebook (Panel A) and visibility (Panel B). All outcome variables exclude instances where firms searched for their own listing, except for Column 5 in Panel B "Found Own Listing."

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

Columns 2 and 3 provide information about whether firms were more interested in searching within urban areas or in rural areas. The upstream treatment arm is the only group that had the capacity to search for both, and they searched more in rural areas (41% searched rural areas compared to 26% that searched in urban areas). Columns 4 and 5 show whether there was more interest in searching for retail or service firms. After accounting for the control group search attempts, about 33-42% of treated firms searched for either retail or service firms.

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

In other cases, the cell network may have failed or the USSD shortcode host could have timed out.

5.3 Upstream, Downstream, and Productivity Treatment Effects

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

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

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

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

This is surprising given that this group was by far the most likely to both search and be found by others in the phonebook platform (see usage data in Table 6). One potential explanation is that increased engagement with the platform crowded-out the firms typical engagement with their pre-existing customers relative to the control group. It is also possible that rural customers sought out new firms in face-to-face interactions that is not captured by the number of phone calls. Another possibility is that timing of phone surveys were too infrequent to pick up the timing of phone calls from new contacts. For upstream outcomes, survey questions were oriented around the "most recent input purchase," an event that typically occurs 1-2 times per month. On customer questions, questions were oriented over the previous week or over the past two days because firms engage with customers on a daily basis. Therefore, it is more difficult to pick up net changes in composition of the customer base.

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

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

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

Panel A: Upstream Outcomes

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

Panel B: Downstream Outcomes

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

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

Panel C: Productivity Outcomes

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

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

5.3.1 Relational Contracting Index Components

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

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

On the downstream side, firms reduced each component, but not significantly until aggregated into an index that picks up net changes. This suggests that index aggregation is a

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

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.

Table 8: Relational Contracting Index Components

Panel A: Upstream Relational Contracting Index Components

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

Panel B: Downstream Relational Contracting Index Components

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

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

5.4 Heterogeneity by Firm Sector

As described in Section 2.2, search behavior by retail and service firms is likely to differ because retail firms search and purchase more in cities and have lower per unit transportation costs which, in turn, lower search costs in urban areas and make relationships with suppliers based in cities more valuable.

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

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

Columns 1-3 of Panel B report heterogeneous treatment effects for supplier relational contracting index and two measures of transacting with new suppliers. Analogously, columns 4-6 report heterogeneous treatment effects for customer relational contracting index and measures of transacting with new customers. Retail firms increased relational contracting with suppliers by 0.07 standard deviations and service firms increased marginally more. But, only service firms were significantly less likely to transact with a new supplier and had fewer new suppliers as a share of the number of suppliers. Both retail and service firms decrease relational contracting with customers, although service firms decreased by about 0.04 standard deviations more than retail firms. And, there were no differences in customer composition - neither sector experienced significantly more transactions with new customers, as measured through survey recall data.

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

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

Table 9: Heterogeneous Treatment Effects by Firm Sector

Panel A: Search Outcomes

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

Panel B: Relational Contracting Outcomes

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

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

6 Anticipating General Equilibrium Effects

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

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

Yet, it is also possible that prices remain at the higher level. Like many phone-based networking platforms, the digital phonebook studied here creates new opportunities for buyers and sellers to meet when they might not have met otherwise. These new contacts may cause buyers and sellers to decrease their reliance on ex-ante customer networks for sales and increase engagement with new customers. Since customers that benefit from relational contracting receive lower prices, an aggregate change in customer composition where all firms increase contact with new customers could cause the average price level to remain above the previous equilibrium. Evidence that firms with higher downstream relational contracting have lower prices is seen in Panel B of Table 11.3 in the appendix. A one standard deviation increase downstream relational contracting index is associated with a 0.16 standard deviation decrease in the output price index.

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

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

7 Conclusion

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

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

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

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

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

Appendix

8 Additional Tables and Figures

8.A Example of Phonebook Menu System

Figure 8.1: Example of Feature Phone

Image from Weld et al., 2017. Editing by Tiffany Loveridge.

Figure 8.2: Phonebook Application Menus

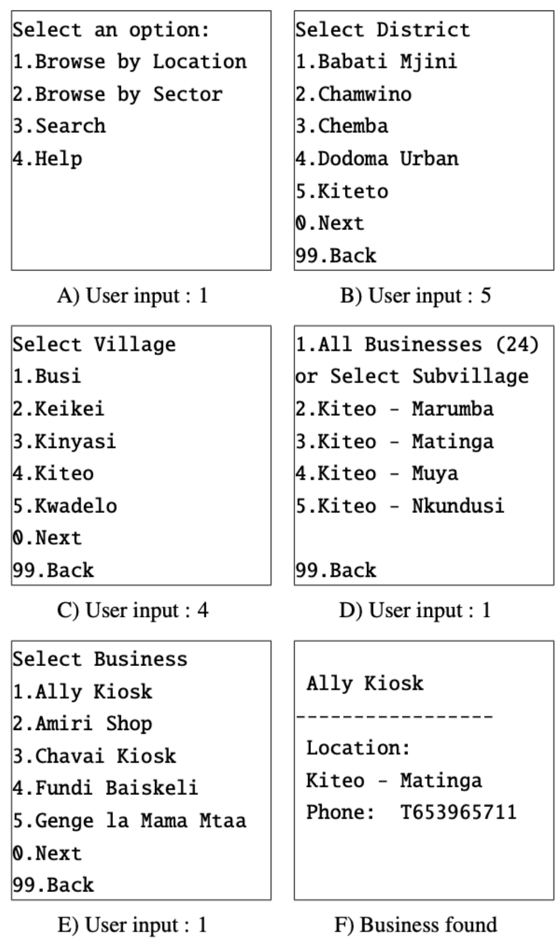
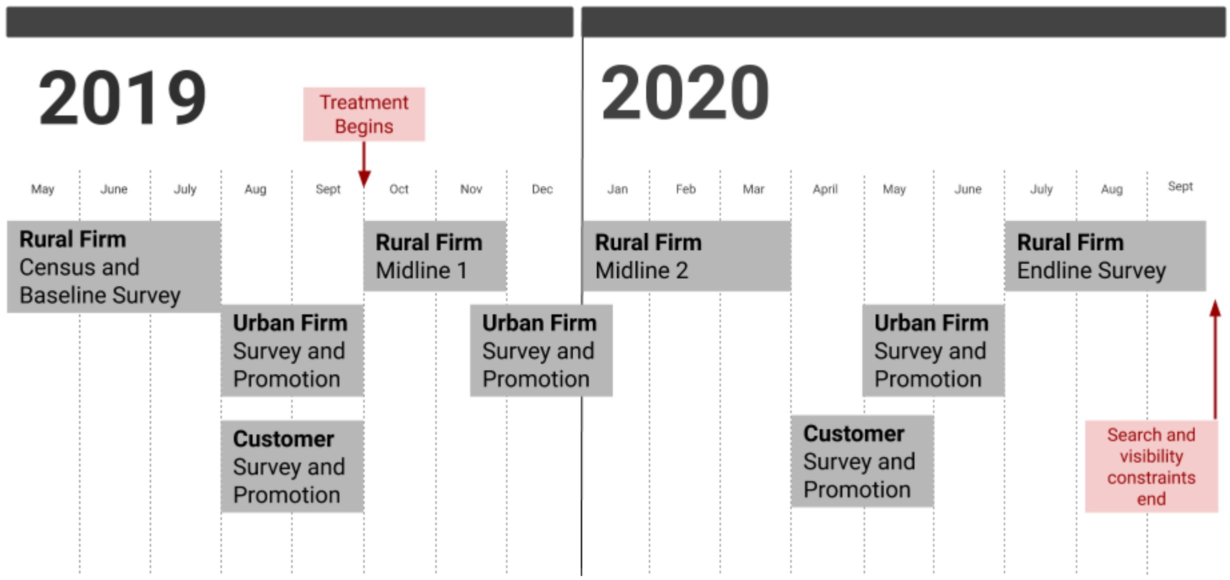


Image from Weld et al., 2017

8.B Experimental Timeline

Figure 8.3: Experimental Timeline



8.C Regional and National Characteristics

Table 8.1: 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

8.D Balance Table

Table 8.2: Balance Table of Baseline Treatment and Control

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

9 Index Construction

Analysis of primary outcomes involves 8 indices: upstream relational contracting, downstream relational contracting, input search activities, upstream phone communication, downstream phone communication, sales revenue index, and input and output price indices. Index aggregation improves statistical power by testing fewer outcomes. Indices were constructed following Kling et al. (2007) which employs a procedure that sums equally-weighted z-scores computed for each component of an index. The z-scores are calculated at the unit-level by subtracting the control group mean and dividing by the control group standard deviation. The index captures the net change for a given set of related outcomes and are interpreted as the number of standard deviations increase or decrease compared to the control. The authors also suggest an imputation procedure for outcomes with missing information. It fills in missing data with the experimental group mean (e.g. the treatment group 1 is assigned the mean of the rest of treatment group 1). Non-response for sensitive outcomes (anything relating to revenues and costs) is common by small business owners in Tanzania. Indices constructed by weighting by inverse covariance matrix of components following Anderson (2008) are provided as a robustness check in Section 10.D.

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

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

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

- **Phone Activity:** For customer and supplier phone activity indices, the components of the each index are whether any calls were received over the previous week, the exact number of calls received over the previous two days, calls made over the previous two days, and whether contacts were new. It captures the net change in phone activity and provides information about whether treatments increase phone engagement with supplier and customer contacts.

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

10 Robustness Checks

10.A Spillovers

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

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

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

owners in their village. Only 10.5% of firms reported discussing any business activity with their neighbors, a relatively small share.

10.B 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 10.1 shows the differential attrition rate by two definitions of attrition. First, columns 1 and 2 show results for the variable 'Periodic non-response', which takes a value of 1 in cases where a firm did not respond to at least one survey. About 35.3% of control firms did not respond to at least one survey round, but there were no differences by treatment group. Second, the outcome variable 'permanent attrition' takes a value of 1 in cases where there was no response after the baseline survey. The permanent attrition rate is much lower - only about 5.3% of control firms attrited after the baseline survey and there were no differences by treatment group. Columns 3-5 report the attrition rates for each survey round, also finding no differences by treatment group.

Table 10.1: Differential Attrition by Treatment Group

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

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

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

The second type of attrition rate based on baseline covariates serves to rule out selective attrition on observables. Table 10.2 in the Table appendix reports two tests of selective attrition based on two definitions of attrition described above - periodic non-response, and permanent attrition. A regression with the attrition status as the independent variable and the baseline balance covariates interacted with treatment status on the right-hand side was run along with an F-test of joint significance of regressors. The F-stat for the periodic attrition regression was 1.63, too low to reject a null hypothesis of zero joint significance at the 10% level (p-value is 0.1143). And the F-stat for permanent attrition group was 0.83, with a p-value of 0.5762, also failing to reject the null of a joint effect. Given that differential attrition by assigned groups and selective attrition on observables do not appear problematic, making the additional assumption that unobservables do not drive differences preserves identification of the average treatment effect (ATE) for the study population (Ghanem et al., 2019). Here, the empirical strategy estimates an intent-to-treat (ITT), which equals the ATE under the assumption of perfect treatment compliance.

Table 10.2: 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.

10.C 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 10.3 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 10.3: 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	.2168	.0049	.0209	.0426	2000
Inputs Purchased Locally	.2871	.0077	.0237	.0426	2000
Joint Test - All Outcomes				.0062	2000

Notes: This table compares p-values for main outcomes using randomization inference. The first two columns show individual p-values for each treatment for main outcomes that can be directly compared to asymptotic p-values and multiple hypothesis testing p-values presented in Table 7. Column 3 is a joint test of significance for both treatments combined for each outcome. Column 4 is a joint test of significance for both treatments for each group of outcomes. The last row reports the p-value of a joint test of significance on all outcomes.

10.D Inverse Covariance Weighted Index Construction

A second approach to index construction proposed in Anderson (2008) utilizes a standardization procedure similar to Kling et al. (2007), but weights components by the inverse of the covariance matrix of outcomes. It has the effect of down-weighting components with little variation across units, and increasing weight on components that are relatively less correlated with other components. This index construction would penalize indices whose components are highly correlated. If between-component correlation were driving results, this index would result in larger standard errors. And if between-component correlation does not drive results, the weighting procedure is equivalent to efficient generalized least squares and can result in smaller standard errors.

All indices that were presented in the main outcomes were constructed following Anderson (2008) and results are shown in Table 10.4. 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 10.4: 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.

11 Discrete Choice Experiment Detail

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

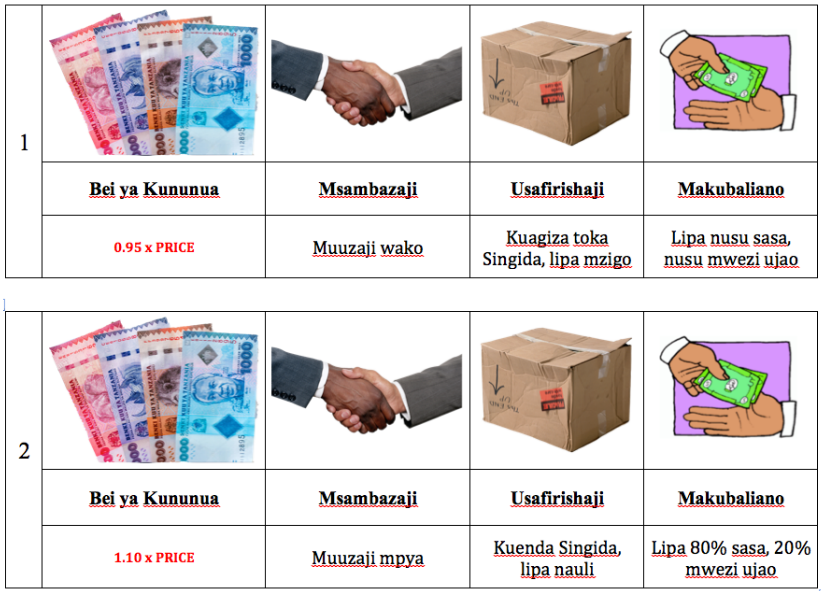
For each contract attribute, one option is associated with having built trust with a supplier. For example, suppliers must trust that credit will be repaid, or they must trust that payment for goods shipped will be received. Table 11.1 below shows each contract attribute and the different levels. Each 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 11.1).

Table 11.1: 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 11.1 provides an example of a contract pairing).

Figure 11.1: 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 (**?**). 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 11.2 shows results from the discrete choice experiment.[12] The sample size comes from the 376 firms that completed the choice experiment multiplied by the 12 contracts they reviewed.[13] Coefficients are the mean and standard deviation of a distribution of tastes in the population that participated in the discrete choice experiment. Price is treated as fixed coefficient, meaning that only a mean is estimated and assumed to be fixed for the population.

Table 11.2: 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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To make coefficients economically meaningful, they can be converted into a measure of WTP by dividing the point estimate of the mean of an attribute level by the price coefficient.

[12] For model specification and further detail on assumptions, see Appendix 11.

[13] The full sample of 507 firms did not complete the discrete choice experiment due to piloting and some cases of non-response. One firm only managed 10 contracts, thus $376 \times 12 - 2 = 4510$.

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.

11.A Baseline Relational Contracting

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

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

Results in Table 11.3 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 11.3: 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.

Essay 2.

Drought and the Food Retail Sector in Kenya

Droughts are detrimental to rural households because they lower crop yields and endanger livestock, generating shortages of essential food resources that would count toward household consumption budgets. Droughts also affect total household consumption by lowering potential revenue earned through sale of crops in output markets (Dercon, 2002). In the absence of insurance and credit markets, households have few avenues for consumption smoothing and may sell household assets or engage in temporary coping strategies to generate income (Hoddinott, 2006; Carter and Lybbert, 2012; Janzen and Carter, 2018). While these impacts and responses at the household or intra-household level are popular research topics, much less is known about how local firms fare in the wake of shocks. Moreover, ex ante, predicting the effect of this type of adverse environmental shock on rural firms is difficult because supply and demand shocks occur simultaneously and affect local and national markets.

To learn about how environmental shocks affect rural markets, I use publicly available micro-data from 6,000 firms in 157 markets spread across four counties in Kenya collected annually from 2013-2017 (McKenzie and Puerto, 2017). During the last period, one quarter of markets covered by the data experienced a drought that lowered production of staple crops. The precipitating event was rain failure in the 2016 and early 2017 cropping cycles that mainly affected northwestern and southeastern Kenya, including one county covered by the data. Using spatial and temporal variation in the drought intensity in a differences-in-differences specification, I study the effect of drought-induced food insecurity on retail outcomes, including revenue, profit, hiring, entry, and exit. The data feature full market censuses from all locations and a panel of women-owned firms that were surveyed six times over four years. These data allow comparing firms engaged in staple food retail (rice, maize, beans, etc.) with service firms and other non-food retailers.

In theory, firms located in areas directly and indirectly affected by drought both face demand and a supply shocks. During the 2016 drought, maize prices increased across Kenya, providing evidence that national maize production losses were large enough to induce a supply shock in all markets, even if production losses were localized to drought areas. In a typical year, agricultural households rely on a mix of foods from own-production and foods purchased from local rural markets. Without complete insurance and credit markets or government transfers, agricultural households facing a production shock have fewer resources to meet consumption needs at the same time that they plausibly have higher demand for food staples purchased from local firms.

In drought areas, firms have customers who experience production and consumption shocks which, in turn, cause a demand shock for all rural firms, and a supply shock for firms in the agricultural value chain (e.g. sellers of drought-affected staple grains and crops). In non-drought areas, firms' customers are also farming households but did not experience a severe production shock and were less likely to engage in coping strategies to recover losses. If production in non-drought areas remained stable, farming household welfare could have increased via higher maize prices from selling crops to the market. Therefore, firms indirectly affected by drought could have seen an increase in aggregate demand if their local economy benefited by selling crops to the rest of Kenya at higher prices.

Empirical results show that in areas directly hit by drought, firm performance declines compared to non-drought areas. According to the market census, firms decrease hiring by 0.13-0.27 workers, a 50% decrease depending on the model specification. Sales decrease by 12-23% relative to the non-drought mean and profits decrease by 13-27%. Yet, the number of competitors increases by 23%. By contrast, in non-drought areas, the number of competitors decreases and firm performance improves - sales increase by 18%, profits by 32%, and hiring increases two-fold while the number of competitors declines by 18%. At first glance, the decline in sales, revenues, and workers suggests that aggregate demand in drought-affected markets decreases, likely related to how rural retailers customer base comprises smallholder farming households who experience crop failures and decreases in income. But, evidence that firm entry increases following drought would suggest that local aggregate demand is distributed across more firms that enter after the shock occurs.

A few factors could contribute to increasing firm entry after drought. First, increasing output prices could induce new firms to enter. Output price data for maize shows a marked increase during the drought period across all markets in Kenya. Therefore, it would not explain differential entry in drought and non-drought areas because output price increases are common across markets. Furthermore, increases in maize output prices are related to a decline in production and increasing cost of acquiring maize to sell in markets, which would not induce competitive entry. Another explanation is that as farming households are made worse-off by lower crop yields, coping strategies include starting small businesses to generate income (Di Falco and Giorgi, 2019). This explanation matches the patterns observed in the data - there are more firms with fewer workers and lower sales and profits. Evidence that firms in non-drought areas increase sales, profits, and hiring with increased firm exit affirms the hypothesis that non-drought markets gain after drought occurs in other locations. Instead of starting new businesses, local workers are hired into existing businesses as they expand.

Data from the panel of women-owned firms show similar patterns in drought and non-drought markets. Women-owned firms in drought areas have lower sales, revenues, workers, and more competitors compared to non-drought areas. The panel allows comparing the same firms over time (unlike the full sample of market census firms which is treated as a repeat cross-section) and reveals a surprising result: firms in drought areas are more likely to remain open during drought and firms in non-drought areas are more likely to exit. Firms remaining open is consistent with local economic circumstances where the opportunity cost of labor decreases so that firm operators are willing to accept worse performance to generate modest returns that enable them to endure the drought. Reasons for exit in non-drought areas are not immediately obvious. Seasonal or year-to-year exit and entry is a common feature of rural markets in developing countries (McKenzie and Paffhausen, 2017). Among firms in the panel, 72% of firms who started in 2013 were operating in the last survey round (corresponding to the period of drought). Only 55% of firms were active during all 6 survey rounds, showing that firms entered and exited year to year. In this case, if market conditions improve in non-drought areas, it may induce firms to exit as better opportunities become available.

Examining response to drought by subsectors reveals important heterogeneity. First, retail and service firms (representing tradeables and non-tradeables) are likely to respond differently in drought if customers propensity to purchase goods or services changes. About 75% of retail firms in both samples sell food goods. Retail firms that sell food staples are more likely to experience supply chain shocks associated with lower crop production. Since customers in drought areas have lower incomes, they are more likely to reduce consumption of non-necessary goods and services, which would predict lower performance among service firms compared to retail firms. Yet, results show that the service sector fares better in drought areas compared to retail firms. This is a surprising result because we would expect retail sales to be higher as households substitute from own-production to purchased food.

To understand heterogeneity within the retail sector, I disaggregate the retail sector into different categories based on types of goods sold - staple grains, vegetables/fruit, and meat/fish, and non-food retail. I observe that sales, profits, and hiring decreases for firms in drought regions in all categories. But, firms that sell higher value food products (vegetables/fruit and meat/fish) fare worse than staple grain sellers. This is consistent with households meeting their basic food needs by purchasing staple foods and lacking additional resources after the drought to purchase non-necessities. The opposite occurs in non-drought areas. Meat/fish sellers sales and profits increase substantially more than the other food and non-food retail categories. This increase for meat/fish retailers suggests that consumers in the local area benefited from higher staple grain prices and increased purchases of luxury foods. Notably, there are no increases in competition in any of the retail categories in non-drought areas. This is consistent with the previous finding that local consumer demand likely increased and firms hired more workers but did not face increases in competition.

Rural markets are an important part of the rural economy and an essential source of food staples for agricultural households around the world. Understanding how rural markets function has important implications for food security - including stability in supply chains, availability of goods and services, and understanding small and medium firms as indicators for broader patterns of economic growth. Tschirley et al. (2015) find that share of consumption from own-production varies from 33% in the bottom quintile of income to 59% in the top quintile for rural households in East and Southern Africa. Poorer, rural households rely most heavily on own-production but the share of household food budgets spent in markets is substantial across all income quintiles, suggesting that the rural firms that sell goods and services are a sizable part of the rural economy.

The public policy response to droughts includes a mix of direct cash transfers and in-kind distribution of foodstuffs. When food markets experience a shock and prices spike, in-kind food distribution could provide a more secure food sources for recipients (Gadenne et al., 2017). On the other hand, direct cash transfers allow people to make purchases and invest in income-generating activities (Blattman et al., 2013) but may incentivize price increases (Cunha et al., 2019). Neither policy instrument has been tested in the presence of an aggregate shock, such as drought. This research informs those discussions by clarifying how rural markets cope with sourcing food and other goods to areas that are experiencing temporary environmental shocks.

Droughts in Sub-Saharan Africa are predicted to increase in frequency in severity as weather patterns shift as a result of climate change (Seneviratne et al., 2012). Researching the effect of climate shocks is imperative in order to understand how changing global climatic conditions are likely to reverberate into local economies. This research highlights how markets function to support or impair food security under adverse circumstances. Although agricultural households bear the brunt of the economic shock through a loss in agricultural output, it is possible that some of their consumption is smoothed through the presence of efficient markets where they can obtain foodstuffs to supplement consumption or sell assets for cash.

12 Supply and Demand Shocks in Rural Markets

The harvest season is a critical time for agricultural households' because they harvest crops that will be consumed throughout the year *and* make crop marketing decisions about whether and how much to sell to earn cash income. Environmental shocks threaten food security by decreasing agricultural yields and changing how agricultural households participate in rural markets. The net effect of an environmental shock on rural firms is ambiguous because they reconcile upward and downward pressure on aggregate demand with a negative crop supply shock. First, firms are affected through a demand channel. Aggregate demand for goods, especially food staples, could increase if agricultural households liquidate assets or seek wage work and increase their expenditure in local food markets to supplement household consumption. Yet, aggregate demand also faces downward pressure because households' agricultural income decreases as a consequence of lower crop production.

Second, firms are affected through a supply channel. One feature of agriculture-dependent economies is that local food supply chains face a negative supply shock if crop production declines because fewer households are selling crops to the market. In the Kenyan context, maize is the primary staple food commodity. In a study of maize traders, Bergquist and Dinerstein (2020) report that the poorest households in Kenya spends 14% of annual expenditure on maize and that maize traders purchase 50% of maize from small and medium scale farmers. A drought shock which affects the maize production of small farmers is likely to induce a negative supply shock for staple food retailers.

The theory of competitive markets predicts that if markets are sufficiently integrated, local firms in drought-affected regions can import foodstuffs from non-drought regions, and food prices will remain relatively stable (assuming that producers in drought-affected regions are price-takers). If prices are stable, and quantity sold rises, firm revenues will increase. However, if the supply shock increases prices, quantity demanded could decline enough to offset any uptick and the feedback effect will lower retail revenues as well as agricultural incomes. If the effect from a negative supply shock dominates, staple food prices would increase, possibly crowding out any gains from any expansion in aggregate demand, assuming retail margins are constant. These market dynamics imply that some sub-national markets are directly exposed to the supply shock, while others experience the indirect effect due to changes in input prices.

12.1 Direct and Indirect Effects of Drought

The firm-level microdata used for analysis come from four counties in Kenya - Kagamega and Kisii in southwest Kenya, and Embu and Kitui in southeast Kenya. Only markets in Kitui experienced severe drought that lasted two harvest cycles. However, drought also occurred in the northern regions, which are not included in the World Bank microdata. In examining the effects of drought, these counties cannot be treated as isolated or autarkic regions because crop failures in areas directly affected by drought spill over to non-drought areas through several mechanisms. First, the supply shock lowers the quantity of marketed crops circulating in the economy. In partial equilibrium, this supply shock raises prices. Second, if consumption levels remain stable, drought-affected farmers must rely more on local markets to purchase food, increasing aggregate demand, putting further upward pressure on prices.

The quantity produced and prices for maize are plotted in Figure 12.1. The figure on

Figure 12.1: Maize Prices and Production in Drought and Non-Drought regions, 2013-2017

the right plots annual maize production (kg/ha) in drought and non-drought regions in the microdata (red and blue lines) and the rest of Kenya (dashed red and blue lines). It shows that there was a maize production decline in 2016-2017, consistent with a negative supply shock induced by crop failures among farmers in drought-affected areas. The drought began in October 2016 and lasted through September 2017. Average production decreased in 2016 compared to 2015 across all counties in Kenya. The directly-affected drought areas available in the micro-data had the sharpest decline and did not recover in 2017. The indirectly-affected, non-drought counties in the micro-data also experienced a relatively sharp decline from 2015-2016 but then exhibit a steep increase in 2017. Closer inspection revealed that only one of the three counties in the non-drought area (Kakamega) had higher than average annual production in 2017, suggesting that the bumper crop was isolated in one county, which is dropped in a robustness check.

The figure on the left plots monthly maize prizes for markets in drought and non-drought regions. The time series data come from the World Food Programme's Vulnerability Analysis and Monitoring (VAM) dashboard. The rest of Kenya - both drought and non-drought areas - also experienced clear maize price spikes during the drought period that peaked in June and July of 2017. This national trend in maize prices provides evidence that even firms in non-drought areas were exposed to supply shocks, especially in maize markets.

The price increase reflects both the negative supply shock and the increase in demand for food staples in markets. It is not clear whether the demand shock or the supply shock contributed more to nation-wide price increases during drought because both put upward pressure on prices. It also appears that maize production declined markedly in drought areas compared to non-drought areas. As such, empirical results reflect the direct and indirect effects of drought. Firms operating in drought areas were directly affected by a local supply shock (crop failures), consumer demand shock, and price increases. Firms operating in non-drought areas experienced indirect consequences of drought caused by price increases and a supply shock in distant regions. Farmers in the non-drought area could have been made better off by the drought since they sold crops in favorable market conditions, as long as they are net-sellers of staple grains rather than net-consumers of staple grains. In that case, markets in non-drought areas could experience an uptick in demand.

In summary, there are three stylized facts about maize prices and production during the 2016-2017 drought that provide a basis to generate hypotheses about how firm performance would respond to this type of environmental shock. First, the crop production shock affected drought areas more than non-drought areas. Second, maize prices increased during the drought period and affected all markets in drought and non-drought areas. Third, consumers in drought areas are worse off following drought due to income effects (incomes are lower and staple prices are higher) and consumers in non-drought areas benefit as sellers of staple goods to the market (although they are not necessarily better off because they also have to pay higher staple prices).

13 Conceptual Framework

These stylized facts inform a conceptual framework drawn from microeconomic theory of market structure to guide interpreting changes in firm performance, changes in number of competitors due to entry and exit, and sectoral heterogeneity in drought and non-drought areas.

13.1 Firm Performance

Whether or not firm performance improves after a drought depends on how much customer demand for market goods changes after the drought shock. The resulting elasticity of demand for market goods is composed of income shocks and substitution effects. Crop losses generate an negative income shock, decreasing total household budgets and price increases in the key staple food decrease households purchasing power in markets. At the same time, households substitute between own-production and market goods. As own-production decreases, demand for market goods, in particular food staples, increases. Prior studies in East Africa have found that staple price shocks lower total household consumption and that demand elasticities for staple foods are less elastic than for other foods (Bai et al., 2020; Rudolf, 2019; Ecker and Qaim, 2011).

If consumer demand decreases after the drought, firms will experience lower revenues and profits relative to firms in non-drought areas. This occurs if the crop failure lowers farming income and subsequent consumer demand to a greater degree than other options that households exercise as coping strategies to increase incomes (by selling assets or seeking wage work). In that case, firm performance (sales, profits, workers) in markets directly affected by drought will be lower than those in non-drought areas.

In the non-drought, or indirect markets, there are two possible demand responses. First, if farmers produce the same quantity of crops, they will benefit as sellers of staple crops if higher prices pass through and they earn more farming income. But, as consumers of staple crops, households also face higher prices in markets, which could cause households to substitute market staples for own-production. Increases in sales, profits, and workers hired is indicative of greater consumer demand. While decreases in sales, profits, and workers hired would indicate that staple price increases lower consumers purchasing power, offsetting any gains from higher crops sales.

13.2 Competition, Entry, and Exit

Outcomes related to sector competition, entry, and exit provide evidence about whether the changes to market conditions caused by drought lead to differential competitive responses in drought and non-drought areas. Again, multiple responses are possible given changes to consumer and supply chain conditions. Lower local consumer demand could cause more firms to exit or temporarily close and fewer new firms to form in non-drought areas. Or the reverse could occur: higher consumer demand induces firm entry and fewer firm closures.

But, in settings with multiple market failures, especially missing credit and insurance markets that would otherwise facilitate consumption smoothing during shocks, these clean predictions from microeconomic theory likely will not hold. With reduced income from crop sales, households in drought-stricken areas may form new businesses to earn some cash income to sustain household consumption. As the opportunity cost of labor decreases, and if start-up costs are low enough, new firms could open despite worsening market conditions and old firms might remain operational that would have otherwise closed. In that case, despite decreases in consumer demand, competition may increase, further decreasing firm performance.

13.3 Differences by Sector

The consequences from drought for firms due to changes in the number of competitors and consumer demand depends on their sector. Household expenditure on market goods includes retail goods and services. Within the retail sector, some firms specialize in selling food staples with relatively inelastic demand while others sell non-necessity, luxury goods with less elastic demand - like vegetables, fruit, fish, and meat. About 70% of firms engage in the retail, or tradeable goods sector. The remaining 30% engage in services or non-tradeable sector. Among retailers, about 75% sell food-related goods - household staples such as maize, rice, sugar, beans, oil, and salt, or fresh market goods such as fruits, vegetables, meat, and fish.

Figure 13.1 provides intuition about how supply and demand shocks might look in a stylized, partial equilibrium graphs. The left figure plots demand and supply curves with expected demand shocks for retail and services firms. Households that experience crop failures may have a higher propensity to consume staple foods and withdraw spending from non-necessity goods and services. The service sector is about 30% restaurants and other food services, 30% tailors and sewing services, and 30% are barbers or salons, while the remaining 10% are split between transportation, bike repairs, welding, carpentry, and other repair services. Following a negative income shock, we could expect payment for services to decline as households defer expenditures on non-necessary services.

Since retail firms will then sell more necessity food goods, a negative income shock among their customer base would cause the proportion of household budgets spent on food staples to increase, crowding out spending in other categories - causing demand for services to shift further inward than demand for retail goods. Yet, once a supply shock is incorporated as in the figure on the right, it is not clear whether retail firms would have better performance compared to service firms, even if aggregate demand for services declines more than for retail goods. And, even if aggregate consumer demand for staple goods increases, if the number of competitors also increases, there may not be any gains for firms as demand is spread over a larger number of firms.

The crop production shock only affects supply chains for firms directly related to the agricultural sector. For the retail sector, this means that they only experience a supply shock for food crops that were affected by drought. The most important food staple is

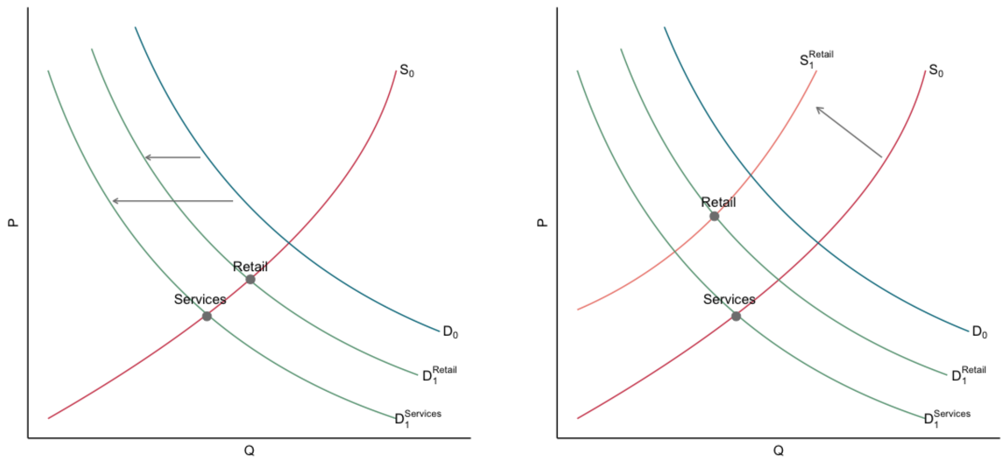


Figure 13.1: Stylized Demand and Supply Shocks in Partial Equilibrium in Drought Areas

maize, which I previously showed to have a price spike and production decline during the 2016-2017 drought. Detailed sub-national data on other food staples for this time period was not consistently available. But, Figures 18.1 plots monthly prices in Nairobi market from two different sources (World Food Programme and FEWSNET) for several other common food commodities in addition to maize - bread, vegetable oil, milk, beans, and sorghum as well as diesel and gasoline prices. Maize exhibits the sharpest increase, but sorghum, milk, beans, and vegetable oil prices also increase during the drought period, although they also tend to exhibit more price fluctuation over the entire time period. Gas and petrol prices, by contrast, are relatively stable during the drought period.

In a typical year, Kenya imposes import taxes on maize to support domestic production. Halfway through the drought in March 2017, the government of Kenya lifted import restriction to increase domestic supply of maize and lower prices (FAO.org, 2017). Kenya also typically engages in trade with neighboring countries, but Uganda and Tanzania both imposed export bans on maize during the drought period (FEWS NET, 2017), indicating that trade was constrained throughout the East African region.

14 Data

The firm-level data come from the World Bank's Microdata Library. The data were originally collected as a part of an randomized impact evaluation of the GET Ahead Business Training program of the International Labor Organization. Details of the evaluation are provided in McKenzie and Puerto (2017). The data include surveys with over 6,000 firms in 157 markets spread across four counties in Kenya collected annually from 2013-2017. It includes medium and large rural markets with at least 15 firms. Market size ranged from 15 to 169 firms, with an average of 52 firms per market. A subset of firms were allocated among treatment arms related to training and mentorship. The researchers employed a clustered randomized design whereby markets were randomized into treatment and control and then firms within markets were randomized into treatment arms. This paper does not formally incorporate the randomized treatments into its analysis. Rather, for the purposes of this paper, I assume that those treatment assignments were uncorrelated to the occurrence of drought and are considered part of the error term.

The firm-level data from the World Bank surveys are organized as two samples, where the women-owned sample is nested within the census sample:

1. **Women-owned firms:** A panel of 3,558 women-owned firms in 157 markets. Respondents are matched across 6 surveys administered from 2013-2017. This was the group targeted to participate in the impact evaluation.

2. **Census firms:** A repeat cross-section of all firms located in each of the 157 markets. These firms cannot be matched across rounds but basic information was collected from each firm including sector, revenue, profits, and employment. There were 3 market census collected in 2014, 2016, and 2017, and the final census occurred during the drought, which affected about half of the 157 markets.

An important caveat in interpreting results is that only some women-owned businesses were eligible for the program. Specifically, they had to have a phone number, were younger than 55, had less than 3 employees, did not sell phone cards or Mpesa, were the owner of the firm (as opposed to employee), had profits less than 4000KSH, and had at least a year of education. The remaining women-owned firms were included in the census, but cannot be matched across rounds. Therefore, results using the the panel of women-owned businesses should be interpreted as representative of this sub-population and not of all women-owned businesses. For the first two rounds of the market census, gender of the firm owner was not collected. Therefore, gender-based comparisons using pre-drought data are not possible.

Table 14.1 shows descriptive statistics for firms included in this analysis. Column 1 are market census firms only, column 2 are women-owned firms, and column 3 are all firms. In the analysis, regressions are run on the full sample of market census firms (column 3) and the sub-sample of women's owned businesses (column 2). As expected, 99% of firms in the women's-owned firm are run by women, while 68% of all firms in the market were run by women in the 2017 census. Across both samples, firm owners' average age is between 38-40 years old, they have about 9 years of education, and their businesses have 8-10 years of tenure. Average sales are between 5,800-6,500 Kenyan shillings per week (about \$56-\$63 USD per week), and profits range from 1,600-1,800 Ksh per week (\$15-\$17 USD). Firms hired an average of .67 workers over the previous week and have between 9-10 competitors in their same sector.

About 70% of firms are in the retail sector, while 30% are in services. The analysis also uses retail sub-sectors to understand how different types of firms respond to drought conditions. About 28% of retail firms primary products are food staples and basic commodities, 42% sell fruits and vegetables, 5% sell meat and fish, and 25% engage in other retail (clothing, household goods, pharmacies, etc).

14.1 Defining Drought

The drought shock variable is defined following the ASAP warning system, which tracks 'anomaly hotspots for agricultural production' using satellite data. The ASAP warning

Table 14.1: Descriptive Statistics of Women-owned Firms and Census Firms

	(1) Market Census Firms		(2) Women-Owned Firms		(3) All Firms	
Variable	N	Mean (SD)	N	Mean (SD)	N	Mean (SD)
Owner Female	6425	0.56	2545	0.99	8970	0.68
		(0.50)		(0.08)		(0.47)
Age of Owner	6425	38.27	2544	40.62	8969	38.94
		(12.41)		(9.21)		(11.64)
Yrs Education	6425	9.57	2545	9.40	8970	9.52
		(3.62)		(3.09)		(3.48)
Age of Firm	6425	7.75	2545	10.43	8970	8.51
		(8.43)		(6.78)		(8.09)
Sales	6393	6548.38	2536	5865.73	8929	6354.50
		(8092.78)		(6897.77)		(7777.80)
Profits	6384	1814.23	2535	1662.27	8919	1771.04
		(2022.78)		(1808.72)		(1965.41)
Total Workers	6423	0.67	2544	0.66	8967	0.67
		(0.88)		(0.87)		(0.87)
Competitors	6245	8.96	2513	10.37	8758	9.37
		(10.30)		(10.41)		(10.35)
Retail Sector	6409	0.70	2543	0.72	8952	0.70
		(0.46)		(0.45)		(0.46)

Notes: The above table reports descriptive statistics (sample size, mean, and standard deviations) for the sub-sample of women-owned firms (column 2), census-only firms (column 1) and the combined census (column 3). The 2017 census was used because it is the only census that collected gender of the business owner. Not all women-owned firms present in each market during censuses are included in the repeat panel, since women-owned firms in the panel are about 28% of the total number of firms in the census, but women-owned firms represent 68% of all firms in the census. Differences-in-differences regressions use samples in Columns 2 and 3.

system synthesizes rainfall and NDVI (greenness indices) information and issues warnings based on their anticipated impact on crop production (Rembold et al., 2019). The drought began in October of 2016, when the short rainy season failed in eastern and northern Kenya, and the long rains failed again for the April-May season in 2017 (Uhe et al., 2017).

Figure 14.1 plots the warning data for all counties in Kenya from the end of 2015 to 2017. The dark red and red bands indicate that the lack of rainfall and low NDVI index occurred during the cropping season, and were thus more consequential for food security outcomes. The figure is ordered based on drought severity by county. The four counties in the World Bank microdata are highlighted in blue boxes. Two out of the four counties (Kisii and Kakamega) did not experience any drought warning, one county (Embu) experienced partial warnings, and one county (Kitui) experienced extensive drought warnings. And, 17 other counties experience more severe drought than Kitui.

Unlike negative rainfall shocks that are measured monthly, the climatic definition of drought is a prolonged period of low rainfall. Therefore, drought was defined by taking the 6-month mean of warning levels. All markets in Kitui county fell within this definition. Markets in Embu county were at the threshold of mild drought conditions. Embu county is dropped in a robustness check since farming households did not uniformly experience crop failures.

The last round of World Bank surveys collected from June to October 2017 for all counties captures the period of drought. But, effectively only one county experienced severe drought (Kitui), while the others were either mild and did not coincide with the cropping season or did not have drought conditions. Sixty out of 157 markets experienced the direct effect of drought - meaning that consumers in their local area likely experienced cropping failures. And the remaining 93 markets experienced the indirect effect of drought because consumers in their area likely did not experience crop failures, but cropping failures in other areas of Kenya put pressure on food supply chains. As described above, Figure 12.1 shows that the cropping failures throughout Kenya correspond to substantial price increases in maize markets, a primary staple food commodity that is important for ensuring food security.

15 Empirical Strategy

A differences-in-differences identification strategy is used to estimate the direct and indirect effects of drought. The drought variable is defined to begin at the same time for all markets, beginning in October 2016. For the census data, there are two pre-drought periods per market and one post-drought period. Markets are linked across years, but firms are not. For the women's-owned firms panel, there are five pre-drought periods, and one post-drought period, and firms are identified for each survey. With multiple pre-periods and one post period, I

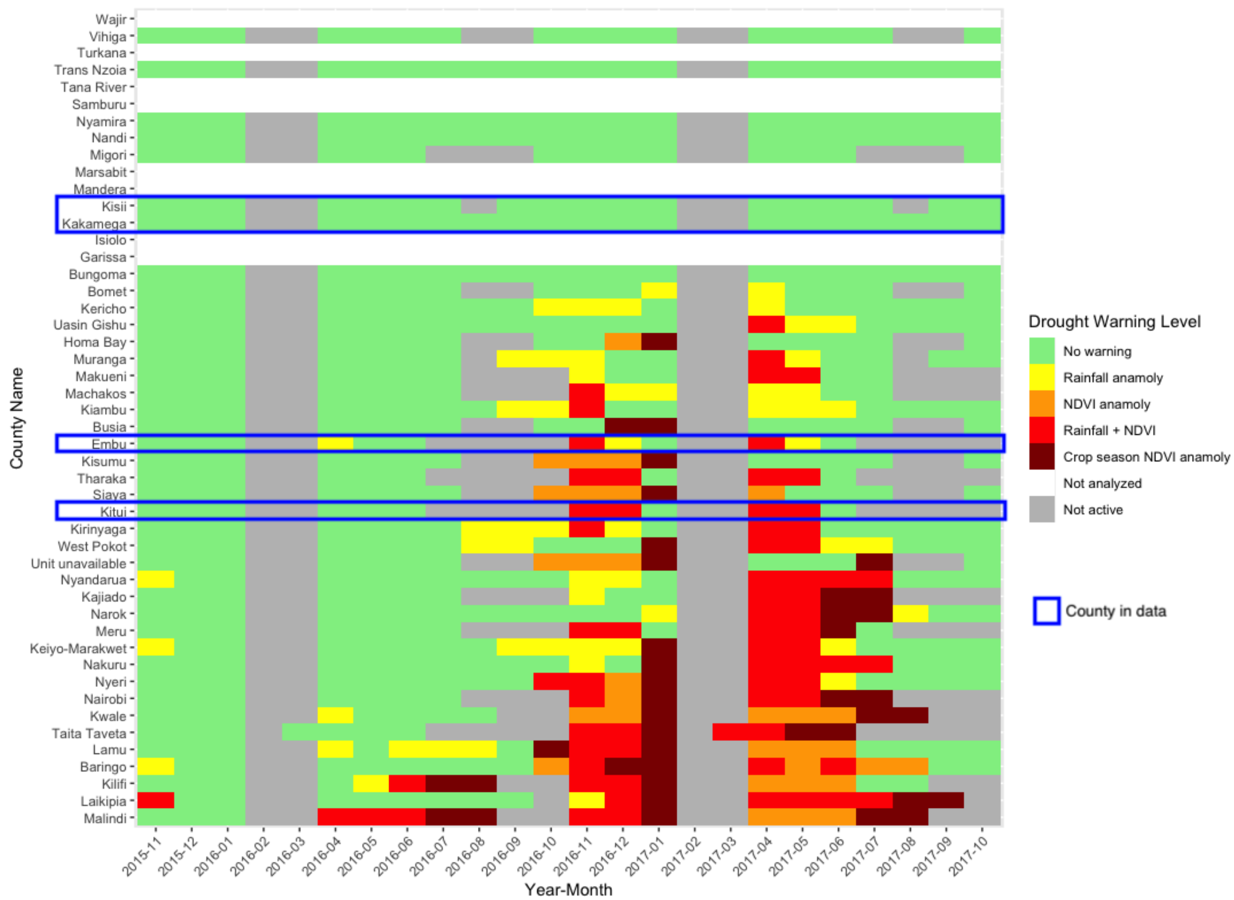


Figure 14.1: ASAP Drought Warnings for Kenyan Counties, 2015-2017

estimate two types of specifications. First, a classic difference-in-difference (Equation 4) permits estimating a 'between group' effect of drought in markets that were directly exposed to crop failures and markets where no crop failure occurred, but experienced indirect effects on supply chains. Second, a two-way fixed effects approach (Equation 5) provides a 'within group' estimate of the direct effect in drought areas compared to the pre-drought period.

15.1 Between-Group Effects: Differences-in-Differences

$$Y_{imt} = \alpha + \beta_1 Drought_m \times Post_t + \beta_2 Drought_m + \beta_3 Post_t + \mathbf{X}_{imt}\Phi + \epsilon_{imt} \tag{4}$$

There are four primary outcomes, Y_{imt}, for firm i, in market m, in year t - total sales revenue over the prior week, profits over the prior week, number of paid workers over the prior week, and number of competitors in the same sector at the time of the survey. For the women-owned firms panel, an additional outcome 'firm open' is defined to equal one if the firm is operating during the survey. In this setting, it is common for small firms to open and close throughout the year or year-to-year. About 20% of the initial sample of women's firms are closed during each survey, although they are not necessarily permanently closed. About 45% of firms were closed for at least one survey, and 28% of the original sample were closed in the final round. This outcome provides evidence about whether firms that experience the direct effects of drought shock are more or less likely to remain open afterwards.

As is typical in a classic differences-in-differences specification, $Drought_m$ equals one for the group of markets which experienced the direct drought shock for all time periods. $Post_t$ equals one if the survey was completed after October 2016, the date that drought conditions started. The parameter β_1 on the interaction of $Drought_m$ and $Post_t$, identifies the effect of drought on areas that were directly affected. The parameter β_2 is the pre-period level difference between drought (direct) and non-drought (indirect) markets. In the preferred specification, market fixed effects are included such that $Drought_m$ drops out. The parameter β_3 represents the effect of post-period in non-drought markets and is interpreted as the indirect effect of drought in markets in the counties where there was no rain failure.

The term $\mathbf{X}_{mt}\Phi$ is a vector of controls. It includes market fixed effects and month-of-year fixed effects. Month-of-year fixed effects are included to capture regular variation that is common across markets due to seasonal changes in market conditions that occur year-to-year.

15.2 Within-Group Effects: Two-way Fixed Effects

$$Y_{imt} = \alpha + \beta_1 Drought \times Post_{mt} + \gamma_m + \tau_t + \mathbf{X}_{imt}\Phi + \epsilon_{imt} \tag{5}$$

The main difference between Equations 4 and 5 is that market fixed effects γ_m and time fixed effects τ_t are included to flexibly control for pre-drought common time and market-level shocks. β_1 identifies the effect of drought in directly affected markets compared to their pre-period levels.

15.3 Differences by Sector: Triple Differences-in-Differences

$$\begin{aligned} Y_{imt} &= \alpha + \beta_1 Drought_m \times Post_t + \beta_2 Drought_m \times Post_t \times \mathbf{Sector}_i + \\ &\beta_3 Post_t + \beta_4 Post_t \times \mathbf{Sector}_i + \gamma \mathbf{Sector}_i + \lambda Drought_m \times \mathbf{Sector}_i + \mathbf{X}_{imt}\Phi + \epsilon_{imt} \end{aligned} \tag{6}$$

To examine differential responses to drought by firm sector, a triple differences specification is used. The vector $\mathbf{Sector}_i$ is defined at the firm level. The first definition is $\mathbf{Sector}_i = \{Retail, Service\}$, where service is set as the reference category. Firm sectors were categorized as either retail or service according to how the firm owner reported their primary sector to the survey team. The second definition is $\mathbf{Sector}_i = \{StapleGrains, Veg/Fruit, Meat/Fish, OtherRetail\}$ among retail firms only, where Staple Grain is the reference category. The objective is to understand how different types of firms respond to the drought shock in markets that were both directly and indirectly affected.

15.4 Identifying Assumptions

In a classic differences-in-differences set-up, the identifying assumption is that trends are parallel before the event of interest and would continue to be parallel if the event had not occurred. The parallel trends assumption implies that counterfactual trends would have continued on the same path absent the drought shock and that the control group trend is a good counterfactual for the treatment group. The identification strategy described here deviates from the typical differences-in-differences in two important ways. First, I employ a difference-in-differences to understand the direct and indirect effects of the drought shock. Therefore, I do not assume that the non-drought area is a perfect control because firms in those markets also experience the drought shock via changes to their supply chains. Figure

12.1(b) showed that price changes in the main staple grain (maize) increased simultaneously in both regions after the drought. Yet, Figure 12.1(a) also showed that only one region experienced crop failures. Thus, effects are interpreted as direct effects of crop failure and the indirect effect of supply chain (price) shocks. Graphs of pre-trends in Figures 19.1 and 19.2 in the appendix affirm that trends are relatively parallel in the pre-drought period and both drought and non-drought markets change during the drought in 2017.

Second, differences-in-differences strategies are typically used to identify the effect of endogenous policy changes where the treatment variable is possibly correlated with the structural error term, such as when governments enact new policies. When sufficient pre-treatment periods are available, it is important to test whether pre-event trends are correlated with the treatment status. Table 20.1 in the appendix reports coefficients on regressions of primary outcomes - sales, profits, workers, competitors, and whether a firm is open - on indicator for drought, indicators for year, and their interactions and reports p-values from F-tests of joint significance on pre-trend interactions. The top panel is the census sample and fails to reject pre-trends for all four main outcomes. The bottom panel reports results for the women-owned firms panel and rejects that pre-trend interactions are zero for 2 out of 5 outcomes (number of workers, and whether the firm is open during the survey round), indicating that for the sample of women-owned firms, parallel trends is a more tenuous assumption than for the full census sample.

Often weather shocks can be considered ‘random’ since agents have no control over their climate conditions. The least conservative assumption would be to assume that drought is a perfectly random shock, uncorrelated with the error term. In that case, the identifying assumption would simply be that no time-varying unobservable confounders led to the drought and that drought is not a proxy for some other unobserved shock that is actually inducing the differences estimated by these regressions. The drought was declared a national emergency in February 2017 and garnered attention and resources from the Kenyan government put toward implementing policies to alleviate strain caused by low production (Government of Kenya, 2017; Uhe et al., 2017). In theory, it is possible that another shock or policy happened simultaneously, but the drought was a high profile event that affected the entire county.

Coefficients from the three primary econometric specifications are interpreted as the causal effect of drought on firms in drought and non-drought regions. Outcomes related to firm performance and market competition provide information about industrial organization of the rural markets respond to an aggregate environmental shock where one region experiences its direct consequences, while the other experiences the indirect consequences from changes in staple food prices and quantity produced. β_1 from equation 1 identifies the direct effect of drought on firms in drought areas relative to firms in non-drought areas (the difference-in-difference). The coefficient β_3 from Equation 1 is the average difference of firms in non-drought areas during the drought period (when post=1) and is interpreted as the effect of drought in markets that did not directly experience drought conditions. β_1 in equation 2 identifies the effect of drought on firms in drought areas compared to prior performance after controlling for year and market fixed effects (a two-way fixed effects within estimator).

16 Results

Results are first presented for differences-in-differences (DD) and two-way fixed effects (TWFE) specifications for market census firms in Table 16.1 and then for the women's-owned businesses panel in Table 16.2. The heterogeneous effects by sector using triple differences are presented for both samples for retail and service firms are in Tables 16.3 and 16.4. Finally, the last result in Table 16.5 examines heterogeneous effects among census firms for retail sub-sectors - staple foods, vegetables and fruit, meat and fish, and other retailers.

16.1 Effect of Drought on Market Census Firms and Women-Owned Firms

Table 16.1 shows results for the full sample of census firms and 16.2 shows results for the panel of women-owned firms. For the DD specifications of market census firms, sales, profits, and the total number of workers decrease in drought areas (β_1) and increase in non-drought areas (β_3). The TWFE of market census firms also show decreases of sales, profits, and workers in drought areas. Market census firms decrease hiring by 0.13-0.27 workers, a 50% decrease in both specifications. Sales decrease by 12-23% relative to the non-drought mean and profits decrease by 13-27% in the DD and TWFE specifications. Further, the number of competitors increases in drought areas and decreases in non-drought areas.

This pattern of increasing competition alongside decreasing firm performance (sales, profits, and number of workers) in drought-affected areas provides evidence that firms are worse off after the drought. It is difficult to distinguish which happened first - whether lower local consumer demand decreased sales, profits, and hiring, or losses in cropping income induced households to start businesses, increased competition and decreased the sales potential of existing firms. To examine which effect is more influential (demand versus competition), a t-test comparing β_1 and β_3 is useful. The coefficient on $Post \times Drought$ is the difference for firms in drought areas compared to firms in non-drought areas whose average change after drought is represented by the coefficient on $Post$. For the full census sample, the coefficients on sales, profits, and hiring in non-drought areas are all larger in magnitude than those for drought areas. A t-test of $\beta_1 + \beta_3 = 0$ for each outcome indicates whether drought firms also experienced an overall increase that is statistically different from zero - suggesting whether firm performance improved after the drought, but to a lesser degree than firms in non-drought areas.

Table 16.1 reports the p-values for the t-test of $\beta_1 + \beta_3 = 0$. The test fails to reject that sales and number of competitors were different than zero, but rejects that profits and workers hired are equal to zero in the post-period in the drought-affected markets. This provides mixed, but inconclusive evidence that firm performance also increased overall compared to the pre-drought period, but was nonetheless worse than firm performance in non-drought markets. There is a substantial difference in changes in competition between drought and non-drought areas - drought areas increase by 2.3 competitors over a mean of 9.8 competitors per sector, compared to a decrease of 1.8 competitors in non-drought areas, suggesting that increased firm entry played a role in spreading local demand across a larger number of firms. It is possible that an in increase in consumer demand in non-drought areas was high enough so that all firms benefited if consumers in non-drought areas are wealthier and spend more in markets if they earned higher income from crop sales. While in drought areas, mild increases in consumer demand were off-set by increased entry.

For the women-owned businesses panel in Table 16.2, sales decrease by 12% in both specifications, profits decrease by 8-10% and workers hired decreases by 14-34%, although the TWFE estimate is not different from zero. The number of competitors increases in both drought and non-drought areas, but estimates are noisier compared to the full census sample. Column 5 in Table 16.2 shows that firms in drought areas are 5 percentage points more likely to remain open compared to those in non-drought areas, although the two-way fixed effect specification estimates a precise null. By contrast, in non-drought areas, competition decreases and firm performance improves - sales increase by 18%, profits by 32%, and hiring increases 2-fold while the number of competitors declines by 18%.

It is surprising that increases in revenues and profits do not lead to increases in firm entry in non-drought areas since they create competitive pressure to bid away profits. Column 3 in Tables 16.1 and 16.2 shows that firms increase hiring by about 0.5 workers in the market census sample and by 0.4 workers among women's owned firms. This suggests that instead of starting new businesses, workers are instead hired into existing businesses as they expand. while firms in drought areas are more likely to remain open compared to firms in non-drought areas, they are overall more likely to exit compared to the pre-period ($-0.178+0.051 > 0$, p-value=0.0000)) and the number of competitors increases ($0.540+0.893 > 0$, p-value=0.0215).

Table 16.1: Results: Market Census Firms

Between Group Effects: Differences in Differences

	(1) Sales	(2) Profits	(3) Total Workers	(4) Competitors
β_1: Post×Drought	-642.577**	-195.043**	-0.125***	2.258***
	(314.490)	(87.378)	(0.032)	(0.727)
β_3: Post	998.661***	446.320***	0.534***	-1.769**
	(254.123)	(60.445)	(0.027)	(0.757)
T-test: $\beta_1 + \beta_3 = 0$	0.1329	0.0004	0.0000	0.3793
Market FE	Y	Y	Y	Y
Year FE	N	N	N	N
Month-of-Year FE	Y	Y	Y	Y
Non-Drought Mean	5534.35	1404.96	0.25	9.81
Obs	20,623	20,542	20,960	20764
Adj R-Squared	0.03	0.05	0.11	0.31

Within Group Effects: Two-Way Fixed Effects

	(1) Sales	(2) Profits	(3) Total Workers	(4) Competitors
β_1: Post×Drought	-1359.46***	-421.49***	-0.27***	5.22***
	(449.82)	(126.34)	(0.04)	(1.01)
Market FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month-of-Year FE	Y	Y	Y	Y
Non-Drought Mean	5946.60	1520.83	0.43	10.25
Obs	20,623	20,542	20,960	20764
Adj R-Squared	0.04	0.05	0.11	0.32

Standard errors in parenthesis, clustered at market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

16.2 Effect of Drought on Competition and Performance by Sector

To explore how household demand for services, retail goods, and food and non-food goods change after the drought shock, I first compare whether retail firms perform better or worse than service firms. Second, I compare whether performance varies by different type of retail - staples foods, vegetable/fruit sellers, fish/meat sellers, and other non-food retailers.

16.2.1 Retail compared to Service Firms

Table 16.3 shows heterogeneous effects for retail and service firms for the market census firms using DD and TWFE specifications. The first two rows are the direct effect of drought on service firms (β_1) and retail firms (β_2), followed by a t-test for the the total effect on retail firms in drought areas ($\beta_1 + \beta_2 = 0$). The third and fourth rows report the indirect effect of drought on service (β_3) and retail (β_4) firms, and a t-test for the total effect on retail firms in non-drought areas ($\beta_3 + \beta_4 = 0$).

Performance of service and retail firms in drought areas are negative in terms of sales, profits, and workers, but differences are not significant. However, the total effect for retail firms is negative and significant for sales, profits, and workers. Both service firms and retail firms face increases in competition - service firms' number of competitors increase by 1.25 firms, while retail firms' number of competitors increase by an additional 0.61 firms, or 1.86 firms total. The TWFE specifications disagree with the DD specification - retail firms appear to have relatively better performance compared to service firms, although the net effect is still negative.

The opposite occurs for firms in non-drought areas. Service firms sales, profits, and workers increase, and retail firms performance increases even further compared to service firms. Retail firms competition decreases by 1.12 firms, while service firms point estimate on number of competitors decreases with a larger standard error. Alongside the DD estimates, it suggests that firm performance in the service sector is relatively more stable compared to retail firms. Service firm performance declines in drought conditions to a lesser extent than retail firms. Similarly service firm performance improves in non-drought conditions to a lesser extent that the improvement for retail firms.

A similar pattern holds for the women-owned firms panel in Table 16.4, although estimates tend to be noisier. In drought areas, retail firms fare worse in terms of sales and profits and there is no difference in hiring, number of competitors, or likelihood of remaining open. In non-drought areas, service firms' performance tends in improve, but the evidence is mixed relative to retail firms - who have worse sales, better profits, and hire more workers. And competition increases for service firms, although there is no significant difference with retail firms. Overall, it confirms a similar pattern that service firms fare slightly better than retail firms in drought areas and fare slightly worse than retail firms in non-drought areas with increases in number of competitors.

Table 16.2: Results: Women-Owned Firms

Between Group Effects: Differences in Differences

	(1) Sales	(2) Profits	(3) Total Workers	(4) Competitors	(5) Firm Open
β_1: Post×Drought	-612.075***	-129.211**	-0.079**	0.540	0.051***
	(194.556)	(53.877)	(0.036)	(0.701)	(0.017)
β_3: Post	466.154***	267.342***	0.378***	0.893	-0.178***
	(165.582)	(39.609)	(0.026)	(0.600)	(0.012)
T-test: $\beta_1 + \beta_3 = 0$	0.2839	0.0008	0.0000	0.0215	0.0000
Market FE	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N
Month-of-Year FE	Y	Y	Y	Y	Y
Non-Drought Mean	5184.64	1250.85	0.23	8.99	0.85
Obs	18982	18953	15679	8141	21239
Adj R-Squared	0.05	0.05	0.08	0.36	0.05

Within Group Effects: Two-Way Fixed Effects

	(1) Sales	(2) Profits	(3) Total Workers	(4) Competitors	(5) Firm Open
β_1: Post×Drought	-636.49***	-101.53**	0.04	1.04	-0.00
	(161.65)	(44.97)	(0.03)	(1.62)	(0.02)
Market FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Month-of-Year FE	Y	Y	Y	Y	Y
Non-Drought Mean	5304.70	1253.24	0.29	10.17	0.82
Obs	18982	18953	15679	8141	21239
Adj R-Squared	0.05	0.05	0.08	0.36	0.09

Standard errors in parenthesis, clustered at market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sales and profit sample sizes are conditional on whether the firm is operating during the survey round. Total workers sample size is smaller because one survey round did not include the question. Sample size for competitors is only available during market census rounds.

Table 16.3: Results: Retail Compared to Service Firms - Market Census Firms

Between Group Effects: Differences in Differences

	(1) Sales	(2) Profits	(3) Total Workers	(4) Competitors
Effect on Service Firms in Drought Areas:				
β_1: Drought × Post	-562.64	-148.58	-0.06	1.25**
	(371.91)	(105.38)	(0.05)	(0.53)
Effect on Retail Firms in Drought Areas:				
β_2: Drought × Post × Retail	-270.26	-63.65	-0.05	0.61
	(402.33)	(106.92)	(0.06)	(0.98)
T-test: $\beta_1 + \beta_2 = 0$	0.0247	0.0296	0.0032	0.0452
Effect on Service Firms in Non-Drought Areas:				
β_3: Post	238.97	228.25***	0.36***	-0.45
	(287.61)	(73.39)	(0.04)	(0.62)
Effect on Retail Firms in Non-Drought Areas:				
β_4: Post × Retail	1234.93***	310.67***	0.21***	-1.12**
	(255.51)	(62.52)	(0.04)	(0.56)
T-test: $\beta_3 + \beta_4 = 0$	0.0000	0.0000	0.0000	0.0450
Retail	1271.65***	-44.43	-0.44***	7.51***
	(168.80)	(40.85)	(0.02)	(0.66)
Drought × Retail	460.23	120.86	0.16***	-2.36**
	(313.97)	(76.27)	(0.03)	(1.11)
Market FE	Y	Y	Y	Y
Year FE	N	N	N	N
Month-of-Year FE	Y	Y	Y	Y
Non-Drought Mean	5534.35	1404.96	0.25	9.81
Obs	20600	20520	20938	20741
Adj R-Squared	0.05	0.05	0.14	0.39

Within Group Effects: Two-Way Fixed Effects

	(1) Sales	(2) Profits	(3) Total Workers	(4) Competitors
Effect on Service Firms in Drought Areas:				
β_1: Post×Drought	-2290.35***	-610.33***	-0.38***	5.82***
	(460.08)	(126.53)	(0.05)	(1.05)
Effect on Retail Firms in Drought Areas:				
β_2: Post×Drought×Retail	942.96***	246.47***	0.22***	-2.08***
	(280.22)	(80.12)	(0.04)	(0.71)
T-test: $\beta_1 + \beta_2 = 0$	0.0060	0.0065	0.0001	0.0002
Retail	1816.54***	94.41***	-0.33***	6.54***
	(142.53)	(34.42)	(0.02)	(0.51)
Market FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month-of-Year FE	Y	Y	Y	Y
Non-Drought Mean	5946.60	1520.83	0.43	10.25
Obs	20600	20520	20938	20741
Adj R-Squared	0.05	0.05	0.14	0.39

Standard errors in parenthesis, clustered at market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sales, Profits, and Total Workers were measured for the previous week and were winsorized at the top 5%. Sales and Profits are in Kenyan shillings. Competitors was computed from market census sector counts.

Table 16.4: Results: Retail and Service - Women-Owned Firms

Between Group Effects: Differences in Differences

	(1) Sales	(2) Profits	(3) Total Workers	(4) Competitors	(5) Firm Open
Effect on Service Firms in Drought Areas:					
β_1: Drought × Post	-155.10	50.77	-0.04	-0.10	-0.01**
	(361.23)	(107.81)	(0.06)	(0.53)	(0.00)
Effect on Retail Firms in Drought Areas:					
β_2: Drought × Post × Retail	-547.67	-211.92*	-0.02	1.12	0.00
	(440.26)	(120.74)	(0.07)	(1.01)	(0.00)
T-test: $\beta_1 + \beta_2 = 0$	0.0044	0.0105	0.1864	0.2720	0.2151
Effect on Service Firms in Non-Drought Areas:					
β_3: Post	263.14	48.48	0.27***	1.00**	0.01***
	(255.80)	(73.69)	(0.04)	(0.48)	(0.00)
Effect on Retail Firms in Non-Drought Areas:					
β_4: Post × Retail	-283.02	165.42**	0.14***	-0.25	-0.00
	(274.77)	(79.18)	(0.04)	(0.74)	(0.00)
T-test: $\beta_3 + \beta_4 = 0$	0.9095	0.0000	0.0000	0.2947	0.0028
Retail	1688.66***	-18.88	-0.44***	7.00***	0.00
	(220.95)	(43.42)	(0.03)	(0.74)	(0.00)
Drought × Retail	472.58	108.59	0.16***	-2.04	-0.00
	(369.83)	(73.82)	(0.04)	(1.29)	(0.00)
Market FE	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N
Month-of-Year FE	Y	Y	Y	Y	Y
Non-Drought Mean	5184.64	1250.85	0.23	8.99	0.85
Obs	17401	17373	14464	8134	17552
Adj R-Squared	0.07	0.05	0.14	0.44	0.02

Within Group Effects: Two-Way Fixed Effects

	(1) Sales	(2) Profits	(3) Total Workers	(4) Competitors	(5) Firm Open
Effect on Service Firms in Drought Areas:					
β_1: Post×Drought	-276.98	-99.60	-0.08*	1.57	-0.01
	(324.06)	(87.24)	(0.05)	(1.49)	(0.00)
Effect on Retail Firms in Drought Areas:					
β_2: Post×Drought× Retail	-534.03	0.40	0.20***	-0.41	0.00
	(385.48)	(97.19)	(0.06)	(0.82)	(0.01)
T-test: $\beta_1 + \beta_2 = 0$	0.0001	0.0985	0.0016	0.4932	0.2682
Retail	1841.19***	36.81	-0.36***	6.28***	0.00
	(176.05)	(35.17)	(0.02)	(0.62)	(0.00)
Market FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Month-of-Year FE	Y	Y	Y	Y	Y
Non-Drought Mean	5304.70	1253.24	0.29	10.17	0.82
Obs	17401	17373	14464	8134	17552
Adj R-Squared	0.07	0.06	0.14	0.43	0.02

Standard errors in parenthesis, clustered at market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sales, Profits, and Total Workers were measured for the previous week and were winsorized at the top 5%. Sales and Profits are in Kenyan shillings. Competitors was computed from market census sector counts.

16.2.2 Retail Sub-Sectors

Since drought conditions directly affect the food supply chain, it is reasonable to expect food retailers to have a different responses than non-food retailers. To examine these differences, Table 16.5 has results from a triple differences regression for market census firms where the retail sector category is disaggregated into subsectors - staple grain retailers, fruit/vegetable retailers, meat/fish retailers, and all other non-food retailers. Service firms were dropped from the analysis. Staple retailers are the reference category such that β_1 is interpreted as the effect of drought on staple retail firms and $\beta_2, \beta_3, and \beta_4$ are the differential effect for the various retail sectors. Because the net effect is also of interest, t-tests of total effect on retail categories are also included.

By examining the effect on subsectors of retail firms in drought areas, a few patterns emerge. First, firm performance decreases for all subsectors, but it decreases substantially more for meat/fish retailers compared to other types of retailers. Second, vegetable/fruit retailers, meat/fish retailers, and other retailers have fewer competitors compared to staple retail firms, but the total effect for those subsectors are not significantly different from zero. Staple retail firms experience a large uptick in competition - nearly 4.2 entrants compared to a mean of 10.5 firms per sector, a 40% increase. It is possible that barriers to entry into the staple food market are lower compared to the other types of firms. And potential entrants likely perceive that household demand for staple food will increase after crop failures. The result that vegetable/fruit retailers and especially meat/fish retailers decline substantially suggests that local consumers decreased consumption of these specialty foods compared to staples. This is consistent with households having to first meet their basic food needs by purchasing staple foods and not having additional resources after the drought to purchase non-necessities.

Coefficients for β_5 to β_8 repeat the same pattern for non-drought areas. The opposite occurs in non-drought areas. Staple food retailers sales, profits, and hiring increases (β_5). Vegetable/fruit sellers and other retailers are not different from staple sellers but increase overall in number (as seen in the t-tests for $\beta_5 + \beta_6 = 0$ and $\beta_5 + \beta_8 = 0$). Meat/fish sellers increase substantially more than the other retail categories, which suggests that consumers in the local area benefited from higher staple grain prices and increased purchases of luxury foods. Notably, there are no increases in competition in any of the retail categories. This is consistent with the previous finding that local consumer demand likely increased and firms hired more workers but firms did not enter.

16.3 Robustness Checks

Figure 21.1 in the appendix plots point estimates for the main treatment indicator $Post \times Drought$ across a range of specifications for main outcomes from the market census sample. The specifications checked include dropping Embu county, dropping Kakamega county, dropping market and month-of-year fixed effects for each TWFE and DD specifications. Embu county was dropped as a control county because it was marginally affected by drought according to the ASAP indicators and thus could cause downward bias in point estimates. Kakamega county was dropped as a check because that county reported high production of maize in 2017, indicating that local farmers had a bumper crop, which could could generate upward bias in estimates of the effect of drought because it was more prosperous making differences with drought-affected areas larger than they would have been in a normal year.

Across all four main outcomes, TWFE models result in larger point estimates compared to DD specifications. TWFE that drop Embu county are largest in magnitude, followed by TWFE with the full sample, and then TWFE that drop Kakamega, except when the outcome is profits. For DD specifications, dropping Embu county produces larger magnitude point estimates for sales, profits, workers compared to the main DD specification. Dropping Kakamega produces smaller magnitude point estimates than the main DD specification for sales and workers. Estimates for number of competitors are similar for all three. This pattern affirms the predicted direction from excluding each county - retaining Embu county shrinks point estimates to zero and retaining Kakamega pushes estimates away from zero.

Table 16.5: Results: Retail Sub-Sectors - Census Firms

	(1) Sales	(2) Profits	(3) Total Workers	(4) Competitors
Between Group Effects: Differences in Differences				
Effect on Staple Retail Firms in Drought Areas:				
β_1: Drought×Post	-430.34	-244.19	-0.10*	4.19***
	(599.45)	(158.92)	(0.06)	(0.97)
Effect on Retail Sub-Sectors in Drought Areas:				
β_2: Drought×Post×Veg/Fruit Retail	-510.94	0.16	-0.01	-5.25***
	(663.51)	(153.03)	(0.07)	(1.94)
T-test: $\beta_1 + \beta_2 = 0$	0.0311	0.0410	0.0548	0.4957
β_3: Drought×Post×Meat/Fish Retail	-7396.06***	-1016.53*	-0.71***	-4.02**
	(2122.82)	(550.12)	(0.19)	(1.59)
T-test: $\beta_1 + \beta_3 = 0$	0.0002	0.0156	0.0000	0.9004
β_4: Drought×Post×Other Retail	-178.57	150.79	0.01	-2.64
	(812.24)	(203.97)	(0.08)	(1.71)
T-test: $\beta_1 + \beta_4 = 0$	0.3541	0.5822	0.1846	0.2629
Effect on Staple Retail Firms in Non-Drought Areas:				
β_5: Post	851.71**	463.45***	0.54***	0.22
	(405.00)	(89.99)	(0.03)	(0.71)
Effect on Retail Sub-Sectors in Non-Drought Areas:				
β_6: Post×Veg/Fruit Retail	-89.21	-122.09	-0.02	1.53
	(388.54)	(87.12)	(0.03)	(1.26)
T-test: $\beta_5 + \beta_6 = 0$	0.0053	0.0000	0.0000	0.1440
β_7: Post×Meat/Fish Retail	5038.91***	765.20***	0.26***	-0.88
	(825.76)	(180.13)	(0.07)	(1.12)
T-test: $\beta_5 + \beta_7 = 0$	0.0000	0.0000	0.0000	0.5876
β_8: Post×Other retail	55.24	-4.46	0.08*	-0.35
	(489.77)	(113.12)	(0.05)	(0.82)
T-test: $\beta_5 + \beta_8 = 0$	0.0548	0.0001	0.0000	0.8806
Veg/Fruit Retail	-3751.66***	-402.57***	-0.04**	11.37***
	(280.87)	(53.84)	(0.02)	(1.32)
Meat/Fish Retail	-1196.44**	104.65	0.02	-3.88***
	(518.75)	(117.79)	(0.03)	(1.19)
Other Retail	-1544.55***	96.48	0.04*	-3.84***
	(325.34)	(65.13)	(0.02)	(0.72)
Drought×Veg/Fruit Retail	-266.81	-182.21	-0.09***	-3.75*
	(539.66)	(119.04)	(0.03)	(2.18)
Drought×Meat/Fish Retail	4873.76***	775.70**	0.64***	-0.61
	(1656.44)	(378.70)	(0.15)	(1.54)
Drought×Other retail	89.74	-201.25	-0.09***	0.35
	(587.21)	(124.15)	(0.03)	(1.05)
Non-Drought Mean	5561.76	1356.98	0.26	10.53
Obs	14700	14629	14926	14862
Adj R-Squared	0.12	0.09	0.16	0.67

Standard errors in parenthesis, clustered at market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sales, Profits, and Total Workers were measured for the previous week and were winsorized at the top 5%. Sales and Profits are in Kenyan shillings. Competitors was computed from market census sector counts. Regressions include month-of-year and market fixed effects.

17 Conclusion

Examining firm performance following an environmental shock that lowers crop production can help clarify how rural markets respond to supply chain shocks and shifts in local demand. Grabrucker and Grimm (2020) found that small firms can benefiting after weather shocks, but were not able to measure changes in competition. Micro-data used in this study featured two types of markets: 1.) markets directly affected by drought whose local consumer base experienced a crop production shock, and 2.) markets indirectly affected by drought via nation-wide increases in maize prices, but whose consumer base did not experience a production shock. Studying outcomes on firm performance alone is not sufficient to characterize rural market dynamics because firm entry and exit are important components.

I use micro-data collected by researchers at the World Bank for an impact evaluation that fortuitously collected full market census which permitted assessing firm entry and exit. Differences-in-differences regressions showed that on average across all firm sectors, market census and women-owned firms in drought areas had worse performance (sales, profits, and hiring), but that firm entry increased, suggesting that part of firm performance is related to a larger number of firms competing for smaller local aggregate demand. Furthermore, firm performance improved (sales and profits), hiring increased, and more firms exited in non-drought areas - which is consistent with productive firms hiring while less productive firms exit the market.

In addition to describing entry and exit, evaluating performance heterogeneity by firm sectors reveals that firms in the retail sector have lower sales, profits, and hiring, and slightly more competitors than firms in the services sector. In theory, we would expect the drought shock to be most relevant for firms operating in the food sector, in particular in the staple food sector. Consumers in drought areas had a negative income shock. Prior work on consumer elasticities has shown that household spending on food staples is more inelastic than spending on non-staple foods. Triple difference regressions showed even though staple food retailers had worse performance in drought areas, they had fared better compared to vegetable/fruit sellers, meat/fish sellers, and other retailers. This pattern suggests that consumers demand for food staples was relatively inelastic compared to more luxury food items, especially livestock and fish. Firm entry also increased in the staples sector. Since the opportunity cost of labor decreases after a large-scale production shock, new and existing firm owners may be willing to bear worse market conditions and accept lower revenues.

Small firms are an important part of the rural economy throughout developing regions because they sell food staples and other goods to agricultural households even though they are not very profitable. A long literature in development economics has demonstrated that multiple market failures in credit and insurance prevent agricultural households from optimally investing in farming and non-farming activities (de Janvry et al., 1991). Other work has shown that weather shocks cause households to engage in coping strategies, such as selling household assets or starting businesses. This paper contributes to this literature by demonstrating that new firms enter drought-affected areas despite worse local aggregate demand. It also shows that firm owners in non-drought could benefit from staple price increases if farming households sell staple crops at higher prices. However, more data on consumer behavior in both settings is needed to understand the effect of maize price increases on agricultural households.

Appendix

18 National Market Price Series from 2013-2017

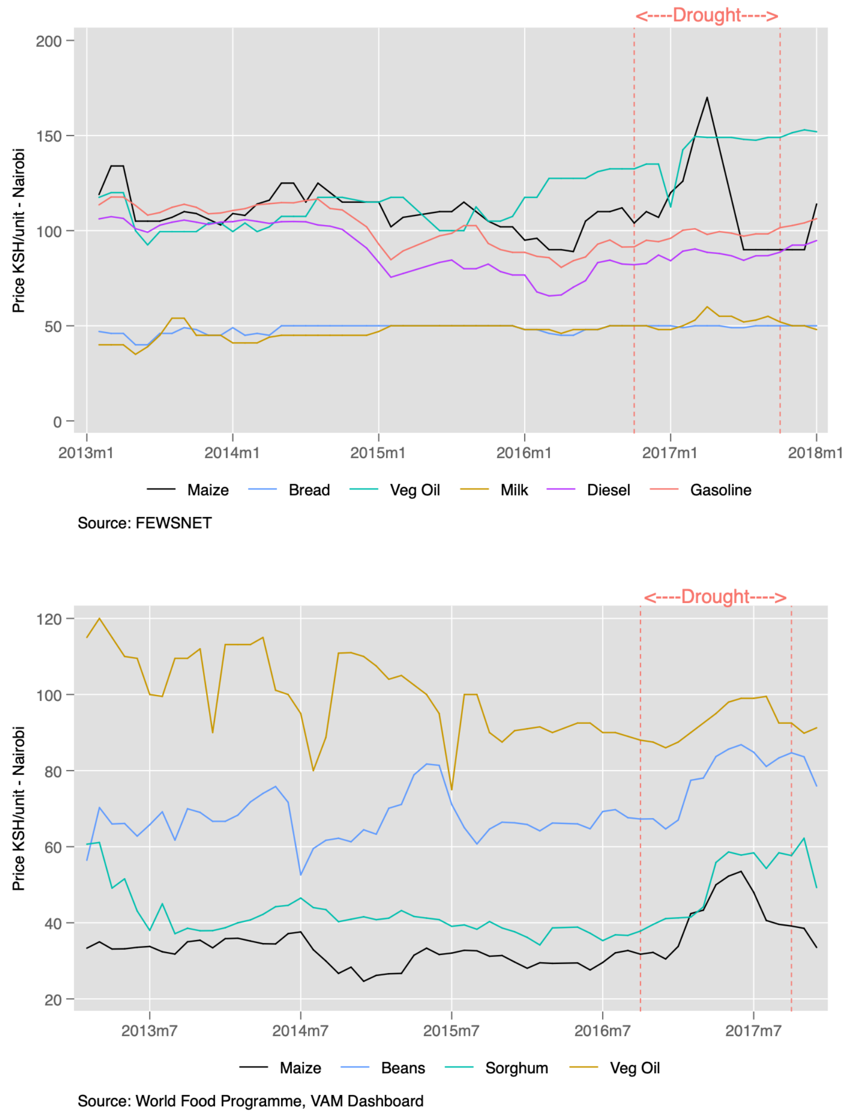


Figure 18.1:
FEWS NET and WFP Prices for Food Staples and Gas/Petrol in Primary National Market (Nairobi)

19 Parallel Trends

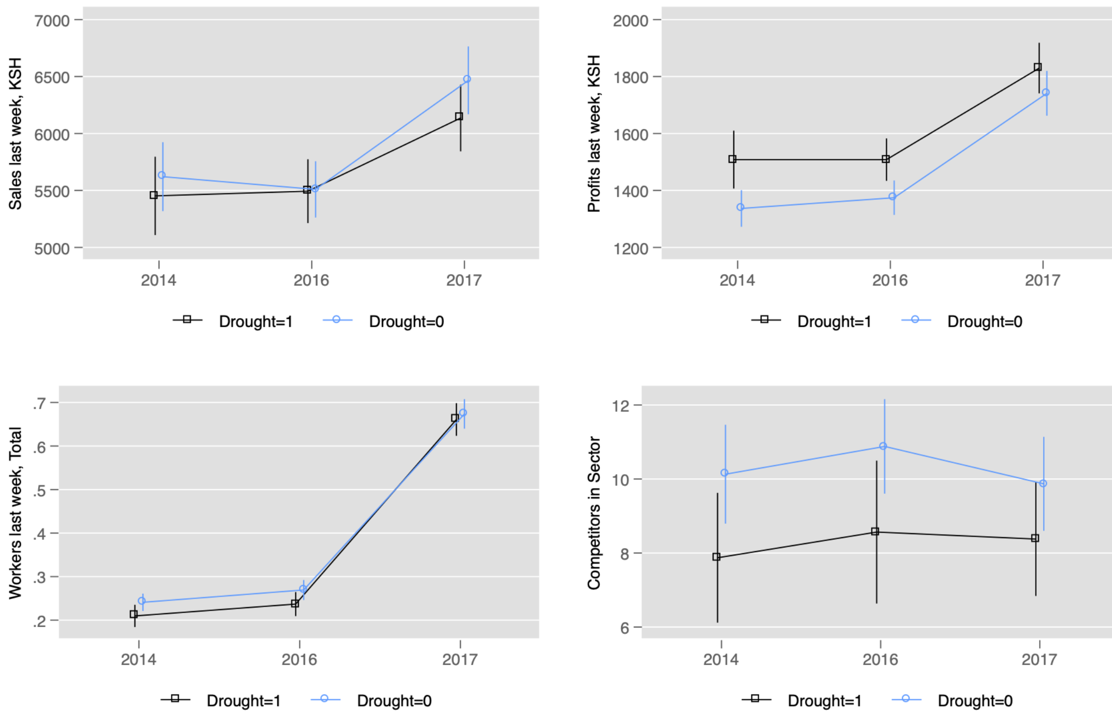


Figure 19.1: Trends for Market Census Firms

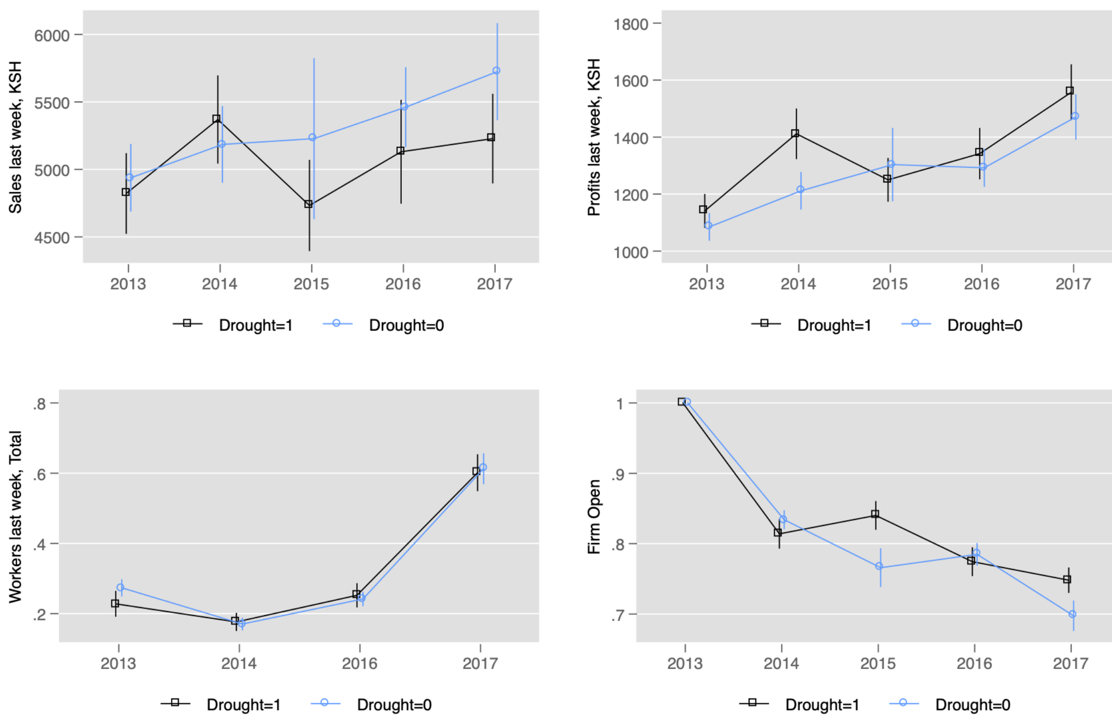


Figure 19.2: Trends for Women-Owned Firms

20 Evaluating Pre-Trends

Table 20.1: F-test for Joint Significance of Pre-Trends

F-Test on Pre-Trends: Census Firms

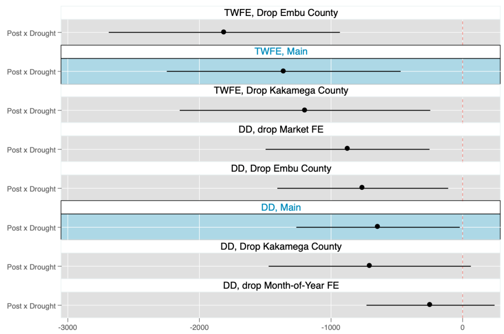
	(1) Sales	(2) Profits	(3) Total Workers	(4) Competitors
Drought=1 × Year=2014	161.546	82.736	-0.018	-0.767
	(310.939)	(83.504)	(0.032)	(0.987)
Drought=1 × Year=2016	314.580	44.976	-0.020	-0.823
	(248.300)	(69.139)	(0.032)	(0.846)
F-test	0.4337	0.6129	0.8225	0.5816
Obs	20623	20542	20960	20764
Adj R-Squared	0.00	0.01	0.08	0.01

F-Test on Pre-Trends: Women-owned Firms Panel

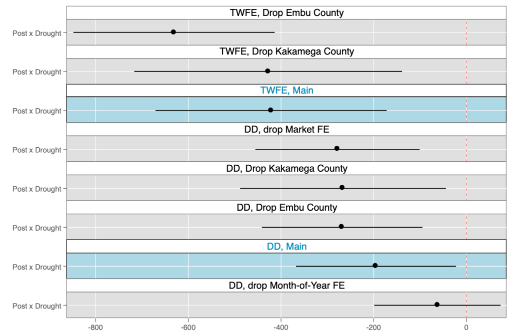
	(1) Sales	(2) Profits	(3) Total Workers	(4) Competitors	(5) Firm Open
Drought=1 × Round=1	371.072	-30.625	-0.034		-0.005
	(233.009)	(64.977)	(0.041)		(0.016)
Drought=1 × Round=2	347.757	87.850	0.023	-0.865	-0.025
	(249.974)	(70.842)	(0.041)	(0.734)	(0.017)
Drought=1 × Round=3	430.660*	4.709			-0.010
	(239.496)	(70.455)			(0.017)
Drought=1 × Round=4	278.387	65.685	-0.005	-0.242	-0.024
	(230.702)	(66.407)	(0.042)	(0.650)	(0.015)
Drought=1 × Round=5	227.100	-51.474	0.063		0.024
	(245.961)	(59.998)	(0.047)		(0.018)
F-test	0.5781	0.2688	0.0761	0.4764	0.0014
Obs	17369	17341	14442	8141	19457
Adj R-Squared	0.01	0.02	0.05	0.01	0.03

Standard errors in parenthesis, clustered at market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table reports coefficients on regressions of primary outcomes - sales, profits, workers, competitors, and whether a firm is open - on indicator for drought, indicators for year (or survey round), and their interactions and reports p-values from F-tests of joint significance on pre-trend interactions. The top panel is the census sample and fails to reject pre-trends for all four main outcomes. The bottom panel reports results for the women-owned firms panel and rejects that pre-trend interactions are zero for 3 out of 5 outcomes. Survey rounds were used because there were two surveys in 2016.

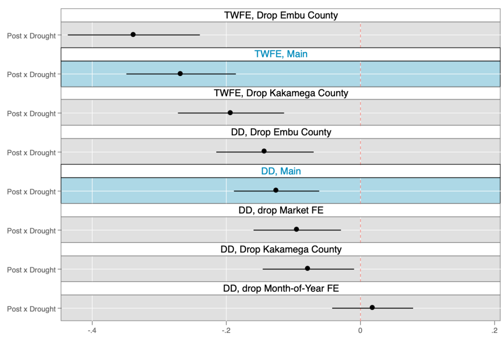
21 Robustness Checks



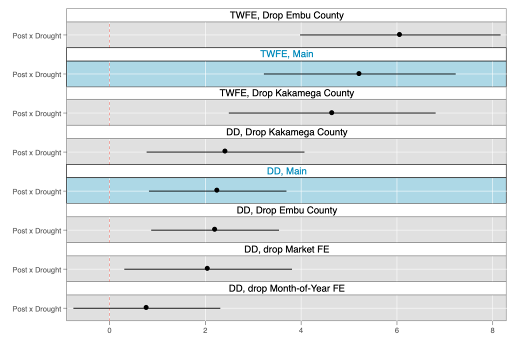
(a) Sales



(b) Profits



(c) Workers



(d) Competitors

Figure 21.1: Robustness Checks for Main Outcomes, Market Census Firms

Essay 3.

The Role of Rural Firms in Smoothing Price Variation: A Case Study from Tanzania

Commodity price variation is a typical feature of markets in developing countries. Rural firms that source commodities as inputs to their business face substantial price variation when purchasing goods in urban markets. Many rural households purchase household food staples and other essential commodities from rural businesses. Seasonal price increases for staple foods have been shown to lower welfare for consumers who struggle to substitute to foods with the same nutritional quality (Green et al., 2013; Bai et al., 2020). Yet, relatively little economic literature examines retail passthrough rates of these food staples to clarify how passthrough rates affect local food security. How much of this input price variation passes through to output prices for rural customers? Does it vary based on whether a firm operates in rural area or an urban area? And what mechanisms explain differences in pricing behavior? I use a panel of input and output prices for 387 urban retail firms and 507 rural retail firms to evaluate passthrough from input price changes on key staple foods sold in urban and rural areas. Panel fixed effects are used to isolate the effect of input price shocks and to compare urban and rural firm pricing behavior.

Retail firms purchase goods paying input prices, and re-sell them at a mark-up without adding value beyond transport charging output prices. I first document that retail output prices are sensitive to changes in input prices and that passthrough rate elasticities are larger for input price decreases than input price increases. Across urban and rural firms, a one percent increase in input price is associated with a 0.30-0.62% increase in output prices and a one percent decrease in input prices is associated with a 0.33-0.85% decrease in output prices, depending on the types of goods included in the sample. In general, passthrough rates are larger for staple food commodities than other commodities that are more perishable or have more quality differentiation, such as vegetables and medicine. I then show that rural firms have lower passthrough rates than urban firms following a negative input price shock, providing evidence that rural firms smooth input prices increases more than urban firms. For staple foods, rural firms passthrough more cost savings and less cost increases. A one percent increase in input prices relates to a 0.53% increase in output prices and a one percent decrease in input prices is associated with a 0.83% decrease in output prices. Once other differentiated commodities are added to the sample, rural firms' passthrough rates on input price decreases are lower than urban firms, meaning they do not pass on cost savings as much as urban firms.

Drawing conclusions about structural differences between urban and rural firms based on passthrough rates is difficult because different passthrough rates may simply reflect different demand elasticities - where lower passthrough rates reflect more elastic demand that deters firms from marking up output prices too much because consumer demand falls quickly. In that case, results are consistent with Atkin and Donaldson (2015) who show that mark-ups are lower in rural markets compared to urban markets because demand is more elastic as prices rise. This paper adds to the literature by testing different mechanisms across a wide range of food staples, perishable foods, and differentiated products to understand how elasticities differ within rural areas and between urban and rural markets.

Market conditions for urban and rural firms differ for a number of reasons. I discuss how demand, community pressure and social ties, information frictions, transaction costs, and competitive structure could relate to different passthrough behavior for rural and urban firms. I use proxy variables for transaction costs and social ties as 'community mechanisms' to understand how passthrough rates vary with different features of rural communities. These community mechanisms include two variables that capture remoteness - distance and bus fare to the nearest city. The last community mechanism is community population size, which captures features of small communities, such as social ties. I also construct two 'competition mechanisms' to evaluate the extent to which rural firms respond to 1.) increases in entrants and 2.) the total number of firms that operate in their subsector.

Community Size and Social Ties: Larger community size is associated with fewer pro-social behaviors since agents are less connected via social ties (Allcott et al., 2007). Tighter social ties in rural communities can act as a type of informal insurance where community members help each other when someone in their kinship network experiences a financial shock (Breza et al., 2019; Kinnan et al., 2021). Although many village risk-sharing arrangements concern the exchange of gifts, money, labor, and other types of support, it is reasonable to expect rural firms to participate in informal insurance by providing credit, price discounts, or bearing more staple price risk by not fully passing on input price increases. Rural firm owners may not think of themselves as vehicles for partial insurance that defend their customers from staple price increases. Instead, it may be that customers in smaller communities have relatively more bargaining power than customers in larger communities, which contributes to lower tolerance for price increases.

Using community size as a proxy for social ties, I find that firms in smaller communities have 15-22% lower passthrough rates for staple foods than firms in larger communities when their input prices increase. Evidence following an input price decrease is weaker but move in the opposite direction - firms in smaller communities have 4-7% higher passthrough to output prices when input prices go down, meaning they pass through cost savings. On the other hand, lower passthrough rates may also indicate that firms have more market power in small communities. If market power was the primary explanation, both price increases and decreases would have lower passthrough rates, indicated that monopolistic firms do not change output prices. I only find lower passthrough rates for price increases, suggesting that firms in smaller communities smooth output prices after negative price shocks more than positive price shocks.

Transaction costs and information frictions: Rural firms tend to be located in remote locations and pay additional transaction costs to source inputs from cities. To compensate for higher transaction costs, the average mark-up on staple foods for rural firms is 19% compared to 15% for urban firms. Higher transaction costs are also associated with higher information frictions which raise the cost of learning about new market information, including changes in prices (Allen, 2014; Aggarwal et al., 2018). As a result, rural customers likely have prior beliefs about prices of key food staples and information frictions could cause rural firms to smooth price variation because rural customers would be slower to learn about and accept price changes. I do not find evidence that information frictions slow output price passthrough. I find that more remote firms have higher passthrough rates for price increases and price decreases than firms closer to urban centers. If information frictions slowed price updating, we would see less passthrough of both price increases and decreases.

Competitors: If markets were perfectly competitive, economic theory predicts that firms would perfectly passthrough input price changes to output prices so that elasticities would approach one. I compare whether variation in the number of competitors and change in number of competitors is associated with different passthrough rates among rural firms and if those differences are consistent with a competitive market framework. If the number of competitors drives pricing behavior, passthrough rates should be sensitive to increases or decreases in the number of firms operating in the same sector. Under a standard perfect competition framework, more competitors should be associated with higher passthrough rates as it decreases the ability of firms to uphold collusive agreements by increasing the likelihood that a firm will lower a price to the competitive level. At the other end of the spectrum, in a collusive arrangement, passthrough rates would be lower since it is easier to tacitly or explicitly coordinate prices if few firms are present in a market.

I find that new firm entry and total number of other competitors are associated with higher passthrough rates both types of input price shocks, showing that competitive pressure also matters. I also find suggestive evidence that for staple foods, firms do not passthrough cost savings that result from input price decreases even in the presence of higher competitive pressure. Compared to urban firms, rural firms output price passthrough elasticities are estimated to be between 0.02-0.10% higher given a one percent decrease in input prices. Within the rural firm sample, higher competitive pressure is associated with 0.07-0.11% lower passthrough. On net, competitive pressure makes rural firms have similar passthrough elasticities as urban firms, suggesting that variation in competition is an important determinant for staple prices.

Food price variation is a significant problem for households in rural areas of developing countries. There are two main sources of food price variation - national-level seasonal variation and national-level price shocks that occur following drought, flood, or other macroeconomic shocks. Seasonal price variation occurs yearly and tends to follow agricultural harvest cycles. Bai et al. (2020) showed that seasonal price variation increases diet costs by 6% in Tanzania and decreases consumption of more nutritious foods. Kaminski et al. (2016) find that seasonal variation for maize and rice in Tanzania is two to three times higher than in international markets and decreases caloric intake among poor households in rural and urban areas. This research differs from others in that I study idiosyncratic input price shocks that small firms face as a consequence of price uncertainty generated by seasonal price variation or other information and search frictions. I also consider whether rural firms have lower passthrough rates and therefore smooth input price variation for their customers. I examine asymmetry in price shocks in order to understand whether input price decreases have higher or lower passthrough rates than input price decreases. This paper contributes to the literature on price variation in rural markets by clarifying the extent to which rural retailers have low passthrough rates.

22 Passthrough in Urban and Rural Markets

The structure for urban and rural markets differs based on a variety of factors that could affect passthrough and pricing behavior. Three types of factors are explored: 1.) Features of the customer base and demand, 2.) Transaction costs and information frictions, and 3.) Number of competitors.

22.1 Features of the Customer Base and Demand

A firm's customer base has different aggregate demand and demand elasticities depending on whether it is located in an urban or a rural market. By virtue of being located in populous areas, urban firms have a larger pool of potential customers compared to rural firms that operate in small and medium sized rural towns. Urban firms rely on a steady stream of urban-based customers that are less likely to engage in farming and more likely to have regular incomes, leading to overall more consistent demand. By contrast, rural firms have smaller customer bases whose cash income is irregular. Many rural customers engage in agricultural production, which leads to seasonal changes in demand for foodstuffs purchased from retailers. With relatively low and unstable income compared to urban customers, it is reasonable to expect rural customers have higher price elasticity of demand and are more sensitive to price changes compared to urban customers.[14]

Another important element of the customer base is the extent to which buyers and sellers engage in anonymous transactions or build relationships with customers. Larger community size is associated with fewer pro-social behaviors since agents are less connected via social ties

[14]Using panel data from Tanzania, Rudolf (2019) finds an own-price elasticity of demand for maize to be more elastic in urban areas compared to rural areas (with estimated elasticities of -.475 and -.167, respectively), arguing that urban households have greater ability to substitute to different foods if maize prices increase. Yet, Ecker and Qaim (2011) use data from Malawi and find own-price elasticities for maize that are relatively lower in urban compared to rural areas (-.722 and -.877, respectively) and rural areas have higher elasticities for 14 out of 23 foods tested. This aligns with studies that use meta-analysis research designs to compare own-price elasticities across countries which generally find that own-price elasticities for foodstuffs are higher in lower income settings (Green et al., 2013; Muhammad et al., 2015; Muhammad et al., 2017). Rudolf also finds higher elasticities for the rural poor compared to urban poor as does Boysen (2016), using Uganda data. Therefore, relatively higher own-price elasticity of demand for staples in rural areas is a reasonable assumption.

(Allcott et al., 2007). Given the smaller customer base from a small population, rural firms are more likely to be familiar with their customers and may face community pressure to keep prices low. In the rural firms survey, 82.3% of rural firms said most of their customers come from their village and 28.9% of rural firms indicated that they did not transact with any unknown customer over the previous week. Of course, urban firms also build relationships with their customers. But by virtue of living in cities, they have a higher probability of transacting with unfamiliar customers compared to firms in rural markets. Tighter social ties in rural communities can act as a type of informal insurance where community members help each other when someone in their kinship network experiences a financial shock (Breza et al., 2019; Kinnan et al., 2021).

22.2 Transaction Costs and Information Frictions

In addition to being more familiar with customers with higher elasticities of demand, rural firms are located in remote locations. As a consequence, they pay additional transaction costs associated with sourcing inputs from cities and transporting them to rural areas to sell. To compensate for higher transaction costs, the average mark-up on staple foods for rural firms is 19% compared to 15% for urban firms. Higher transaction costs are also associated with higher information frictions which raise the cost of learning about new market information, including changes in prices. As a result, rural customers likely have prior beliefs about prices of key food staples and information frictions would cause them to be slower to update price expectations once prices change.

All of these features of the customer base mean that rural firms are less likely to passthrough price changes and thus are more likely to smooth input price fluctuations. For example, if an urban firm faces an input price increase and updates their output price, they know that their customers are relatively well-informed, there are more potential customers, and customers can tolerate price fluctuations leading to overall less elastic demand. And urban firms have a larger pool of customers who are less able to exert community pressure to keep prices low.

On the other hand, if a rural firm pays a higher price for inputs and updates their output price, their customers may be slower to update expectations to accept higher output prices, can exert community pressure to keep prices low, and are more price sensitive since price changes have greater consequences for their household budgets.

22.3 Number of Competitors

Despite higher and more stable aggregate demand, urban firms operate in markets with more competitors, defined as the number of firms in a market that sell the same types of goods (dry-goods stores, cereals/grains sellers, vegetable sellers, etc.). Urban firms in staple food sectors in this sample have an average of 6.8 competitors, while rural firms that sell staple foods have 3.7 competitors. As a share of other firms, staple foods sellers make up 33% of all firms in urban markets and 18.4% of firms in rural markets. This generates pressure on urban firms to deliver competitive prices. But, having many firms that sell similar products in the same location also facilitates information sharing among firms and can resolve price uncertainty if firms tacitly or explicitly agree to update prices collectively.

If markets were perfectly competitive, economic theory predicts that firms would perfectly passthrough input price changes to output prices. In the simplest model, input price increases and decreases are expected to symmetrically passthrough to output prices and is evidence of competitive market structure. As a result, passthrough rates are often used to evaluate market power of firms (Sumner, 1981). In practice, passthrough rates in some markets may differ based on whether input prices increase or decrease (Peltzman, 2000; Bonnet and Villas-Boas, 2016). However, without additional assumptions about the curvature of a demand curve, passthrough rates alone are not sufficient to identify the competitive structure of markets (Bulow and Pfleiderer, 1983). In maize markets in Kenya, Bergquist and Dinerstein (2020) show experimental evidence that maize traders passthrough rates from a cost savings intervention are closer to a collusive model than a model of Cournot competition.

In lieu of identifying the competitive structure of markets (e.g. perfect competition, monopolistic market structure, or collusion), I compare whether variation in the number of competitors is associated with different passthrough behavior by urban and rural firms and if those differences are consistent with a competitive market framework. If the number of competitors drives pricing behavior, passthrough rates should be sensitive to increase or decreases in the number of firms operating in the same sector. Under a standard perfect competition framework, more competitors should be associated with higher passthrough rates as it decreases the ability of firms to uphold collusive agreements by increasing the likelihood that a firm will lower a price to the competitive level. At the other end of the spectrum, in a collusive arrangement, passthrough rates would be lower since it is easier to tacitly or explicitly coordinate prices if few firms are present in a market.

23 Context and Data Sources

23.1 Data

This study uses data collected from urban and rural firms in Singida and Dodoma regions in central Tanzania. Rural firms' customer base is largely comprised of agricultural households that purchase foodstuffs and other household goods from local retailers. Often, rural firms travel to purchase business inputs - either in larger towns or urban centers, linking rural consumers in an urban-to-rural supply chain that supplies goods and services that households do not grow or manufacture for themselves. Four rounds of survey data from 240 rural firms and three rounds of survey data from 230 urban firms were collected from 2019-2020.

23.1.1 Urban and Rural Firms

Markets are defined as either an entire rural village or a neighborhood in an urban center. There are 17 urban markets spread among 3 urban centers - 10 in Dodoma City, 4 in Singida City, and 3 in Manyoni Town. Dodoma has a population of 410,000 people (fourth largest city in Tanzania) and is the principal trading center for the region as well as the political capital for Tanzania. Singida City is the capital of Singida region and has a population around 150,000. Manyoni Town is a medium-sized trading center, with 25,000 people. Urban centers were identified after establishing Singida and Dodoma as target regions. Figure 23.1 shows these regions in Tanzania and the locations of urban markets (dark blue dots) and rural markets (light blue dots).[15]

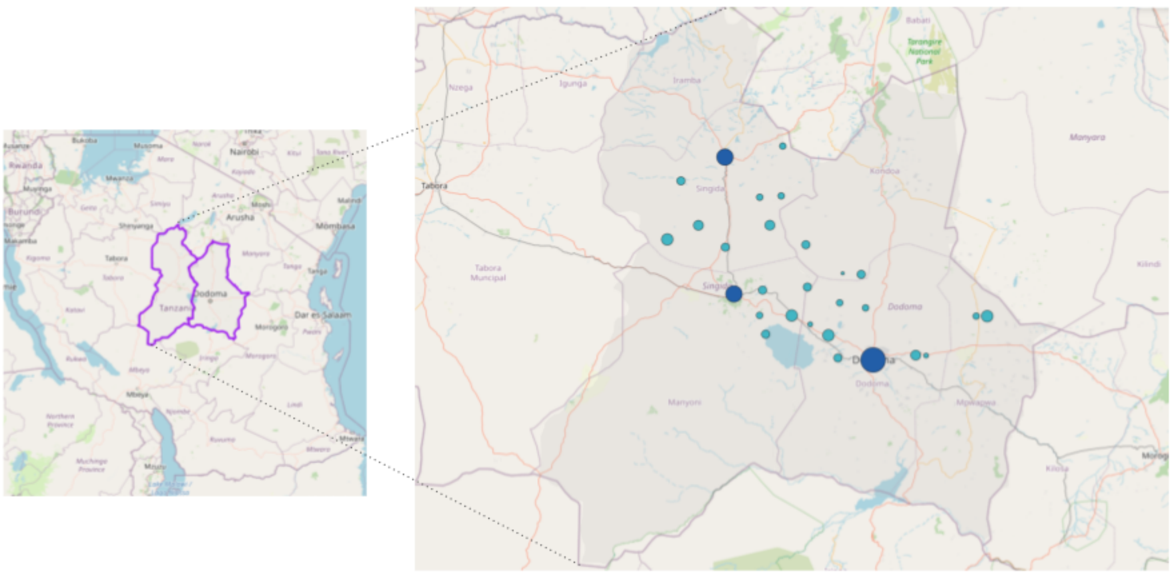


Figure 23.1: Location of surveyed urban markets (dark blue) and rural markets (light blue) in Tanzania

Rural markets comprise relatively large rural villages (*vijiji* in Tanzania administrative classification) with populations between 3,000 and 10,000. 25 rural markets were randomly selected among the universe of villages with more than 3,000 people located between Dodoma City, Singida City, and Manyoni Town after stratifying on population, distance the nearest market, and region. In each rural community, all firms were invited to participate in an on-going project to provide a digital phonebook to rural consumers in Tanzania Dillon et al., 2020. Similarly, urban firms in each city were approached to participate in the project. About 82% of rural firms and 75% of urban firms decided to participate. The urban firm

[15]The southern half of Singida region was not included because it contains only communities with small populations and overlaps with a large national park.

census only includes retail firms. The original sample of rural firms includes both retail and service firms. To ensure that the samples are comparable, I only use price data from retail firms in rural areas.

Table 23.1 displays summary statistics for urban and rural retail firms. Urban and rural firms vary significantly in every dimension - urban firms are on average older, firm owners are older, they are almost three times more likely to have hired any workers in the previous week, and hired three times as many workers. But, the modal urban firm has zero paid workers (45% hired any worker the previous week compared to 16% of rural firms). Rural retail firm owners are more likely to be women - 31% of rural retailers are women-owned compared to 23% of urban firms.

Rural firms operate in villages with an average population of 4,850 people. The largest rural village in the sample has 10,000 people and the smallest has 3,200. The average urban center population is about 250,000. This is heavily weighted to the size of Dodoma City, which has the largest population. The catchment area for urban firms likely does not include the entire population since many people in urban areas shop primarily in neighborhood shops. Urban firms also sometimes act as wholesalers for rural firms around the region, but this is not always the case. They sell to a mix of urban customers, rural consumers that travel to buy for their households, and rural firms that travel to cities to purchase inputs. About 80% of rural retailers purchase inputs for inventory from urban areas and the remaining 20% re-stock inventories from other rural sellers. Both urban and rural firms prices could include bulk discounts, frequent customer discounts, or other prices changes. But, these activities are common in all markets. To the extent that firms have pricing policies, firm fixed effects will absorb those policies as long as they are time-invariant. The average rural firm is located 64 kilometers from the nearest urban center - either Dodoma, Singida, or Manyoni. Rural markets have an average of 13 retail firms, of which 72% are staple food sellers. Urban markets have an average of 27 retailers, of which 44% sell staple foods.

Two measures provide information about the number of other sellers that firms compete

Table 23.1: Urban and Rural Retail Firm Characteristics

		(1) Rural		(2) Urban
	N	Mean (SD)	N	Mean (SD)
Firm Characteristics:				
Woman-Owned Firm	230	0.313	192	0.229
		(0.465)		(0.421)
Age of firm	230	5.233	187	6.834
		(5.560)		(8.096)
Owner age	230	36.396	188	38.500
		(11.099)		(9.868)
Years of education	230	7.900	191	9.073
		(3.630)		(3.898)
Any workers (0/1)	230	0.157	240	0.446
		(0.364)		(0.498)
Number of workers	230	0.243	240	0.783
		(0.682)		(1.265)
Market Characteristics:				
Village/city population	230	4851.030	238	245252.101
		(1352.536)		(168370.007)
Distance to urban center	230	63.886	240	0.000
		(31.217)		(0.000)
Number of retailers in market	230	13.430	240	27.183
		(5.542)		(15.508)
Share selling staple foods	230	0.722	240	0.438
		(0.449)		(0.497)
Firm Competitors:				
Number of competitors, self-reported	230	7.687	239	9.226
		(4.880)		(5.072)
Number of competitors, census count	230	3.161	240	4.083
		(1.907)		(2.749)
Net increase in competitors (0/1)	230	0.365	240	0.546
		(0.483)		(0.499)
Net decrease in competitors (0/1)	230	0.204	240	0.129
		(0.404)		(0.336)
No change in number of competitors (0/1)	230	0.430	240	0.325
		(0.496)		(0.469)

Notes: All means are significantly different at least a 95% level with in their market. First, the self-reported measure of number of competitors is 7.7 for rural firms compared to 9.2 for urban firms. Second, the research team counted the number of competitors based on their assessment of which firms sell the same goods. For the census count measure, rural firms have an average of 3.2 competitors in their sector while urban firms have an average of 4.1 competitors. The census count is an underestimate because sectors were defined to mutually exclusive - that is if a firm sold both staple grains and fruits and vegetables, they would be categorized according to the product with the highest sales. And only participating firms were counted, so it only represents 75-82% of firms. But, in the self-reported measure, firms were asked "How many sellers in this market sell the same goods as you?" Thus, they provide a count based on a more flexible definition of other sellers that operate roughly in the same sector and provide a measure of perceived competition. The self-reported measure is used in regressions.

23.1.2 Price Data

Retail firms in urban and rural areas operate in a range of sub-sectors, including general stores selling dry-goods, vegetable/fruit sellers, water and soda vendors, pharmacies, clothing sellers, spare parts stores, and hardware stores. Each survey, firms were asked the most recent input and output price during each survey round. For food goods, units were converted to Tanzanian shillings per kilogram or litre. To anticipate possible changes in quality, firms were also asked if the quality of goods changed. Firms only reported any quality change for 2-8% of items each round, suggesting that quality differentiation was not a major factor during the survey period. The main sub-sample of firms focuses on prices for staple foods - maize grain, maize flour, rice, beans, and sugar.[16] The second sample has staple foods and other products that are more perishable or have more quality differentiation are introduced to improve power - water, soda, bananas, potatoes, tomato, potato, onion, and three types

[16]The difference between maize grain and maize flour is that flour is processed and sold in bags with set quantities. Maize grain, on the other hand, is unprocessed and sold by the kilogram. Maize flour is the primary dietary staple. Most rural communities have maize mills where agricultural households take maize grain to grind into flour. But, this is a different product from the variety sold in rural stores.

of medicine (paracetamol, amoxicillan, and diclopar). These were chosen based on having at least 20 prices in both urban rural markets. The last sample includes all products which have input and output price information, regardless of the number of observations or the degree of product differentiation.

Table 29.1 in the appendix shows descriptive statistics of input and output prices for staples foods. As expected, average output prices are higher for rural firms than for urban firms for all goods except maize grain. Rural firm input prices are higher than urban firms for all goods except sugar. Average mark-ups in shillings range from 124Tsh for maize flour to 352Tsh for beans among urban firms and 109Tsh for maize grain to 403Tsh for sugar among rural firms. Rural firms charge higher mark-ups as a percentage of the input price for all goods except maize grain. Average percent mark-ups for rural firms range from 20% for maize flour and beans to 22% for maize grain. Average mark-ups for urban firms range from 6% for sugar to 19% for beans. The higher mark-up makes sense given that rural firms incur additional transportation costs to bring goods from urban to rural areas. Medians are included to highlight that the monetary denomination builds in some price stickiness. Most prices will change by 100 shillings at a time, sometimes 50 shillings, but rarely less than that, which is about $0.02 to $0.04 USD.

23.2 Staple Food Price Variation in Tanzania

The World Food Programme's Vulnerability Analysis and Monitoring (VAM) dashboard provides information about the extent of price variation for key staple foods throughout Tanzania. They report monthly price data for markets located throughout Tanzania for a selected set of food staples - maize grain, beans, rice, sugar, and wheat flour. Figure 33.3 in the appendix plots the average price in 6 markets in Tanzania for the 2019-2020 period that overlaps with the rural and urban firm data. Prices for Dodoma are highlighted in red and the other markets are the 5 closest regional markets with monthly price series data.

Table 23.2 reports averages, standard deviations, and coefficient of variation for key food

Table 23.2: WFP Prices for Staples from 2019-2020

	Mean Tsh/kg	sd	Coefficient of Variation (CV)	CV - Lowest Month	CV - Highest Month
Beans	1787.89	287.29	0.16	0.09	0.19
Maize	620.60	151.35	0.24	0.12	0.32
Rice	1666.19	207.19	0.12	0.08	0.19
Sugar	2625.91	257.66	0.10	0.06	0.16
Wheat flour	1381.68	187.51	0.14	0.09	0.21

staples in 6 markets. Coefficient of variation is a measure of price dispersion that controls for the magnitude of the mean. The coefficient of variation varies from 0.10 for sugar to 0.24 for maize annually in urban markets in Tanzania. Under a normal distribution, it implies that about 68% of prices are between 24% below the mean and 24% above the mean and 95% of prices are within 48% below and above the mean (2 standard deviations). This pattern is similar in the firms data - the coefficient of variation for output prices for rice is 0.12, beans is 0.14, maize is 0.34, and sugar is 0.11. Within-year seasonal variation is more variable - ranging from 0.09 to 0.19 for rice in the lowest and highest month, 0.12 to 0.32 for maize, and 0.06 and 0.16 for sugar - due to the agricultural harvest cycles and seasonality in household income. This indicates that price dispersion changes quite a bit month-to-month - some months have tighter price distributions while others exhibit higher within-month variation.

24 Empirical Approach

All firms in the sample are retail firms whose primary business activity is purchasing goods and reselling them at a mark-up. Firms' input prices are the wholesale price paid by the firm and the output price is the the marked-up price that firms charge their customers. I estimate the following econometric specification using multi-way fixed effects with variation in 'treatment' timing, where the 'treatment' variable is a firm-level input price shock:

Main Specification:

$$
\begin{aligned}
\Delta lnP_{ifmt}^{output} &= \alpha + \beta_1 \mathbb{1}\{Increase_{ifmt}\} \times \Delta lnP_{ifmt}^{input} \\
&+ \beta_2 \mathbb{1}\{Decrease_{ifmt}\} \times \Delta lnP_{ifmt}^{input} \\
&+ \gamma_i + \lambda_t + \mathbf{X}_{ifmt}\Phi + \epsilon_{ifmt}
\end{aligned}
$$

Where:

$$
\begin{aligned}
\Delta lnP_{ifmt}^{output} &= lnP_{ifmt}^{output} - lnP_{ifmt-1}^{output} \\
\Delta lnP_{ifmt}^{input} &= lnP_{ifmt}^{input} - lnP_{ifmt-1}^{input}
\end{aligned}
$$

The primary outcome variable is the first difference of the logged output price of item i, for firm f, in market m, at time t. The 'treatment' variables for input price changes are defined as an indicator function set to one if the firm's input price for item i increased or decreased compared to previous survey round multiplied by the first difference of the logged input price. The coefficients of interest are β_1 and β_2 and are interpreted as elasticities that capture passthrough asymmetry depending on whether the firm experienced a price increase or decrease.

Initial regressions include survey-round fixed effects, λ_t, to control for time invariant unobservables during each survey time period and would capture seasonal shifts in demand that are common across markets. First differencing the price variable is equivalent to de-meaning using dummy-variable fixed effects. Including item fixed effects, γ_i, in addition to first differences is like adding item-specific linear time trends to control for for item-specific changes over time. The term $\mathbf{X}_{ift}\Phi$ represents a vector of controls and includes a treatment dummy and market size. Standard errors are robust and clustered at the market level, permitting arbitrary within-market correlation.

24.1 Defining Item Samples

I define three sub-samples of retail items based on how much product differentiation is likely to lead to quality differences:

1. **Staple Foods:** The sample of staple food items includes rice, beans, maize grain, maize flour, and sugar. Rural retail firms reported these items as the most commonly sold items in their stores. Compared to the other items, these food staples have the least quality differentiation and are relatively homogeneous in terms of being non-branded commodities that are sold by weight in unmarked bags.[17]

2. **Commodities:** The second sample includes other food and non-food commodities that have more quality differences than staple foods but nonetheless are relatively similar. The commodities subsample includes all of the food staples, plus bananas, tomato, potato, onion, soda, water, and three of the most common pharmaceutical medicines sold in rural pharmacies. These food items are more perishable and have more observable quality differences.

3. **All Items:** The third sample includes the first two plus differentiated products. It includes 44 items total, including bike tubes and tires, shoes, cloth, ready-made clothing, cement, construction nails, etc. Differentiated products have more variation in quality and different demand curves compared to food staples.

The three different sub-samples were created to provide information about whether mark-up strategies for staple foods differ from other products. Each sub-sample increases the sample size and increases the presence of product differentiation to show whether mark-ups are robust to different types of items or if they are only consistent within the staple foods category. Three models are estimated for each item sub-sample. The first model has item and time fixed effects. The second model adds market fixed effects to control for time invariant

[17] In practice, there are different varieties of food crops, especially for rice and beans. To control for this during surveys, firms were asked prices for specific varieties that are most common in rural areas.

unobservables that are common within markets and would capture time invariant differences in local market institutions, market access, and remoteness. The third model adds firm fixed effects and removes the item fixed effects. In surveys, firms were asked prices on the same items during each survey round such that item fixed effects are absorbed by the firm fixed effects.

24.2 Identification Under Strict Exogeneity

The identification assumption requires strict exogeneity by assuming that conditional on common time-invariant unobservables at item, survey round, market, and firm levels, no other unobserved heterogeneity is correlated with the error term. In practice, this is a strong assumption because firms endogenously select into the prices they pay for inputs. Fixed firm preferences for input prices are absorbed by the firm fixed effects so that the third econometric specification approaches this standard and approximates the causal effect of input price shocks on passthrough rates. This assumption is violated if firms change their search intensity over time, incurring different search costs to obtain inputs. For example, if a firm searched the first period in three locations to find business inputs that meet their price, quantity, or quality requirements and in the second period the firm only searched one location or talked to one vendor, then their time-varying search costs would vary and would violate strict exogeneity.

To test the role of variation in search costs, I use a variable from the rural firm survey that intends to capture input search intensity. The 'Search Index' variable includes the number of suppliers that a firm communicated with, purchased from, and the number of different locations travelled during each survey round. It is a proxy for time-varying input search costs.

Table 30.1 in the appendix shares results from regressions of the search index on the logged input price and the first difference of the logged input price using the item sub-samples and fixed effects specifications. The first two columns of each sub-sample in the regression with logged input price as the outcome variable (colums 1-2, 4-5, and 7-8) are all negative and different from zero. Firms that search more tend to have lower input prices. However, after controlling for firm fixed effects, the effect size decreases to a precise zero, providing evidence that firm search costs are relatively stable over time. The second panel regresses the first difference of the logged input price on the search intensity and estimates precise zeros for all specifications. It suggests that firms have stable, relatively time-invariant preferences for input prices and do not update their input search behavior to seek better prices.

25 Results

This section presents results for passthrough rates in two tables. First, results from regressions that pool urban and rural firms establish that firms passthrough input price changes to output prices. Second, results from regressions that examine rural and urban firm heterogeneity show that rural firms' passthrough rates are smaller than urban firms passthrough rate when input prices increase for staples. The subsequent section explores possible mechanisms to explain differences in output price changes.

Each table includes results for each item sub-sample - Staple foods, differentiated commodities, and all items. Each sub-sample has three regressions: 1). item and time fixed effects, 2.) item, time, and market fixed effects, and 3.), time and firm fixed effects. Preferred specifications are those with firm fixed effects. Variables *increase* and *decrease* are abbreviations for the terms $\mathbb{1}\{Increase_{ifmt}\} \times \Delta lnP^{input}_{ifmt}$ and $\mathbb{1}\{Decrease_{ifmt}\} \times \Delta lnP^{input}_{ifmt}$ from the empirical specification described in section 24.

25.1 Passthrough - Pooling Urban and Rural Firms

Results in Table 25.1 pool rural and urban firms. The table reports the first stage result that firms update output prices when input prices change. For the staple foods sub-sample

Table 25.1: Passthrough Rates - Pooling Rural and Urban Firms

	Dep Var: D.Ln Output Price								
	Staples			Commodities			All Items		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Increase	0.634***	0.615***	0.616***	0.264*	0.257*	0.299*	0.327**	0.325**	0.351**
	(0.073)	(0.076)	(0.076)	(0.131)	(0.137)	(0.152)	(0.146)	(0.153)	(0.159)
Decrease	0.823***	0.839***	0.854***	0.329***	0.334***	0.331**	0.649***	0.631***	0.658***
	(0.060)	(0.063)	(0.036)	(0.105)	(0.113)	(0.130)	(0.096)	(0.105)	(0.150)
Round FE	X	X	X	X	X	X	X	X	X
Item FE	X	X		X	X		X	X	
Market FE		X			X			X	
Firm FE			X			X			X
Obs	926	926	926	1381	1381	1381	1648	1624	1624
Adj R-Squared	0.7364	0.7355	0.7571	0.2542	0.2517	0.2372	0.6038	0.6055	0.5796

Standard errors in parenthesis, clustered at market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

in Columns 1-3, the passthrough rate elasticity is about 0.62 in the preferred specification, and is stable with different sets of fixed effects. That is, a one percent increase in the input price is associated with a 0.62% increase in the output price. Passthrough rates decrease to between 0.26-0.30% when the sample size increases to include differentiated commodities in columns 4-6. When the sample size increases to include all products, passthrough rates are slightly higher - falling between 0.33-0.35%.

For input price decreases, passthrough rates are between 0.82-0.85% for staples, 0.33% for differentiated commodities, and 0.63-0.66% for all items. In all models passthrough rates for input price decreases are higher than input price increases showing that firms pass through cost savings more then cost increases. Passthrough rates are higher for staples compared to the larger samples that include more perishable and differentiated goods. High passthrough rates are a signal of market competition - where perfect competition with no frictions or market failures would see 100% passthrough for both increases and decreases.

Passthrough rates alone are not sufficient to draw conclusions about market structure because the own-price elasticity of demand could also explain variation in passthrough. It is reasonable to expect staple foods to have higher passthrough rates because they have more firms competing to sell them and there is little product differentiation. But, it could also be that differentiated products have relatively more elastic demand, so that price increases cause demand to decrease more quickly as prices rise.

25.2 Passthrough - Urban and Rural Firm Heterogeneity

To examine rural and urban firm heterogeneity, I use the following empirical specification:

$$
\begin{aligned}
\Delta P_{ifmt}^{output} =& \alpha + \beta_1 \mathbb{1}\{Increase_{ifmt}\} \times \Delta lnP_{ifmt}^{input} \\
&+ \beta_2 \mathbb{1}\{Decrease_{ifmt}\} \times \Delta lnP_{ifmt}^{input} \\
&+ \beta_3 \mathbb{1}\{Increase_{ifmt}\} \times \Delta lnP_{ifmt}^{input} \times Rural_f \\
&+ \beta_4 \mathbb{1}\{Decrease_{ifmt}\} \times \Delta lnP_{ifmt}^{input} \times Rural_f \\
&+ \delta Rural_f + \gamma_i + \lambda_t + \mathbf{X}_{ifmt}\Phi + \epsilon_{ifmt}
\end{aligned}
$$

It is similar to the primary equation in section 24, with the addition that input price shocks are interacted with an indicator term $Rural_f$ equaling one if a firm is located in a rural market. The coefficients, β_1 and β_2 on the terms that are abbreviated to $Increase$ and $Decrease$ in tables are the passthrough rates for input price changes in urban areas while the coefficients, β_3 and β_4, on the interaction terms reflect the difference of rural firms' output prices compared to urban firms.

Across all models in Table 25.2, urban firms have positive passthrough rates, ranging from 0.74-0.96% for both price increases and decreases for all sub-samples. Similar to Table 25.1, input price increases have higher passthrough rates for staples in columns 1-3 compared to samples with more differentiated products in columns 4-9. But unlike Table 25.1, passthrough rates for price decreases are higher for differentiated products compared to staple foods - approximately 0.80% for staple foods for the preferred model with firm fixed effects up to 0.96% for samples with differentiated commodities and all items using the preferred specification in columns 3, 6 and 9.

Table 25.2: Passthrough Rates - Rural and Urban Firms

	Dep Var: D.Ln Output Price								
	Staples			Commodities			All Items		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Increase	0.895***	0.870***	0.952***	0.652***	0.620***	0.681**	0.742***	0.744***	0.781***
	(0.144)	(0.164)	(0.214)	(0.187)	(0.220)	(0.275)	(0.095)	(0.096)	(0.138)
Decrease	0.743***	0.756***	0.803***	0.781***	0.813***	0.949***	0.884***	0.868***	0.963***
	(0.071)	(0.088)	(0.053)	(0.084)	(0.092)	(0.183)	(0.047)	(0.057)	(0.024)
Rural×Increase	-0.339**	-0.332*	-0.420*	-0.487**	-0.459*	-0.505*	-0.577***	-0.582***	-0.599***
	(0.142)	(0.164)	(0.221)	(0.204)	(0.236)	(0.291)	(0.124)	(0.129)	(0.163)
Rural×Decrease	0.109*	0.107	0.028	-0.563***	-0.590***	-0.733***	-0.640***	-0.622***	-0.738***
	(0.059)	(0.074)	(0.051)	(0.105)	(0.115)	(0.203)	(0.086)	(0.095)	(0.087)
Rural	0.040**			-0.007			-0.024		
	(0.017)			(0.024)			(0.022)		
Round FE	X	X	X	X	X	X	X	X	X
Item FE	X	X		X	X		X	X	
Market FE		X			X			X	
Firm FE			X			X			X
Obs	926	926	926	1381	1381	1381	1648	1624	1645
Adj R-Squared	0.7419	0.7402	0.7650	0.3372	0.3346	0.3551	0.7075	0.7045	0.7092

Standard errors in parenthesis, clustered at market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The coefficients on $Rural \times Increase$ are all negative, indicating that passthrough rates are lower for rural firms. For the staple foods sample, for a 1% increase in input prices, urban firms' output price increases 0.95% - near to what would be predicted by perfect competition, while rural firms only increase output prices by 0.53%, resulting in 55% lower passthrough rates than urban firms. When the sample expands to include differentiated products, rural firm passthrough rate shrinks to be 23-32% lower than urban firms. Consistent with Atkin and Donaldson (2015), the lower passthrough rates are consistent with a regime of higher demand elasticities in rural areas - meaning that rural customers are less tolerant of price increases. This pattern is also consistent with having more competitive pressure in the market structure in urban areas because higher passthrough rates are consistent with a competitive market structure.

Turning to price decreases, a different pattern emerges. For staple foods, rural firms have 3-14% higher passthrough rates, but estimates are not statistically significant in the preferred specification. It shows that for staples, rural firms passthrough more cost savings and less cost increases. A one percent increase in input prices relates to a 0.53% increase in output prices and a one percent decrease in input prices is associated with a 0.83% decrease in output prices. Once the sample increases in columns 4-9, coefficient signs reverse and are consistent with the previous pattern where rural firms do not passthrough cost savings as much as urban firms. In the preferred specifications in columns 6 and 9, coefficients are negative 0.73-0.74 for price decreases, resulting in passthrough rate elasticities which are 23% lower than urban firms. Overall, it shows that output prices for rural firms exhibit more rigidity compared to urban firms.

26 Possible Mechanisms

What explains differences in passthrough rates among rural firms across item samples? Is there evidence that differences in market structure or community characteristics are relevant factors? The following equation is estimated to understand which mechanisms explain differences in passthrough by rural firms.

$$\begin{aligned}\Delta P_{ifmt}^{output} =& \alpha + \beta_1 \mathbb{1}\{Increase_{ifmt}\} \times \Delta ln P_{ifmt}^{input} \times \mathbf{Mechanism}_{fm} \\ &+ \beta_2 \mathbb{1}\{Decrease_{ifmt}\} \times \Delta ln P_{ifmt}^{input} \times \mathbf{Mechanism}_{fm} \\ &+ \gamma_i + \lambda_t + \mathbf{X}_{ifmt}\Phi + \epsilon_{ifmt}\end{aligned}$$

Three community level mechanisms and two competition mechanisms are included to compare which, if any, features of rural communities or features of the competitive environment explain differences in passthrough rates. All variables are continuous and standardized to z-scores so that they are comparable. The coefficients nested in β_1 and β_2 represent the percent change in the first difference of the logged output price given a one standard deviation increase in the mechanism variable following a one percent increase or decrease in logged input prices. For example, a one percent increase in input price and a one standard deviation increase in distance to urban center is associated with about a 0.12% increase in the output price for the staple foods sample. In other words, passthrough increases with distance.

The three community mechanisms are distance to urban center, bus fare to urban center, and rural population size. The community mechanisms are time-invariant and defined at the market (e.g. community) level and interacted with input price shock variable otherwise they would be absorbed by market and firm fixed effects. They provide information about the role of information frictions and transaction costs and strength of social ties or community pressure in smoothing input price passthrough. In theory, communities that are more isolated with longer travel times to a city would have higher information frictions and transaction costs. And communities with smaller populations are more likely to have stronger social ties. The mechanisms distance to urban center and bus fare would capture information frictions and transaction costs and community population size would capture social ties. Bus fare differs from distance because it captures other features of rural communities that make accessing a city more difficult - like road quality.

The two competition mechanisms are the change in the number of competitors and the absolute number of competitors are defined for each firm within each market. The change in number of competitors captures firms pricing response after a new entrant joins their market. It is defined as a percent change in the number of competitors to reflect the fact that increasing competitors from 1 to 2 is more meaningful than an increase in number of competitors from 10 to 11. The absolute number of competitors captures the general competitive pressure associated with have a larger number of rivals. The number of competitors is weighted by market size because larger markets are likely to serve larger populations with more demand. The weighted number of competitors therefore reflects cases where firms have relatively more competitive pressure for a given market size.

Table 26.1 reports results for these regressions. Distance to urban center is associated with higher passthrough rates for both increases and decreases, but only price increases consistently meet rejection criteria across all samples and specifications. It means that more remote firms passthrough price changes to a greater degree than firms closer to urban centers. Similarly, busfare is weakly related to higher passthrough rates, although few estimates are statistically different from zero. I previously theorized that information frictions could potentially smooth price variation because rural customers would be slower to anticipate and accept price changes. If this were the case, we would see less passthrough of both price increases and decreases. Higher observed passthrough rates shows that firms require additional compensation for higher transportation costs.

Interactions with population size provide clearer evidence that smaller communities are associated with lower passthrough rates. Community population size is defined as the inverse so that coefficients are oriented in the same direction as the distance and bus fare variables. For input price increase, passthrough rates decrease as the population gets smaller. A one standard deviation increase in population size is related to a 0.09-0.12% decrease in logged output price for the staple foods sub-sample. As the sample size increases to includes differentiated products in columns 4-9, point estimates remain negative at slightly smaller, but are not different from zero. Following price increases, small communities do not raise prices as much as firms in larger communities. Evidence following an input price decreases are positive but near zero for all models. This is consistent with literature showing that strong social ties are associated with risk-sharing behavior that includes pricing behavior of rural firms.

Despite some evidence that community pressure or social ties are associated with lower output prices, coefficients on firm entry and total number of other competitors shows that competitive pressure also matters. A one standard deviation increase new entrants is associated with a 0.04-0.06% increase in output prices across all sub-samples, but are only precisely estimated for the staples sub-sample. A one standard deviation increase in the total number of competitors is positive in most specifications, but are near zero and imprecise for the staples sub-sample. Taken together, it shows the input price increases are generally associated with higher passthrough rates that is consistent with having more competitive pressure.

Patterns for input price decreases are more mixed. For the staples sub-sample, point estimates are negative for both change in entrants and the number of competitors. This is a counter-intuitive result because in perfect competition framework, higher competitive pressure would in theory increase passthrough rates for price increases as well as price decreases. The fact that price increases goes in the expected direction, while price decreases are negative suggests that firms in rural areas may retain some of the cost savings if they incur a positive input cost shock. However, once the sample size expands in columns 4-9, point estimates for price decreases are all positive, ranging from 0.03-0.07 for change in competitors, and 0.12-0.18 for number of competitors, suggesting that rural firms do not consistently retain cost savings for more perishable and differentiated goods.

To understand more about the net effect of output price changes regardless of whether the input price increased or decreased, Table 32.2 in the appendix shares results for symmetric passthrough. Across the differentiated commodities and full items sample, the number of competitors is consistently associated with higher passthrough rates. Point estimates are also positive for the change in competitors, but are less precise. But, for the staples sample alone, point estimates are negative but imprecise. It suggests that output prices for food staples are more rigid compared to other item groups and firms only smooth price variation for a subset of food staples.

Table 26.1: Passthrough Rates - Mechanisms for Rural Firms

	Dep Var: D.Ln Output Price								
	Staples			**Commodities**			**All Items**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Increase	0.573***	0.572***	0.563***	0.396***	0.399***	0.400***	0.384***	0.388***	0.388***
	(0.061)	(0.063)	(0.065)	(0.060)	(0.062)	(0.066)	(0.060)	(0.063)	(0.062)
Decrease	0.880***	0.878***	0.864***	0.286***	0.286***	0.285***	0.306***	0.305***	0.301***
	(0.037)	(0.038)	(0.038)	(0.055)	(0.057)	(0.054)	(0.053)	(0.054)	(0.051)
Community Mechanisms									
Increase × Distance	0.117***	0.115***	0.113**	0.106*	0.107*	0.084	0.086*	0.079	0.058
	(0.036)	(0.035)	(0.042)	(0.055)	(0.059)	(0.079)	(0.048)	(0.055)	(0.075)
Decrease × Distance	0.003	0.007	0.011	0.129*	0.128*	0.145*	0.134**	0.136**	0.142*
	(0.033)	(0.033)	(0.036)	(0.065)	(0.068)	(0.082)	(0.062)	(0.066)	(0.081)
Increase × Busfare	0.050	0.061	0.043	0.036	0.033	0.038	0.020	0.020	0.032
	(0.035)	(0.036)	(0.043)	(0.039)	(0.043)	(0.065)	(0.037)	(0.045)	(0.070)
Decrease × Busfare	0.058*	0.048	0.020	0.016	0.015	0.003	0.007	0.009	0.003
	(0.033)	(0.031)	(0.034)	(0.056)	(0.057)	(0.074)	(0.050)	(0.052)	(0.065)
Increase × Inv. Population	-0.094**	-0.087**	-0.123**	-0.085	-0.092	-0.084	-0.060	-0.054	-0.052
	(0.042)	(0.041)	(0.045)	(0.072)	(0.076)	(0.095)	(0.053)	(0.060)	(0.082)
Decrease × Inv. Population	0.032	0.035	0.062	0.022	0.029	0.026	0.030	0.028	0.039
	(0.040)	(0.041)	(0.042)	(0.034)	(0.038)	(0.048)	(0.035)	(0.039)	(0.053)
Competition Mechanisms									
Increase × Change Comp	0.038**	0.036**	0.060**	0.049	0.049	0.046	0.056	0.053	0.049
	(0.015)	(0.015)	(0.028)	(0.054)	(0.058)	(0.099)	(0.056)	(0.061)	(0.096)
Decrease × Change Comp	-0.074**	-0.071**	-0.110***	0.054	0.051	0.034	0.066	0.065	0.042
	(0.026)	(0.028)	(0.035)	(0.055)	(0.056)	(0.064)	(0.055)	(0.055)	(0.063)
Increase × Num. Comp	-0.003	0.000	0.055	0.125**	0.132**	0.137**	0.160***	0.166***	0.176***
	(0.047)	(0.048)	(0.064)	(0.056)	(0.057)	(0.061)	(0.055)	(0.058)	(0.060)
Decrease × Num. Comp	-0.055	-0.060	-0.096*	0.146**	0.141**	0.179**	0.134*	0.123	0.156*
	(0.037)	(0.039)	(0.048)	(0.065)	(0.067)	(0.077)	(0.078)	(0.081)	(0.086)
Round FE	X	X	X	X	X	X	X	X	X
Item FE	X	X		X	X		X	X	
Market FE		X			X			X	
Firm FE			X			X			X
Obs	744	744	744	1074	1074	1074	1168	1168	1171
Adj R-Squared	0.7552	0.7538	0.7540	0.3275	0.3197	0.2571	0.2902	0.2842	0.2321

Standard errors in parenthesis, clustered at market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

27 Robustness Checks

To understand how sensitive estimates are to different specifications, I conduct two robustness checks. First, I use a matching algorithm to match input prices for rural and urban firms to control for systematic variation in input price changes that could bias estimates for heterogeneous effects. Second, I re-combine input price increases and decreases to one variable of the first difference of logged input prices to understand whether symmetric passthrough rates are consistent with findings from asymmetric specifications presented in the main results.

27.1 Matching on Input Price Changes

One threat to interpreting differences in passthrough for urban and rural firms would occur if each type of firm has systematically lower or higher input price differences. If urban firms' cost shocks are larger in magnitude than rural firms', it could simply be that they have more room to make upward and downward adjustments, so that their average input price difference is systematically higher. In principal, the elasticity estimation and item fixed effects help control for this. But, to further restrict the influence of outliers that may drive differences, I used a matching algorithm to generate exact matches on input price differences and drop any observation that is not matched across rural and urban firm samples. Table 31.1 presents results for check for sub-samples with at least 1 nearest neighbor match, and for 3 nearest neighbor matches. For the first panel with one exact match, this drops 6-15% of observations and for the second panel with three exact matches, this drops 21-43% of observations. In all specifications, the direction of changes are the same as the main findings: Rural firms have lower passthrough rates for price increases. Rural firms also have lower passthrough rates for price decreases for most specifications except for the 1 nearest neighbor match for staple foods, which is consistent with main results and provides further evidence that staple foods costs savings are passed through to a greater degree in rural areas.

27.2 Symmetric Passthrough

Tables 32.1, 32.2, and 32.3 replicate specifications from the main results section except for imposing symmetric responses for price increases and decreases. Elasticities in Table 32.1 are the average elasticity for both input price increases and decreases and is interpreted as the elasticity for a one percent input price change. Point estimates for symmetric regressions are higher than estimates for price increases and lower than estimates for price decreases in Table 25.1, as expected. Table 32.2 shows results by urban and rural firms and shows that for all specifications average passthrough rates are lower for rural firms for all item sub-samples, similar to the main results in Table 25.2. Finally, when community and competition mechanisms are evaluated with symmetric input price shocks, we see that distance and bus fare to urban centers are related to higher passthrough rates. But, point estimates on community size are close to zero- masking the heterogeneity in the main results that resulted from separating increases and decreases. And the number of competitors is associated with higher average passthrough rates, but point estimates are negative but close to zero for staples. Again, it appears that pricing strategies for staple foods are different than those for more differentiated commodities.

Results for symmetric passthrough are useful to identify areas where asymmetry leads to a different interpretation. Dividing price increases and decreases in the main paper permitted a more nuanced description of pricing behavior. For example, in Table 25.2, rural firms had higher passthrough rates for input price decreases and smaller passthrough rates for price increases for staple foods. Yet, once combined as in 32.2, rural firms have smaller passthrough rates for all estimates. Nevertheless, understanding checking symmetric passthrough rates is useful to establish the net effect of price changes.

28 Conclusion

I use data on input and output prices to estimate passthrough rates following changes in input prices for three types of goods – staple foods, perishable foods, and differentiated products. Retail passthrough rate elasticities are larger for input price decreases than for input price increases when urban and rural firms are pooled. A one percent increase in input prices is associated with a 0.30-0.62% increase in output prices and a one percent decrease in input prices is associated with a 0.33-0.85% decrease in output prices, depending on the types of goods included in the sample. Rural firms have 55% lower passthrough rates than urban firms for staples goods and 23-32% lower passthrough for perishable and differentiated products. Following input price decreases, firms have 23% lower passthrough rates than urban firms for perishable and differentiated products.

For staple foods, rural firms have slightly higher but not significant passthrough rates. Urban firms passthrough rate for input price decreases is lower than for input price increases, meaning prices rise faster than they fall. For rural firms the opposite is true - prices fall faster than they rise. A one percent increase in input prices relates to a 0.53% increase in output prices and a one percent decrease in input prices is associated with a 0.83% decrease in output prices. It shows that for staples, rural firms passthrough more cost savings and less cost increases, suggesting that rural firms bear some price risk by smoothing output prices despite experiencing higher input prices. Output price smoothing helps households bear seasonal price variation and improves households' ability to afford nutritional diets.

In exploring community mechanisms among rural firms, distance and bus fare to urban centers is associated with higher passthrough rates for both input price increases and decreases, indicating that passthrough rates rise with transaction costs. Smaller community population size is associated with significantly lower passthrough rates for input price increases and slightly higher but insignificant passthrough rates following input price decreases. Although lower passthrough rates are also consistent with having market power, the fact that there is asymmetry where input price increases have lower passthrough and input price decreases have higher passthrough suggests that customers have more favorable terms. If market power was the primary driver, both increases and decreases would be smaller. For competition mechanisms, I find that a higher change in number of competitors is associated with higher passthrough for input price increases, and lower passthrough for input price decreases for staple foods. For commodities and differentiated product samples, a higher number in absolute number of competitors is associated with higher passthrough rates for both input price increases and decreases, in line with what theory predicts would be the case for competitive markets.

Seasonal price variation means that month-to-month changes in input prices are common. In addition, information frictions and search costs raise price uncertainty for retail firms when they purchase goods for re-sale. As a result, input prices go up and down throughout the year. Understanding passthrough rates is important because the extent to which these changes passthrough to output prices paid by customers affects the purchasing power of rural households. Output price smoothing helps households bear seasonal price variation and improves households' ability to afford nutritional diets.

Appendix

29 Input and Output Prices Descriptive Statistics

Table 29.1: Price Characteristics by Firm Type for Staples

	Urban Firms			**Rural Firms**		
	Mean	sd	Median	Mean	sd	Median
Rice						
Input Price, 1 kg	1646	185	1650	1658	213	1700
Output Price, 1 kg	1883	184	1900	1934	228	2000
Tsh Mark-up	241	98	250	277	120	250
Percent Mark-up	0.15	0.07	0.14	0.17	0.08	0.15
Input price increase	261	162	250	226	117	200
Input price decrease	-281	192	-250	-361	209	-350
Beans						
Input Price, 1 kg	1845	260	1800	1874	236	1800
Output Price, 1 kg	2185	505	2000	2237	248	2200
Tsh Mark-up	352	305	250	365	168	300
Percent Mark-up	0.19	0.11	0.15	0.20	0.11	0.18
Input price increase	300	159	300	277	206	200
Input price decrease	-164	48	-200	-265	171	-200
Maize Grain						
Input Price, 1 kg	577	212	578	598	212	560
Output Price, 1 kg	706	248	620	692	201	675
Tsh Mark-up	129	109	100	109	86	100
Percent Mark-up	0.27	0.29	0.20	0.22	0.20	0.15
Input price increase	219	124	250	279	94	300
Input price decrease	-396	176	-430	-338	229	-430
Sugar						
Input Price, 1 kg	2345	189	2240	2334	125	2320
Output Price, 1 kg	2486	268	2400	2733	298	2800
Tsh Mark-up	142	144	60	403	253	400
Percent Mark-up	0.06	0.06	0.03	0.17	0.10	0.17
Input price increase	198	167	140	127	94	120
Input price decrease	-45	50	-45	-94	87	-80
Maize Flour						
Input Price, 1 kg	1144	188	1080	1259	220	1320
Output Price, 1 kg	1262	191	1320	1498	242	1500
Tsh Mark-up	124	117	80	245	120	240
Percent Mark-up	0.12	0.12	0.07	0.20	0.12	0.20
Input price increase	334	121	340	213	136	190
Input price decrease	-313	116	-340	-399	192	-460

30 Evaluating Strict Exogeneity Assumption

Table 30.1: Regressing input prices on input search intensity

	Dep Var: Ln Input Price								
	Staples			**Commodities**			**All Items**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Search Index	-0.054***	-0.053***	-0.008	-0.046***	-0.044***	-0.019	-0.033***	-0.032**	0.011
	(0.007)	(0.006)	(0.011)	(0.012)	(0.014)	(0.024)	(0.011)	(0.012)	(0.024)
Round FE	X	X	X	X	X	X	X	X	X
Item FE	X	X		X	X		X	X	
Market FE		X			X			X	
Firm FE			X			X			X
Obs	1801	1801	1801	2499	2499	2499	4115	4115	4115
Adj R-Squared	0.8094	0.8140	0.4108	0.9532	0.9533	0.8000	0.9502	0.9502	0.6924
	Dep Var: D.Ln Input Price								
	Staples			**Commodities**			**All Items**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Search Index	-0.002	0.000	-0.014	0.001	0.004	-0.015	0.022	0.022	0.025
	(0.008)	(0.008)	(0.020)	(0.015)	(0.018)	(0.029)	(0.021)	(0.021)	(0.033)
Round FE	X	X	X	X	X	X	X	X	X
Item FE	X	X		X	X		X	X	
Market FE		X			X			X	
Firm FE			X			X			X
Obs	1087	1087	1087	1468	1468	1468	2303	2303	2303
Adj R-Squared	0.3008	0.2938	0.2522	0.0948	0.0911	0.0833	0.0677	0.0644	0.0363

Standard errors in parenthesis, clustered at market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The top panel outcome variable is the log input price regressed on a search intensity index with different sets of fixed effects. The search index components include the number of suppliers that a firm communicated with, purchased from, and the number of different locations. The bottom panel outcome variable is the first difference of the logged input price regressed on the search index with different sets of fixed effects.

31 Robustness Check: Matched Input Price Changes

Table 31.1: Dropping observations without overlap

	Panel A: At least 1 nearest neighbor exact matching on input price change								
	Staples			**Commodities**			**All Items**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Increase	0.998***	0.986***	1.017**	0.650***	0.616***	0.672**	0.728***	0.736***	0.784***
	(0.282)	(0.319)	(0.389)	(0.185)	(0.222)	(0.297)	(0.102)	(0.102)	(0.147)
Rural	0.046			0.004			-0.017		
	(0.028)			(0.024)			(0.023)		
Rural×Inc.	-0.301	-0.306	-0.370	-0.473**	-0.439*	-0.458	-0.549***	-0.560***	-0.572***
	(0.255)	(0.297)	(0.391)	(0.210)	(0.245)	(0.320)	(0.138)	(0.140)	(0.182)
Decrease	0.677***	0.685***	0.732***	0.786***	0.815***	0.975***	0.881***	0.858***	0.957***
	(0.087)	(0.110)	(0.070)	(0.111)	(0.117)	(0.202)	(0.052)	(0.066)	(0.027)
Rural×Dec.	0.150**	0.149	0.100	-0.583***	-0.612***	-0.777***	-0.642***	-0.614***	-0.727***
	(0.074)	(0.097)	(0.078)	(0.151)	(0.161)	(0.240)	(0.109)	(0.121)	(0.123)
Obs	788	788	788	1228	1228	1228	1523	1502	1520
Adj R^2	0.7169	0.7112	0.7413	0.3042	0.3015	0.3109	0.7085	0.7048	0.7061
	Panel B: At least 3 nearest neighbors exact matching on input price change								
	Staples			**Commodities**			**All Items**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Increase	1.045***	1.014**	1.089*	0.745***	0.724**	0.750	0.746***	0.741***	0.826***
	(0.377)	(0.434)	(0.569)	(0.215)	(0.296)	(0.494)	(0.136)	(0.134)	(0.179)
Rural	0.037			0.037*			0.004		
	(0.030)			(0.021)			(0.019)		
Rural×Inc.	-0.269	-0.250	-0.429	-0.483**	-0.468	-0.556	-0.516***	-0.513***	-0.631***
	(0.333)	(0.401)	(0.572)	(0.238)	(0.310)	(0.511)	(0.155)	(0.155)	(0.206)
Decrease	0.646***	0.650***	0.597***	0.932***	0.960***	0.979**	0.924***	0.912***	1.002***
	(0.122)	(0.154)	(0.182)	(0.151)	(0.187)	(0.398)	(0.047)	(0.063)	(0.020)
Rural×Dec.	-0.054	-0.068	0.083	-0.618***	-0.633***	-0.606	-0.589***	-0.580***	-0.646***
	(0.112)	(0.148)	(0.194)	(0.173)	(0.205)	(0.408)	(0.088)	(0.101)	(0.090)
Obs	528	528	528	921	921	921	1278	1258	1275
Adj R^2	0.6724	0.6638	0.6635	0.3126	0.3189	0.2396	0.7408	0.7352	0.7315
Round FE	X	X	X	X	X	X	X	X	X
Item FE	X	X		X	X		X	X	
Market FE		X			X			X	
Firm FE			X			X			X

Standard errors in parenthesis, clustered at market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

32 Robustness Check: Symmetric Passthrough

Table 32.1: Symmetric Passthrough Rates - Pooling Rural and Urban Firms

	Dep Var: D.Ln Output Price								
	Staples			**Commodities**			**All Items**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ΔlnP^{input}	0.740***	0.740***	0.753***	0.294***	0.293***	0.315***	0.508***	0.494***	0.529***
	(0.032)	(0.033)	(0.043)	(0.082)	(0.084)	(0.095)	(0.095)	(0.097)	(0.125)
Round FE	X	X	X	X	X	X	X	X	X
Item FE	X	X		X	X		X	X	
Market FE		X			X			X	
Firm FE			X			X			X
Obs	926	926	926	1381	1381	1381	1648	1624	1624
Adj R^2	0.7336	0.7314	0.7511	0.2537	0.2509	0.2376	0.5871	0.5913	0.5625

Standard errors in parenthesis, clustered at market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 32.2: Symmetric Passthrough Rates - by Rural and Urban Firms

	Dep Var: D.Ln Output Price								
	Staples			**Commodities**			**All Items**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ΔlnP^{input}	0.781***	0.784***	0.853***	0.711***	0.709***	0.803***	0.834***	0.823***	0.898***
	(0.052)	(0.056)	(0.078)	(0.125)	(0.130)	(0.105)	(0.055)	(0.060)	(0.051)
Rural	-0.005			-0.001			-0.017		
	(0.011)			(0.016)			(0.013)		
Rural×	-0.061	-0.066	-0.153*	-0.519***	-0.516***	-0.604***	-0.630***	-0.619***	-0.692***
ΔlnP^{input}	(0.060)	(0.063)	(0.082)	(0.134)	(0.140)	(0.117)	(0.077)	(0.084)	(0.074)
Round FE	X	X	X	X	X	X	X	X	X
Item FE	X	X		X	X		X	X	
Market FE		X			X			X	
Firm FE			X			X			X
Obs	927	927	927	1383	1383	1383	1651	1627	1648
Adj R^2	0.7162	0.7140	0.7624	0.3349	0.3313	0.3585	0.7011	0.6983	0.7030

Standard errors in parenthesis, clustered at market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 32.3: Symmetric Passthrough Rates - Rural Market Mechanisms

	Dep Var: D.Ln Output Price								
	Staples			**Commodities**			**All Items**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ΔlnP^{input}	0.737***	0.735***	0.734***	0.335***	0.336***	0.336***	0.337***	0.337***	0.334***
	(0.034)	(0.035)	(0.038)	(0.028)	(0.028)	(0.031)	(0.033)	(0.034)	(0.035)
$\Delta lnP^{input}\times$ Distance	0.057**	0.059**	0.065**	0.103***	0.104***	0.095***	0.104***	0.105***	0.092**
	(0.024)	(0.024)	(0.024)	(0.033)	(0.033)	(0.034)	(0.033)	(0.033)	(0.034)
$\Delta lnP^{input}\times$ Busfare	0.061***	0.057***	0.036	0.043	0.042	0.044	0.027	0.027	0.034
	(0.020)	(0.019)	(0.025)	(0.033)	(0.033)	(0.035)	(0.029)	(0.031)	(0.031)
$\Delta lnP^{input}\times$ Inv. Pop	-0.013	-0.008	-0.011	0.000	0.000	0.011	0.010	0.009	0.022
	(0.026)	(0.026)	(0.035)	(0.022)	(0.023)	(0.026)	(0.024)	(0.025)	(0.029)
$\Delta lnP^{input}\times$ Change Comp.	-0.009	-0.011	-0.022	0.050	0.049	0.039	0.060	0.059	0.046
	(0.014)	(0.015)	(0.020)	(0.040)	(0.042)	(0.052)	(0.040)	(0.042)	(0.050)
$\Delta lnP^{input}\times$ Num Comp.	-0.036	-0.040	-0.033	0.115***	0.114***	0.126***	0.124***	0.121***	0.136***
	(0.027)	(0.028)	(0.039)	(0.035)	(0.036)	(0.039)	(0.038)	(0.039)	(0.041)
Round FE	X	X	X	X	X	X	X	X	X
Item FE	X	X		X	X		X	X	
Market FE		X			X			X	
Firm FE			X			X			X
Obs	744	744	744	1075	1075	1075	1169	1169	1172
Adj R^2	0.7425	0.7417	0.7404	0.3266	0.3177	0.2524	0.2911	0.2856	0.2310

Standard errors in parenthesis, clustered at market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

33 Additional Tables and Figures

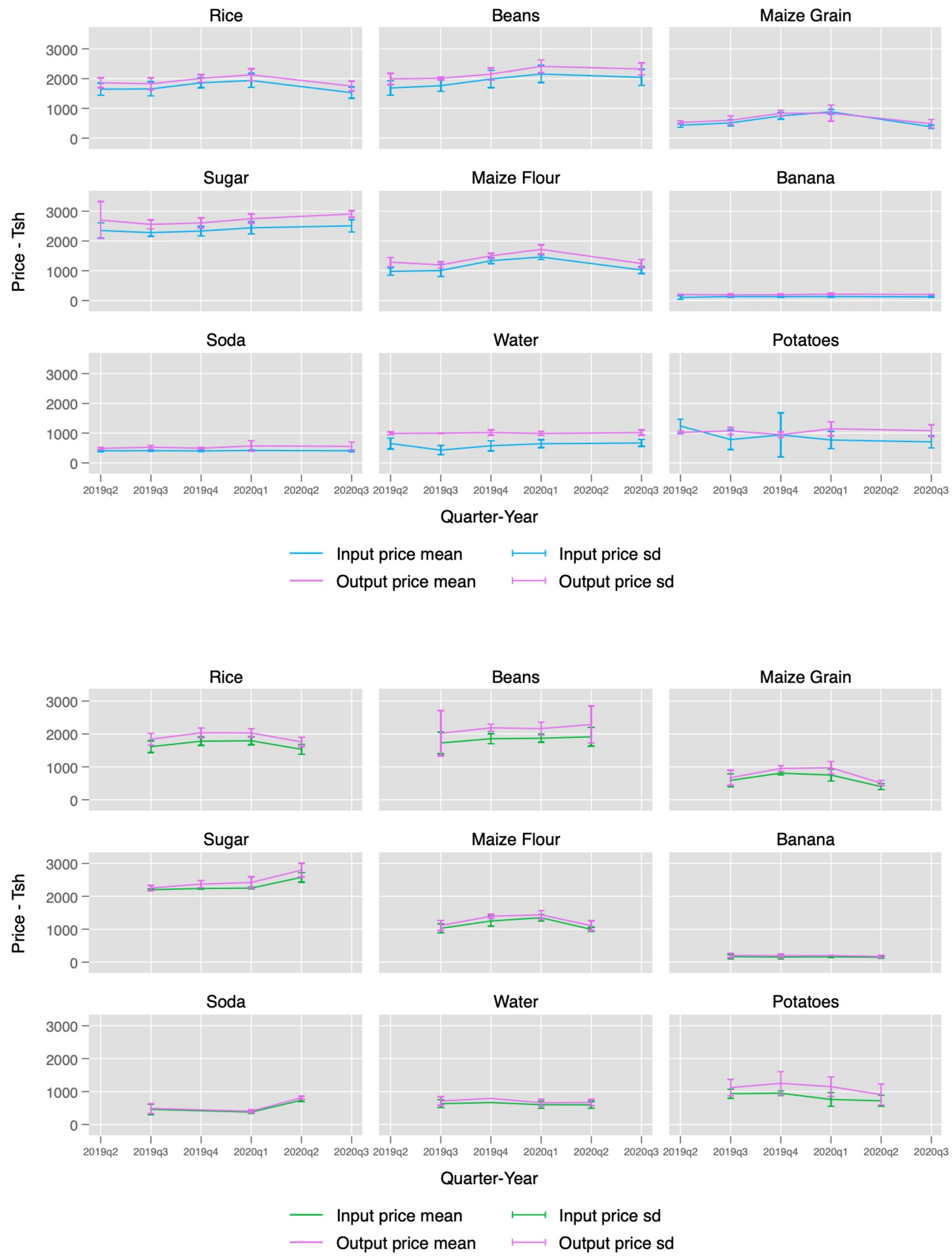


Figure 33.1: Input and output price means and standard deviations in rural and urban markets

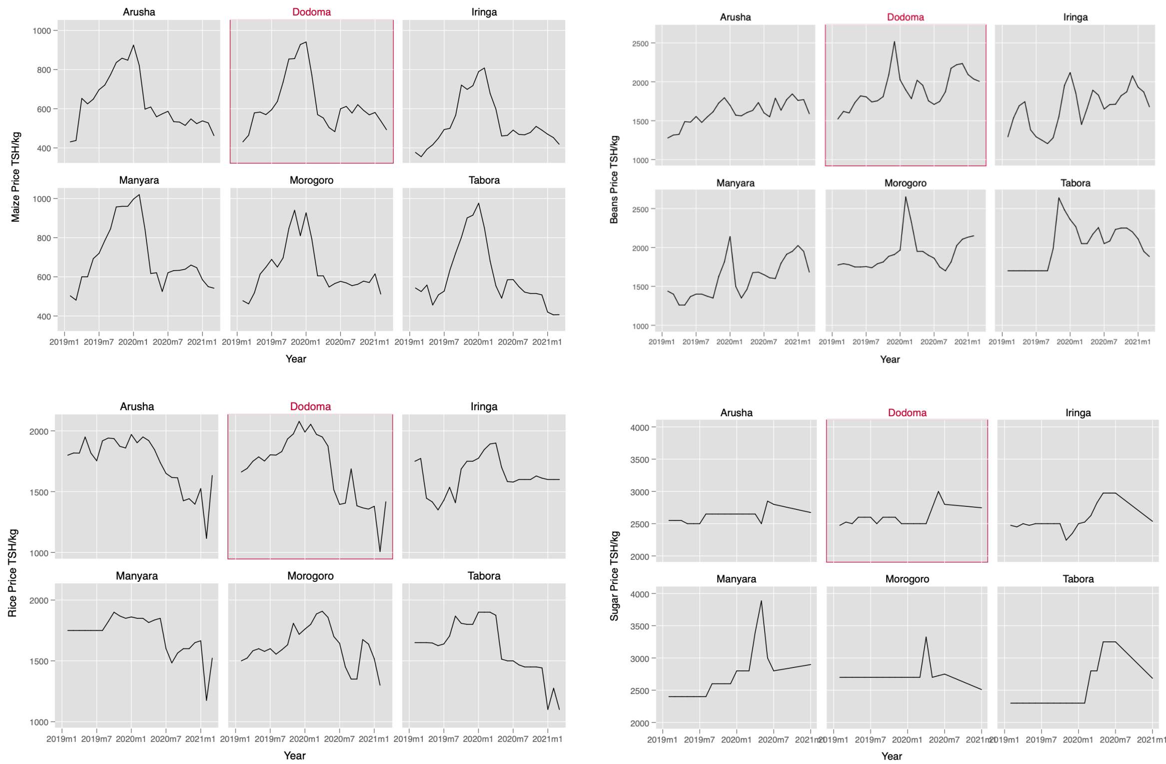


Figure 33.2: World Food Programme prices for Maize, Beans, Rice, and Sugar in 6 markets from 2019-2020

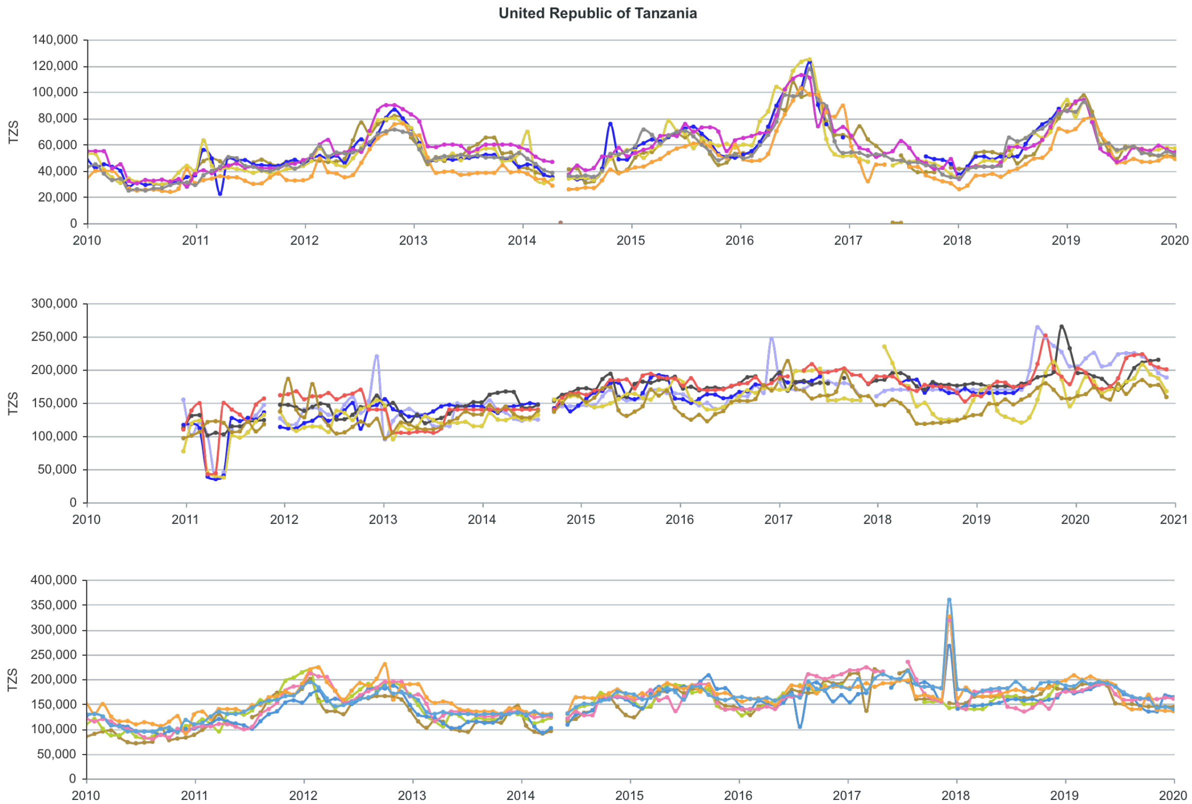


Figure 33.3: Long-run trends in World Food Programme prices for Maize, Beans, and Rice in 6 markets from 2010-2020

References

Abadie, A., Athey, S., Imbens, G., and Wooldridge, J. (2017). When Should You Adjust Standard Errors for Clustering?

Aggarwal, S., Giera, B., Jeong, D., Robinson, J., and Spearot, A. (2018). Market Access, Trade Costs, and Technology Adoption: Evidence from Northern Tanzania.

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

Allcott, H., Karlan, D., Möbius, M. M., Rosenblat, T. S., and Szeidl, A. (2007). Community size and network closure. *American Economic Review*, 97(2):80–85.

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

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

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

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

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

Atkin, D. and Donaldson, D. (2015). Who's getting Globalized? The Size and Nature of Intranational Trade Costs. *Working Paper*, (February).

Attanasio, B. O., Barr, A., and Cardenas, J. C. (2012). Risk Pooling, Risk Preferences, and Social Networks. 4(2):134–167.

Bai, Y., Naumova, E. N., and Masters, W. A. (2020). Seasonality of diet costs reveals food system performance in East Africa. *Science Advances*, 6(49):1–11.

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

Benjamini, Y. and Hochberg, Y. (1995). Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing. *Journal of the Royal Statistical Society: Series B (Methodological)*, 57(1):289–300.

Bergquist, L. F. and Dinerstein, M. (2020). Competition and Entry in Agricultural Markets: Experimental Evidence from Kenya†. *American Economic Review*, 110(12):3705–3747.

Bernard, A. B., Moxnes, A., and Saito, Y. U. (2019). Production networks, geography, and firm performance. *Journal of Political Economy*, 127(2):639–688.

Blattman, C., Fiala, N., and Martinez, S. (2013). Credit Constraints, Occupational Choice, and the Process of Development: Long Run Evidence from Cash Transfers in Uganda. *Working Paper*.

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

Bonnet, C. and Villas-Boas, S. B. (2016). An analysis of asymmetric consumer price responses and asymmetric cost pass-through in the French coffee market. *European Review of Agricultural Economics*, 43(5):781–804.

Boysen, O. (2016). Food demand characteristics in uganda: Estimation and policy relevance. *South African Journal of Economics*, 84(2):260–293.

Breza, E., Chandrasekhar, A., Golub, B., and Parvathaneni, A. (2019). Networks in economic development. *Oxford Review of Economic Policy*, 35(4):678–721.

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

Bulow, J. and Pfleiderer, P. (1983). A Note on the Effect of Cost Changes on Prices. *Journal of Political Economy*, 91(1):182–185.

Busso, M. and Galiani, S. (2019). The causal effect of competition on prices and quality: Evidence from a field experiment. *American Economic Journal: Applied Economics*, 11(1):33–56.

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

Campos, F. and Gassier, M. (2017). Gender and enterprise development in sub-Saharan Africa: A review of constraints and effective interventions.

Carter, M. R. and Lybbert, T. J. (2012). Consumption versus asset smoothing: Testing the implications of poverty trap theory in Burkina Faso. *Journal of Development Economics*, 99(2):255–264.

Casaburi, L. and Reed, T. (2021). Using individual-level randomized treatment to learn about market structure . (March).

Cunha, J. M., De Giorgi, G., and Jayachandran, S. (2019). The Price Effects of Cash Versus In-Kind Transfers. *Review of Economic Studies*, 86(1):240–281.

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

de Janvry, A., Fafchamps, M., and Sadoulet, E. (1991). Peasant Household Behaviour with Missing Markets : Some Paradoxes Explained Author (s): Alain de Janvry , Marcel

Fafchamps and Elisabeth Sadoulet Published by : Wiley on behalf of the Royal Economic Society Stable URL : http://www.jstor.org/stable/22348. *The Economic Journal*, 101(409):1400–1417.

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

Dercon, S. (2002). Income Risk, Coping Strategies, and Safety Nets. *The World Bank Research Observer*, 17(2):141–166.

Di Falco, S. and Giorgi, G. D. (2019). Farmers to Entrepreneurs. *Working Paper*.

Dillon, B., Aker, J. C., and Blumenstock, J. (2020). How Important is the Yellow Pages? Experimental Evidence from Tanzania.

Duflo, E., Banerjee, A., Finkelstein, A., Katz, L. F., Olken, B. A., and Sautmann, A. (2020). In Praise of Moderation: Suggestions for the Scope and Use of Pre-Analysis Plan for RCTs in Economics.

Ecker, O. and Qaim, M. (2011). Analyzing Nutritional Impacts of Policies: An Empirical Study for Malawi. *World Development*, 39(3):412–428.

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

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

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

Fafchamps, M. and Quinn, S. (2016). Networks and Manufacturing Firms in Africa: Results from a Randomized Field Experiment.

FAO.org (2017). Kenya allows duty-free imports of yellow maize. http://www.fao.org/giews/food-prices/food-policies/detail/en/c/471655/.

FEWS NET (2017). Regional Supply and Market Outlook report. Technical report.

Gadenne, L., Norris, S., Singhal, M., and Sukhtankar, S. (2017). In-Kind Transfers as Insurance.

Ghanem, D., Hirshleifer, S., and Ortiz-Becerra, K. (2019). Testing Attrition Bias in Field Experiments.

Ghani, T. and Reed, T. (2020). Relationships on the Rocks : Dynamic Contracts in a Market for Ice. pages 1–58.

Government of Kenya (2017). Government declares drought a national disaster. Technical report.

Grabrucker, K. and Grimm, M. (2020). Is There a Rainbow after the Rain? How Do Agricultural Shocks Affect Non-Farm Enterprises? Evidence from Thailand. *American Journal of Agricultural Economics*, 00(00):1–25.

Green, R., Cornelsen, L., and Dangour, A. D. (2013). The effect of rising food prices on food consumption : systematic review with meta-regression. *BMJ (Online)*, 3703(June):1–9.

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

Hardy, M. and McCasland, J. (2018). It Takes Two: Experimental Evidence on the Determinants of Technology Diffusion.

Hoddinott, J. (2006). Shocks and their consequences across and within households in rural Zimbabwe. *Journal of Development Studies*, 42(2):301–321.

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

Janzen, S. A. and Carter, M. R. (2018). After the Drought: The Impact of Microinsurance on Consumption Smoothing and Asset Protection. *American Journal of Agricultural Economics*, 101(3):651–671.

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

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

Jeong, D. (2019). Creating (Digital) Labor Markets in Rural.

Kaminski, J., Christiaensen, L., and Gilbert, C. L. (2016). Seasonality in local food markets and consumption: Evidence from Tanzania. *Oxford Economic Papers*, 68(3):736–757.

Kinnan, C., Samphantharak, K., Townsend, R., and Cossio, D. A. V. (2021). Insurance and Propagation in Village Networks. *NBER Working Paper*, 53(9):1689–1699.

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

Lewis, M. (2008). Price dispersion and competition with differentiated sellers. *Journal of Industrial Economics*, 56(3):654–678.

Luco, F. (2019). Who benefits from information disclosure? The case of retail gasoline. *American Economic Journal: Microeconomics*, 11(2):277–305.

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

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

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

Macchiavello, R. and Morjaria, A. (2020). Competition and Relational Contracts in the Rwanda Coffee Chain.

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

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

McKenzie, D. and Paffhausen, A. L. (2017). Small Firm Death in Developing Countries.

McKenzie, D. and Puerto, S. (2017). Growing Markets Through Business Training for Female entrepreneurs : a Market-level Randomized Experiment in Kenya. *World Bank Policy Research Working Paper*, 7993(3):1–53.

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

McKenzie, D. and Woodruff, C. (2017). Business practices in small firms in developing countries. *Management Science*, 63(9):2967–2981.

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

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

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

Muhammad, A., D'Souza, A., Meade, B., Micha, R., and Mozaffarian, D. (2017). The Influence of Income and Prices on Global Dietary Patterns by Country, Age, and Gender. *Amber Waves:The Economics of Food, Farming, Natural Resources, and Rural America*, 2017(10).

Muhammad, A., Seale, J. L., Meade, B., and Regmi, A. (2015). International evidence on food consumption patterns: An update using 2005 international comparison program data. *International Food Consumption Patterns and Global Drivers of Agricultural Production*, pages 1–104.

Müller, G. and Ray, S. (2007). Asymmetric price adjustment: Evidence from weekly product-level scanner price data. *Managerial and Decision Economics*, 28(7):723–736.

North, D. C. (1991). Institutions. *Journal of Economic Perspectives*, 5(1):97–112.

Oberfield, E. (2018). A Theory of Input-Output Architecture. *Econometrica*, 86(2):559–589.

Peltzman, S. (2000). Prices rise faster than they fall. *Journal of Political Economy*, 108(3):466–502.

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

Rembold, F., Meroni, M., Urbano, F., Csak, G., Kerdiles, H., Perez-Hoyos, A., Lemoine, G., Leo, O., and Negre, T. (2019). ASAP: A new global early warning system to detect anomaly hot spots of agricultural production for food security analysis. *Agricultural Systems*, 168(July 2018):247–257.

Rudolf, R. (2019). The impact of maize price shocks on household food security: Panel evidence from Tanzania. *Food Policy*, 85(April):40–54.

Seneviratne, S. I., Nicholls, N., Easterling, D., Goodess, C. M., Kanae, S., Kossin, J., Luo, Y., Marengo, J., Mc Innes, K., Rahimi, M., Reichstein, M., Sorteberg, A., Vera, C., Zhang, X., Rusticucci, M., Semenov, V., Alexander, L. V., Allen, S., Benito, G., Cavazos, T., Clague, J., Conway, D., Della-Marta, P. M., Gerber, M., Gong, S., Goswami, B. N., Hemer, M., Huggel, C., Van den Hurk, B., Kharin, V. V., Kitoh, A., Klein Tank, A. M., Li, G., Mason, S., Mc Guire, W., Van Oldenborgh, G. J., Orlowsky, B., Smith, S., Thiaw, W., Velegrakis, A., Yiou, P., Zhang, T., Zhou, T., and Zwiers, F. W. (2012). Changes in climate extremes and their impacts on the natural physical environment. *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation: Special Report of the Intergovernmental Panel on Climate Change*, 9781107025:109–230.

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

Startz, M. (2018). The Value of Face-to-Face: Search and Contracting Problems in Nigerian Trade.

Sumner, D. A. (1981). Measurement of Monopoly Behavior : An Application to the Cigarette Industry Author (s): Daniel A . Sumner Source : Journal of Political Economy , Vol . 89 , No . 5 (Oct ., 1981), pp . 1010-1019 Published by : The University of Chicago Press Stable URL. *Journal of Political Economy*, 89(5):1010–1019.

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

Tschirley, D., Reardon, T., Dolislager, M., and Snyder, J. (2015). The Rise of a Middle Class in East and Southern Africa: Implications for Food System Transformation. *Journal of International Development*, 27:628–646.

Uhe, P., Philip, S., Kew, S., Shah, K., Kimutai, J., Otto, F., Jan Van Oldenborgh, G., Singh, R., Arrighi, J., and Cullen, H. (2017). The drought in Kenya, 2016-2017. Technical Report April, Climate and Development Knowledge Network and World Weather Attribution Initiative.

USAID (2018). Kenya Enhanced Market Analysis. Technical Report September.

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

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

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

Young, A. (2019). Channeling Fisher: Randomization tests and the statistical insignificance of seemingly significant experimental results. *Quarterly Journal of Economics*, 134(2):557–598.