Border Trade and Information Frictions: Evidence from Informal Traders in Kenya *

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Abstract

In low- and middle-income countries, a large share of trade is conducted by small-scale informal traders – mostly women – and is missing from official trade statistics. Using the natural experiment of a border closing, a randomized controlled trial, and panel data collection, I study the role of information frictions in traders' choices of markets and border crossings at the Kenyan-Ugandan border and the consequences for livelihoods and prices in agriculture markets. First, I show that traders' choice of markets and routes is sticky. Second, some of this stickiness is driven by limited information about profitable arbitrage opportunities and true (tariff) costs of crossing the border. Third, I build a model incorporating these frictions, which I test using an RCT. I find that giving information on tariff costs and local prices to traders (via a cellphone platform) increases switching across markets and routes, leading to large increases in traders' profits and significant formalization of trade. Consistent with the model, information provision has general equilibrium effects – specifically, a reduction in consumer prices in agricultural markets. Taken together, the results point to the centrality of information frictions in informal trade and highlight the promise of new information technology to ameliorate them.

Keywords: Trade, Agriculture, Corruption, Informality, Information

JEL codes: D40, D73, D83, F13, F14, H26, O13, Q17

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1 Introduction

In low- and middle-income countries, informal trade accounts for a substantial fraction of total trade. Such trade is dominated by women, with little education and often from rural communities. In the Southern African Development Community, informal cross-border trade accounts for an estimated USD 17.6 billion annually, or 30 to 40 % of total regional trade (Southern-Africa-Trust (2008)). Despite its importance, there is limited data regarding informal trade. An obvious reason is that informal trade flows are not recorded in official trade statistics. Moreover, because informal traders are frequently on the move, collecting reliable data is not straightforward. The sparse data currently available comes from surveyors stationed at border crossings, who estimate the volume of trade that passes. Finally, given that a significant amount of informal trade goes through unofficial crossings, some of the costs take the form of bribes; and data collection on corruption presents its own unique challenges (Hadley and Rowlatt (2019)).

Due to the scarcity of data on small-scale traders and the complexity of the environment, just a handful of studies provide empirical (descriptive) insights on this sector, e.g., Titeca and Kimanuka (2012), Hadley et al. (2018). In line with typical frameworks, traders maximize their profits by locating low-priced markets for buying and high-priced markets for selling, taking into account transportation, border, and other trade costs. Little is known, however, about the costs incurred by small-scale traders, who likely face a different cost structure than larger-scale traders. There are a number of plausible scale economies in trade, including in transport costs, tariff rates, corruption incidence, and — crucially for this paper — information acquisition. These traders tend to operate outside traditional business circles, complicating access to market information as well as information about policies or regulations related to crossing the border. In addition to the costs incurred to get accurate information, the lack of information motivates official border agents to extract money from small-scale traders[1], further increasing their trade costs (Klopp et al. (2022)).

[1] Small-scale traders are more likely to face coercive corruption (pay more than the official tax rates), whereas larger-scale traders enter in collusive agreements with officials to split rents.

This paper examines the significance of information frictions in informal trade and how they distort consumer prices. To answer these questions, I collect high-frequency panel data on trade outcomes for a sample of 1,100 traders in Kenyan markets close to the Kenyan-Ugandan border, throughout 2020 and 2021. These informal traders are domestic traders or cross-border traders, and either use formal border crossings or cross the border via unofficial crossings in order to avoid taxes and smuggle goods[2]. This paper therefore refers to trade routes as (i) domestic trade, (ii) international trade through official crossings, (iii) international trade through informal crossings.

I first present descriptive findings on the informal trade sector, including how different types of routes co-exist and how stickiness reduces traders' opportunities to choose optimal markets and routes – in other words, missing out on arbitrage opportunities. I use a natural experiment[3] – the closure of the official border due to Covid-19 – to derive those findings. I hypothesize that the stickiness can be explained by information frictions. Then, I develop a model that incorporates information frictions. I test the model using a randomized controlled trial in which I provide traders with access to a platform that includes information on market prices and official border costs. Through the experiment, I examine whether informational frictions restrict access to markets and trade route utilization. As predicted by the model, I demonstrate that an intervention that decreases information frictions has general equilibrium impacts on market prices. Lastly, I quantify the scale of the intervention's impacts and the role of information and informal trade, using calculations of welfare and cost-effectiveness, and counterfactual simulations of the model.

The trader level approach in this paper allows me to meaningfully contribute to the existing literature focusing on the role of information technologies (such as mobile phones) on agriculture market integration[4]. The existing literature, which mostly uses market level data, shows that increased access to mobile phone networks reduces price dispersion across markets. It rationalizes this (without direct evidence) through a framework in which technol-

[2]The literature and governments are moving away from defining those traders as smugglers and instead referring to informal cross-border traders. Conceptually, traders using unofficial crossings can be associated with smuggling.

[3]Despite calling it a "natural experiment", it is clear that the event does not generate perfect exogenous variation. This event is only used to generate findings that motivate the rest of the paper.

[4]I describe my contributions to the literature in more details below.

ogy increases information transmission and reduces search costs for traders; leading to a shift of trade across space and potential welfare improvements. However, I am able to directly explore the mechanisms at play. First, I directly measure who has information and the type of information received. Second, I observe trader level choice of markets and trade routes; implying I can explain market price effects through changes in traders' choice of markets but also routes (which includes internationalization). Third, having detailed data on traders' revenues and costs (in addition to markets and routes used) allows me to differentiate market effects stemming from changes in marginal costs (e.g., traders are buying from cheaper markets) and changes in marginal revenue (e.g., traders are selling in better markets). Thanks to my data, I can therefore look at how information frictions impact competition in markets and how much they contribute to the existence of market power. Lastly, my paper shows that information frictions play a role in traders' stickiness across markets and trade routes, which is novel in this literature.

Understanding informal trade and its inherent frictions is important for policy in my study area (the Kenya-Uganda border) and in sub-Saharan Africa generally. First, in addition to being a major component of trade, informal traders contribute to livelihoods and food security by connecting farmers with consumers (Ackello-Ogutu (1997); Little (2005)). They frequently serve as the main point of contact in agricultural markets: only 3% of traders in my sample who were found in Kenyan markets, are registered businesses. Second, these informal traders are small firms and their owners are often women heading low-income households, at a time when women's economic empowerment is a major development concern (Klopp, Trimble, and Wiseman (2022)). Third, informal trade results in missed opportunities for tax revenue collection. In order to boost tax revenues, governments and other organizations have made substantial investments (e.g., One Stop Border Posts[5]) and implemented policies (e.g., Simplified Trade Regime in East Africa[6]) to reduce costs and formalize trade. Fourth, due to their size and gender, these small-scale traders are disproportionately impacted by non-tariff

[5] Institutional framework, facility and associated procedures that enable goods, people and vehicles to stop in a single facility to undergo necessary controls to exit one State and enter the adjoining State.

[6] The Simplified Trade Regime was created to make it easier and faster for small-scale cross-border traders with products that are grown or manufactured in the EAC to clear customs.

barriers such as corruption and harassment at the border, and governments' efforts such as the implementation of One Stop Border Posts are also intended to address harassment and corruption (DMT Final report (2017); Brenton (2013)).

In the first part of the paper, I use my high frequency panel data to establish descriptive facts. I document that traders face costs that account for over 80% of their sales. Expenses include purchase and transport costs as well as border costs that depend on which border crossing they choose[7]. Second, informal traders specialize in types of routes (domestic, formal border crossing and informal border crossing) and markets, despite the fact that large price variations between markets creates arbitrage possibilities. Nonetheless, market and route stickiness can be overcome with a sufficiently severe shock: the closing of the official border crossing. This compelled traders who used to travel through the official border to use either informal routes or domestic supply chains. I find that switching is sticky: when the border reopened a few months later, just 25% of traders returned to their original markets and routes. Lastly, traders do not operate with full information; only 38% of informal traders report knowing the market price for their primary commodity in other markets, only 51% report informing themselves about market prices, and over 50% report not always knowing the taxes they should pay at the border.

Building on these facts, I formulate a model in which risk-averse traders select markets and routes. I present a micro-foundation of market and route stickiness through information frictions, including uncertainty regarding purchasing prices, demand in selling markets, and official border fees. The model predicts that reducing information frictions will increase the number of markets traded in (Prediction 1), traders' sales and profits (Prediction 2), and cross-border trade and formalization (Prediction 3). The model finds ambiguous effects on bribes (Prediction 4), and predicts general equilibrium effects such as a decrease in consumer prices in selling markets (Prediction 5) and ambiguous effects in buying markets (Prediction 6).

I test each of these hypotheses using a randomized controlled trial designed to test the theory and find empirical evidence for the model's main predictions. A random 50%

[7] In another paper I characterizes border costs based on whether a formal or informal border crossing is utilized. These costs estimates are obtained as part of an "audit study" experiment in which trained traders crossed both borders while I exogenously altered important factors.

of traders in my sample received access to market information through a phone platform developed by Sauti East Africa that reports market price information, official taxes and tariffs, and exchange rates. I additionally randomize the treatment intensity[8] at the market level to account for spillovers and to evaluate price impacts in general equilibrium. The treatment increases the likelihood of trading by 5 percentage points and the likelihood that trading is their primary source of income by 4 percentage points. Treatment increases the number of types of goods traded by each trader by 8%. Turning to supply chains, the number of selling and sourcing markets increases by 7-11% for treated traders, and the number of trips increases by 0.4 trips (Prediction 1). Access to information increases treated traders' sales and profits by 6 and 7%, respectively (Prediction 2). I see no indication of treatment impacts on markups, indicating perfect passthrough. Treatment increases the number of cross-border traders (rather than using domestic routes) by 20% and leads to the formalization of trade; i.e., treatment boosts trade through the official crossing point (Prediction 3). The model predicts ambiguous effects on bribes; I find no substantial effects of treatment on levels of bribery or instances of corruption and harassment (Prediction 4).

Beyond these direct treatment effects, there are broader market level effects that I am able to estimate. Focusing on general equilibrium results, I show large market price effects: marketplaces with a higher share of treated traders see a reduction of 7% in consumer prices (Prediction 5). The effect on market prices in buying markets is less straightforward; still, I estimate a 7% fall in buying prices in initial buying markets (Prediction 6). These significant effects on market prices demonstrate that information frictions heavily distort markets.

In the last part of the paper, I quantify the magnitude of the effects. First, relating my results to the literature on more general gravity models, it is natural to compare information friction costs to transport costs. I show that the reduction of information frictions induced by the intervention is large and equivalent to transport costs incurred by being 150 kms away from the border (when markets in my sample are all within 40 kms of the border). Second, I provide welfare calculations and cost-effectiveness estimates of information technologies

[8] I therefore have variation in the share of treated traders across markets.

such as the one used in this intervention. I find meaningful welfare gains, equivalent to USD 683 per trader per year; 88% stemming from consumer surplus (from reduced market prices) and 12% from government surplus (from increased tax revenues). At an approximate cost of USD 7 per user, this ranks the intervention as highly cost-effective. Third, through counterfactual simulations of the model, I can predict the effect of closing specific routes on prices and welfare. I first look at the effect of closing the official route. I compare the results from the model to out-of-sample reduced form estimates using the official border closure shock. The model predicts an increase in price in markets close to the border, which approximately matches the reduced form results from the border closure shock (8%). Lastly, using the model, I assess consequences of shutting down informal crossings (in addition to formal crossings) and show that informal trade does play an important role in smoothing prices, especially during border shocks. Therefore potential welfare gains from trade formalization need to be measured against the role informal crossings play in smoothing prices during these shocks.

Contributions to the literature

This paper contributes to the literature on information frictions in agricultural markets – specifically, papers looking at the use of cell phones to alleviate information frictions, e.g., Aker (2010), Jensen (2007) and Allen (2014). In line with the literature, my paper highlights the importance of information frictions in trade in developing countries. These papers use the expansion of mobile phone networks to look at how a reduction in information frictions affects market price dispersion. The research is centered around the (plausible) assumption that the expansion of phone networks led to traders collecting more market information. In contrast, my paper directly gives traders access to information through their phones, allowing me to understand the mechanisms at work, both in terms of access to information and use of information. In terms of access, I know which traders actually received information (rather than which markets have access to mobile phone networks) and therefore can directly link the reduction of information frictions to the use of mobile phone technology. I also explore mechanisms in terms of usage to understand how traders search for information and how that translates into actual trade behaviors, i.e., choice of markets and trade routes. For a more general overview of the role of mobile phone technologies in development, Aker and Mbiti (2010) provide a good summary. In addition, the models used in the literature frame information frictions as search costs (Stigler (1961)); and therefore use sequential search models (Stiglitz (1989)). In my paper, I suggest that information frictions can also be framed as uncertainty about market conditions for risk-averse traders.

My paper also speaks to the literature about information frictions in *domestic* agriculture trade. Fafchamps and Minten (2012) and Mitra et al. (2018) explore whether informing farmers about market prices can help grow their business by allowing them to sell their goods to traders in better-priced markets, rather than at the farm gate. Generally, the literature finds little evidence that access to information affects farmers or market conditions. My paper focuses on traders rather than farmers, which seems to be the right segment of the value chain to target, as transporting goods is a main feature of their business.

Third, this paper contributes to the literature on frictions in *international* or *cross-border* trade and the role of informality. More generally, the role of information frictions in market access and contracts for small firms has been studied; e.g.,Atkin and Donaldson (2015), Atkin, Osman, and Khandelwal (2017), Hjort, Iyer, and de Rochambeau (2020). Startz (2021) explores search and contracting frictions between traders and international suppliers. My paper directly adds to such research on search frictions by testing the existence of search costs – taking the form of information frictions about market prices – through a RCT. Turning to the role informality plays in international trade, the literature on informal trade is relatively small and predominantly qualitative. Using national aggregates of trade flows by product, a few papers quantitatively explore determinants of informal versus official trade flows – mostly observable costs such as tariffs (Bensassi, Jarreau, and Mitaritonna (2019)) or trade facilitation policies (Siu (2020)). My paper contributes by proposing a micro-economics approach through trader-level data and border crossing choice. I also use a representative sample of traders, collected in markets at the border, rather than relying on observational data from traders crossing the border. Beyond this official-unofficial choice of border crossing, my paper also considers the role of information frictions in the choice between domestic and international trade. Models generally assume that more productive firms are international traders, while less productive firms remain domestic traders. I provide evidence that information frictions about market prices and taxes are barriers to international trade and that relaxing those frictions allows small-scale firms to engage in international trade, while helping consumers with lower prices. To my knowledge, this is the first paper to conduct an experiment on cross-border traders that explores the interdependence between domestic and international trade, including official and unofficial crossings.

My paper considers corruption and bribes as a direct cost to international traders, and explores whether information frictions play a role in corruption and bribe levels. In line with the framework in Sequeira and Djankov (2014), the type of corruption observed at the official crossings varies by trader size[9]; however, small-scale traders face both collusive and coercive corruption. As in Croke et al. (2021), I explore whether coercive corruption can be due to lack of information about true taxes. As for collusive corruption (such as Reid and Weigel (2019)), small traders often use informal crossings to avoid taxes and coercive corruption, prevalent at official crossings. I find suggestive evidence that traders face lower taxes and bribes when they have information about official taxes and market prices. However, this small effect masks both a likely increase in border costs from increased demand for cross-border routes (compared to domestic routes), and a potential decrease in bribes from traders' improved bargaining power.

Lastly, my paper contributes to a growing literature on intermediaries in trade and the role of traders in value/supply chains. Grant and Startz (2022) and Iacovone and McKenzie (2022) highlight the role of intermediaries in a value chain. Similarly to Bergquist and Dinerstein (2020) and Startz (2021), I show that traders contribute to high selling prices in agricultural markets through market structure. My paper extends this literature by highlighting the role of information frictions in inflating those high consumer prices.

The remainder of the paper is organised as follows. In Section 2, I provide some background about the project location and trade in East Africa. I describe my experimental design

[9] Anecdotal evidence suggests that large-scale traders -not the focus of this paper- tend to engage in collusive corruption with border agents.

and data in Section 3. In Section 4, I lay out key motivating stylized facts and in section 5 a theoretical model based on these. I present my empirical framework in section 6 and main findings in Section 7. Finally, in Section 8, I give welfare estimates and use the model to run counterfactual analysis, and Section 9 concludes.

2 Background and Context

2.1 Location

This project is located in markets around Busia, a town situated at the border between Kenya and Uganda. Busia is one of the main border crossings between the two countries. In 2018, Busia's border posts were replaced by a One Stop Border Post (OSBP), which is now regarded as one of the flagship OSBPs. Malaba, a smaller official border crossing between Kenya and Uganda, is situated 35 kilometers from Busia and is also used by traders who operate in the area. Busia, like many other border towns, relies on commerce. This has shaped the town in many ways; Busia (and by extension most of the county) counts many markets that attract suppliers, traders and buyers from all over the country, as well as from other neighboring countries. Agricultural products and food found in markets come from diverse sources, as some traders source from domestic suppliers while others cross the border to reach foreign suppliers. The area's economy – including employment – is centered around trade, and Busia's border crossing is considered the main focal point in the town's urban planning and mobility infrastructure.

2.2 Domestic and Cross-Border Trade: Formal and Informal Crossings

This paper focuses on small-scale informal traders who are found in markets in the areas surrounding Busia's border crossing. In this paper, informal traders are defined as businesses that operate without being officially registered. These small-scale traders can either be domestic traders (use domestic supply chains) or be cross-border traders (international traders). Due to the proximity of the border crossing, a disproportionate number of traders are cross-border traders (at least prior to the pandemic). Busia is not only one of the main official border crossings in East Africa, it also accounts for 74% of total informal agricultural trade flows between Kenya and Uganda. Informal cross-border trade (often referred to as ICBT in the literature) – trade activities which are not recorded in official trade statistics – is pervasive in developing countries. Much of this trade is conducted by small-scale traders who cross the border multiple times a week to source or market agricultural goods. A phone survey carried out in 2017 by Sauti East Africa showed that 80% of the traders are women, and an average trader trades 1.8 types of goods sourced from 1.7 markets and sold in 2.2 markets (Sauti-East-Africa (2017)). Traders in my sample who are cross-border traders can either trade through an official crossing, i.e., an OSBP (at Busia or Malaba) or through informal crossings. In Busia, people refer to the border as "porous"; there are ways to cross it informally without having to go through the formal checkpoints. Those routes, which are located on either side of the official checkpoints, are called informal routes (or "panya" routes in Swahili). The best-known ones in Busia are Sofia and Marachi (referred to as *main* informal border crossings in this paper). Although official border posts are manned by Kenya/Uganda Revenue Authority officials, the informal routes are manned by the police who are known to extract bribes in exchange for silence.

2.3 Costs and Information

Besides the costs incurred to purchase their goods, there is little evidence on the other costs faced by informal traders. It is, however, likely that they face cost structures that are very different to larger official traders. For one, they do not benefit from likely returns to scale in purchasing goods, transport, and, importantly for this paper, access to information. They do not operate in standard business circles and therefore have to rely on informal networks to get information. Informal traders lack reliable, accessible and accurate trade and market information. In addition to costs associated with finding reliable market information, lack of information and informality exposes traders to corruption and harassment.

At the official border crossings, informal traders — mostly women — often face challenging conditions and high barriers to trade, such as the prevalence of corruption among border officials, frequent harassment, and other personal safety risks. In their 2017 final report, Uganda Women Entrepreneurs Association (UWEAL) and TradeMark East Africa (TMEA) surveyed female cross-border traders across Uganda to identify key Non-Tariff Barriers (NTB) to trade. The four most frequently occurring NTBs were customs clearance issues (67% of respondents), payment of bribes (57%), immigration document requirements (30%) and roadblocks (17%). They also identify Uganda, Tanzania and Kenya as the countries that present the most NTBs. The results from their study are clear: 65% of respondents are able to clear their goods through customs in less than two hours, but the speed of clearance is bribe-driven. Forty-one percent of respondents pay a bribe every time they cross the border. Through survey evidence, they identify information asymmetry as being the main reason that female cross-border traders face unofficial charges and harassment in their attempts to conduct trade. Many women cross-border traders are not aware of the tariffs they should be paying, or of their rights or trade procedures. Clearing agents and border officials exploit this information gap to extract money for personal gain. A survey carried out between November 2016 and January 2017 in Busia shows that over 75% of the traders surveyed have encountered incidents of corruption at the border. Moreover, 80% of the respondents report that corruption at the border happens daily or weekly. High rates of harassment, coercive corruption at the official crossings and confusing procedures have been highlighted as reasons for traders to rely on informal crossings (in addition to wanting to avoid taxes).

At informal border crossings, informal traders pay bribes to the police against passage[10]. Safety concerns at informal crossings have also been reported.

2.4 Insights on Intermediaries

High trade barriers and trade costs faced by domestic and cross-border traders – both at the official and informal border crossings – may be exacerbated by the fact that trading involves many types of actors as well as intermediaries. Legal actors include the Kenya Revenue Au-

[10] I have another paper that compares costs (including bribes) in both crossings through an audit study.

thority, the Uganda Revenue Authority, the police and the municipal tax collectors (the first three are only relevant to cross-border traders, municipal tax collectors to all traders). Revenue authorities are assigned to official border posts across the country for a specific amount of time. Anecdotally, revenue officials prefer some border posts to others because there is variation in terms of how much bribe money they can extract across different border posts. Twenty-four percent of traders surveyed report that revenue agents collect bribes at the border.

Municipal collectors collect municipal-level taxes. They are usually seen on either side of the border, located strategically to ensure they can stop everyone who imports or trade goods. They also locate themselves in marketplaces to levy sales-related taxes. Taxes depend on the type and value of the goods. Unlike the Revenue Authority officials, the municipal collectors are also found at informal border crossings.

Although the police do not have a mandate to collect taxes, 69% of the survey respondents report that the police collect bribes from traders, along informal border crossings and at roadblocks. Moreover, 58% report that the police are responsible for harassment at the border.

The other intermediaries include brokers, transporters and clearing agents. Payments to intermediaries are usually set through bargaining. There are also different types of transporters. Most relevant are those who help transport the goods across the border, usually via bike, because no motor vehicles are allowed to cross the border with shipments. Clearing agents help traders clear their goods and get the correct approvals and documents before crossing the border. There are established clearing agent companies that usually deal with large traders, but also individual clearing agents (or at least people who call themselves clearing agents) who patrol the border and offer services to smaller traders. Through the Simplified Trade Regime and Simplified Certificate of Origin, clearing goods should be an easy and quick task for traders with small consignments – such as traders in my sample – and should not require clearing agents. In practice, it seems that clearing agents take advantage of traders' lack of information about trade procedures.

2.5 Trade Policies in the Area

The Simplified Trade Regime and Simplified Certificate of Origin stem from regional integration efforts that acknowledge the role of informal traders as contributors to development, such as a supplementary source of family income to under-employed people. Therefore, to facilitate informal trade, member states from the East African Community (EAC) and the Common Market for East and Southern Africa (COMESA) have adopted Simplified Trade Regimes tailored to small-scale cross-border traders. One of these is the East African Community Certificate of Origin, a trade facilitation document which is used for clearance of goods that have been grown or produced in the EAC partner states and whose value is less than USD 2000. The simplified procedures were introduced in 2007 in an effort to reduce smuggling. In the EAC, 370 products currently qualify for clearance through the Simplified Certificate of Origin. The ease of use of the Simplified Certificate of Origin has allowed cross-border traders to clear their consignments quickly and with less hassle. In line with this definition, I consider ”small-scale traders” to be traders who trade goods valued at less than USD 2000 (per trip).

3 Sample, Data and Descriptive Analysis

3.1 Sample and Data Collection

In January 2020, a census of traders who trade either agricultural goods or shoes and clothing was conducted in Kenyan markets located within a 40-km radius of the Kenya-Uganda border in Busia. One thousand six hundred fifty traders were censused in 30 markets, all located on the Kenyan side of the border. In February 2020, I carried out a round of baseline data collection for 1,100 randomly selected traders. All are small-size traders who transport their goods by foot, bike and motorbikes. Twenty percent are men and 80% are women. About 55% are cross-border traders and 45% are domestic traders. Thirty-seven percent mainly cross the official border while 63% prefer using the non-official border crossings. Eighty percent trade mostly in agricultural products while 20% trade in shoes and clothing. I should note that this sampling strategy captures a representative sample of traders located in Kenyan markets – therefore, they are mostly either Kenyans who trade domestically in Kenya or Kenyan cross-border traders who buy goods in Uganda and sell them in Kenya. This is a different sample than would have been selected if I had sampled traders crossing at the border itself – a sampling strategy often used by governments in an attempt to estimate informal trade. Table 1 Panel A presents the main socioeconomic characteristics of the traders in the sample.

Throughout 2020, a high-frequency phone survey was carried out at intervals of roughly two weeks to a month. Each phone survey round asked traders about their experiences "in the past two weeks". In February 2021, a second baseline (referred to as the updated baseline) was conducted to ensure that I had up-to-date data about traders before the intervention part of the experiment. The intervention was launched in May 2021 and three rounds of follow-up data were collected in June, July and August/September. The final endline was conducted in October and November 2021. My panel therefore counts 18 rounds of data collection, including a baseline, an updated baseline and an endline. Phone surveys collected outcomes on traders' businesses, including the health of their business, the type of goods they trade, and their supply chain. I also collect data on what trade route they choose as well as reports of corruption and harassment. In addition to collecting outcomes on traders' businesses, the phone surveys have also served as a way to collect details about shocks such as market closures, product bans, and market prices. Figure 1 presents the timeline of events and Figure A2 shows the attrition across the high-frequency rounds.

3.2 Other Data Sources

In addition to the survey data, this paper also uses

- Market-level price data from a phone platform generated by the intervention partner. The information experiment, which will be described in more detail below, includes providing price information to traders. I therefore have access to the same market price data, which I use to estimate market-level outcomes. The market data is not collected by the implementation partner; they bring together data from over 10 different sources, standardize it across products and markets, and continuously update the database by the most updated price point.

- Usage data from the phone platform: data on each trader's usage of the platform at the interaction level. This includes details of what the trader requested and what was sent back by the platform, at the interaction level.

4 New Insights on Informal Trade Sector

4.1 Closure of Official Border

The official border between Kenya and Uganda was closed between April 2020 and October 2020 due to the Covid-19 pandemic. The official border was closed to people, including small- and medium-size traders, but trade vehicles were allowed to go through as an attempt to encourage movement of goods and minimize trade disruptions.

The key dates and events related to Covid-19 are as follows: On the 12th of March 2020, the first case of Covid-19 was reported in Kenya and the official borders between Uganda and Kenya were closed. At the end of September 2020, the government announced that the borders were re-opening. In October 2020, the borders re-opened.

I use the closure of the official border as a shock and highlight key insights on the informal trade sector.

4.2 Key Descriptive Patterns

Informal traders can trade across different types of routes

Table 1 Panel A demonstrates that the majority of dealers in my sample are Kenyan importers. They can conduct business across three distinct sorts of routes. Forty-five percent are domestic traders who purchase and sell within Kenya, 19% are cross-border traders who import their goods through official border stations, and 36% use informal crossings. For 95% of them, trading is their primary source of income. Small-scale traders are typically opportunistic and deal in a variety of items, whereas larger traders prefer to specialize in a specific good.

Informal traders face large costs

Table 1 Panel B shows that over 80% of traders' sales are comprised of costs, leaving traders with low profits. Traders' costs include large purchasing costs as well as transport and border costs. Table A2 characterizes border costs, depending on whether traders use the informal or formal crossings. Table A2 does not suffer from selection bias because the data was collected through an "audit study", i.e., trained traders crossed both types of border and reported costs and experiences[11] . Table A2 shows that bribes are extracted at both types of crossings. Bribes are larger at the informal border crossings, while waiting times are longer at the official border crossings.

Large price dispersion and lack of market integration

Prices for agricultural products vary across time, markets and products. Figure 2 plots prices across time for different markets in Uganda and Kenya for markets situated within 100 km of the study site. In a standard trade framework and assuming no friction, with full information and prices taken as given, traders would optimize their business by buying products in markets that have the lowest price and selling in markets that have the highest price, taking travel costs into consideration. Figure 2 shows that market prices vary significantly across markets, and patterns are similar for other goods. This should lead to arbitrage opportunities.

Informal traders specialize

Despite large variation in market price, traders specialize in markets and routes. Figure 3 shows that over 70% of traders use only one type of route to trade their goods, i.e., they only use domestic supply chains, formal crossings or informal crossings. Thirty percent use a combination of those routes – however, barely any traders use both the formal and informal border crossings.

[11] I have another paper that looks at determinants of border costs, especially bribes, at both types of border crossings

Similarly to the route specialization, Figure 3 shows that the specialization also happens at the market level. Eighty-five percent of traders always sell in the same market. The probability of buying in the same market is, however, lower – about 45% of traders always buy in the same market.

Market and route stickiness can be overcome with a large enough shock

Can a large enough shock make traders switch markets and routes? I use the closure of the official border as a shock to look at how traders' choices of routes and market change. The closure of the official border implies that traders who were using official routes faced a large disruption in their supply chain, as they no longer could reach suppliers.

Figure 4 shows that traders who were initially cross-border traders, and therefore most impacted by the border closure shock, did switch routes, to either domestic routes or informal routes. A small proportion exited the activity. Domestic traders, on the other hand, were disproportionately more likely to exit, as they were crowded out by cross-border traders switching to domestic supply chains (Figures A3 and A4). This implies that traders can trade profitably by switching routes and markets, assuming that they are rational profit maximizers.

Switching is sticky

What happens when the border re-opens? Figure 5 shows that only 25% of traders who had switched due to the border closure returned to their initial type of route after the border re-opened. Assuming that traders maximized their utility before the closure of the border, we would expect them to return to their initial optimal choice when the border re-opens. Instead, I find stickiness.

Lack of information

Table 1 Panel C shows that only 38% of traders know market prices for their main good in other markets. Only 51% report informing themselves about market prices and those who do get information rely on word of mouth.

4.3 Rationalizing Stylized Facts

There are several explanations that could explain the stickiness results highlighted above.

1. The world has changed and traders' optimal solutions are therefore different, e.g., uncertainty about future border closings, actual increased border costs (e.g., taxes, Covid requirements).

2. It is costly to get up-to-date information. The border shock pushed them to discover better solutions and there is no reason to switch back to sub-optimal outcomes.

3. Switching costs, e.g., relationships with suppliers, path dependency, route-specific capital.

There may be other explanations. Given the context and the apparent lack of information, this paper focuses on the possible role played by information frictions.

5 Theoretical Framework

Based on these stylized facts, I derive a model that provides the micro-foundations of the stickiness through information frictions about buying prices (or demand in buying markets), demand in selling markets and official border costs.

In this theoretical framework, I am modeling trader i's utility from profits gained from buying and selling a certain quantity of a good at time t. Trader i maximizes her utility by choosing quantities to sell in selling markets as well as which buying market and trade route to use. Trader i faces uncertainty about prices (or equivalently, demand) in buying markets as well as uncertainty about demand in selling markets (except her own selling market) and uncertainty about border costs. As noted above, I define a trade route as a choice between official cross-border trade, informal cross-border trade, or domestic trade (or exit). This theoretical framework also allows me to estimate market prices.

I solve the problem by backward induction. At time t and for a given route k, trader i decides which quantity q_{ihtk} to sell in her home market h and which quantity q_{ijtk} to sell in an alternative market j. Based on the optimal quantities and expected revenues for each of the four market routes, trader i then chooses which buying market-route k to use, in time t, i.e., which one yields higher utility. This is a one-period model; stocking decisions do not play a role.

5.1 Assumptions

Trader i is risk averse, trades in 1 good and sells in Kenya. She can sell in at most two markets: she always sells in her home Kenyan market h, where there is no randomness or uncertainty about demand, and can also sell in an alternative Kenyan market j, where there is randomness and uncertainty about demand. On the buying side, she chooses to buy her goods from one of four possible buying market-routes k: Uganda/Formal, Uganda/Informal, Kenya/Domestic or not at all (Exit). Traders behave as monopolies in selling markets in the sense that they sell differentiated products and have an upward-sloping supply curve with the elasticity of buying market price with respect to quantity $\epsilon^B \geq 0$. In addition to the costs associated with purchasing goods, trader i faces heterogeneous border costs. Note that this model presents traders as monopolies to simplify and provide clarity on the different moving pieces; however, the predictions of the model remain the same if traders are in Cournot competition equilibrium or are price takers with enough treated traders affecting aggregate demand and supply (see Appendix Section B).

Each selling market has a simple downward-sloping demand curve[12] with constant elasticity[13]. Elasticities are assumed to be the same across all selling markets and across time (v does not vary by trader or time).

The inverse market demand function for selling market m is:

$$p_{mt} = \alpha \omega_{mt} q_{mt}^{\frac{1}{v}} \tag{1}$$

[12] See appendix for the model without imposing structure on the demand curve.
[13] Its constant elasticity property makes it tractable in this context, but my conclusions do not depend on this assumption.

where ω_{mt} is some randomness in demand due to market-specific high-frequency demand shocks. The randomness in selling market ω_{mt} is normally distributed $(1, (\sigma^{\omega}_{mt})^2)$. Note that the price elasticity of demand is v ($v \leq -1$) and the inverse price elasticity of demand is $1/v$.

The supply curve function for buying market k is:

$$p_{kt} = \zeta b_{kt} Q^{B}_{kt}(q_{it}, q_{-i,t}) \tag{2}$$

where b_{kt} is some randomness in supply quantity in buying markets due to market-specific high-frequency supply shocks and Q^{B}_{kt} total quantity in market k. The randomness in buying market b_{kt} is normally distributed $(1, (\sigma^{\omega}_{kt})^2)$. Traders take into account the effect of their own demand on buying market prices but do not take into account how that may affect other traders' buying decisions [14].

The randomness in this model appears in four places : (1) the selling market demand shocks ω_{mt} following a normal distribution $(1, (\sigma^{\omega}_{mt})^2)$, (2) the buying market level demand shocks b_{kt} informing price p^{B}_{kt} following a normal distribution (1, $(\sigma^{B}_{kt})^2$), (3) the border shocks bc_{kt} , following a normal distribution (1, $(\sigma^{BC}_{kt})^2$) and (4) λ_{ik} an unobserved/random preference term for route k following an extreme value distribution.

Figure 6 gives a representation of the model.

5.2 Trader's Maximization Problem

5.2.1 Trader's Utility

Trader i maximizes her (risk-averse) utility by maximizing expected revenues and minimizing expected costs. Her utility is a standard profit function including a quadratic term in price gaps between selling and buying markets and in border costs. The utility for trader i, using

[14] Imposing a positive relationship between trader individual demand and market prices in buying markets is not necessary for the results to hold, i.e., traders could be price takers. I include this positive relationship to remain more conservative about the possible effects.

market route k at time t, is as follows. Note that trader i's utility for market route k at time t includes quantities sold in home market h and alternative market j, conditional on using market route k (which is why quantities vary by market route k).

$$MaxV_{ikt} =$$
$$E[\sum_{m=h,j}\{[p^S_{mtk}(q_{imtk}) - p^B_{kt}(q_{ijtk} + q_{ihtk})] * q_{imtk} + \delta[p^S_{mtk}(q_{imtk}) - p^B_{kt}(q_{ijtk} + q_{ihtk})]^2 * q_{imtk}\} - \tag{3}$$
$$[\delta_3 BC_{ikt}(1 + \gamma_{ikt}) + \delta_4 BC^2_{ikt} + \mu d_{ikt}] * (q_{ihtk} + q_{ijtk}) + c_{iht}q_{ihtk} + c_{ijt}q_{ijtk} + \lambda_{ik} + u_{ikt}]$$

Trader i has full information about random demand shocks ω_{ht} in her home market h but faces uncertainty about random demand shocks ω_{jt} in the other selling market j. Passing through the expectations, expected prices become $E[p_{jtk}] = \alpha E[\omega_{jt}]q_{ijtk}^{\frac{1}{v}}$ and $p_{htk} = \alpha\omega_{ht}q_{ihtk}^{\frac{1}{v}}$ and trader i's utility simplifies to the following:

$$MaxV_{ikt} =$$
$$[\alpha E[\omega_{jt}]q_{ijtk}^{\frac{1}{v}} - \delta_2(\sigma^{\omega}_{ijt})^2] * q_{ijtk} + \alpha\omega_{ht}q_{ihtk}^{\frac{1}{v}} * q_{ihtk} - [E[p^B_{kt}(q_{ijtk} + q_{ihtk})] + \delta_1(\sigma^B_{ikt})^2] * (q_{ihtk} + q_{ijtk}) -$$
$$[\delta_3 E[BC_{ikt}](1 + \gamma_{ikt}) + \delta_4(\sigma^{BC}_{ikt})^2 + \mu d_{ikt}] * (q_{ihtk} + q_{ijtk}) + c_{iht}q_{ihtk} + c_{ijt}q_{ijtk} + \lambda_{ik} + u_{ikt} \tag{4}$$

with

- Expected revenues from selling in market h and j, conditional on using market route k: $[\alpha E[\omega_{jt}]q_{ijtk}^{\frac{1}{v}} - \delta_2(\sigma^{\omega}_{ijt})^2] * q_{ijtk} + \alpha\omega_{ht}q_{ihtk}^{\frac{1}{v}} * q_{ihtk}$
- Expected costs split between (i) purchasing costs $E[p^B_{kt}]$, (ii) border costs $\delta_3 E[BC_{ikt}] + \delta_4(\sigma^{BC}_{ikt})^2$ (Tariffs if k = Uganda/Formal and Bribes if k = Uganda/Informal), (iii) bargaining power $1 + \gamma_{ikt}$ (with $\gamma_{ikt} \geq 0$) (iv) distance μd_{ikt} and (v) selling market-specific marginal cost for home market c_{ijt} and alternative market c_{iht}
- λ_{ik} utility associated with using buying market-route k. λ_{ik} includes supplier relation-

ship, experience/comparative advantage, access to information or fixed costs

- $\delta_1 \geq 0$, $\delta_2 \geq 0$, $\delta_3 \geq 0$, $\delta_4 \geq 0$

5.2.2 Order of Maximization

Order of maximization (backwards induction):
Step 1: For each possible market-route k, trader chooses optimal quantities q^*_{ihtk} and q^*_{ijtk} to sell in home market h and alternative selling market j, conditional on using market route k
Step 2: Taking optimal quantity for market route k as given $q_{ikt} = q_{ihtk} + q_{ijtk}$, trader i chooses which market route k^* to use (Uganda/Formal, Uganda/Informal, Kenya/Domestic, Exit) to maximize utility V

5.3 Step 1: Solving for Prices and Quantities in Selling Markets

5.3.1 Solving for Prices

Trader i chooses q_{ihtk} and q_{ijtk} by maximizing V_{ikt}. Trader i therefore computes an optimal pair of quantities sold in home and alternative market q_{ihtk} and q_{ijtk} for each of the four alternative market routes k. The derivations are included in Appendix Section A. I maximize trader's utility by taking first order conditions with respect to quantities in home and alternative selling markets.

Following the standard monopoly optimal pricing strategy, setting the mark-up over marginal costs as a function of the price elasticity of demand in the selling market, I solve for price[15] as a function of the price elasticity of demand in selling market v and price elasticity of supply (elasticity of marginal cost)[16] ϵ^{Buy}_{kt}

[15] See Appendix for derivations of the model without structure
[16] Again, I am assuming the partial effect on expectation of price is the same as the partial effect on price

$$E[p^S_{jtk}] = \frac{1}{1+1/v} * [\zeta E[b_{kt}]Q^B_{kt}(1+\frac{2}{\epsilon^{Buy}_{kt}}) + \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) + \delta_4(\sigma^{BC}_{ikt})^2 + \mu d_{ikt} + c_{ijt} + \delta_1(\sigma^B_{ikt})^2 +$$
$$\delta_2(\sigma^{\omega}_{ijt})^2]$$
$$p^S_{htk} = \frac{1}{1+1/v} * [\zeta E[b_{kt}]Q^B_{kt}(1+\frac{2}{\epsilon^{Buy}_{kt}}) + \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) + \delta_4(\sigma^{BC}_{ikt})^2 + \mu d_{ikt} + c_{iht} + \delta_1(\sigma^B_{ikt})^2] \tag{5}$$

with $1/v = 1/\epsilon^{Sell}_{htk} = \frac{\partial p^S_{htk}(q_{ihtk})}{\partial q_{ihtk}} * \frac{q_{ihtk}}{p^S_{htk}}$ = $1/\ \epsilon^{Sell}_{jtk} = \frac{\partial p^S_{jtk}(q_{ijtk})}{\partial q_{ijtk}} * \frac{q_{ijtk}}{p^S_{jtk}}$ as I am assuming partial effect on expectation of price is the same as partial effect on price $\frac{\partial E[p^S_{jtk}(q_{ijtk})]}{\partial q_{ijtk}} * \frac{q_{ijtk}}{E[p^S_{jtk}]} = \frac{\partial p^S_{jtk}(q_{ijtk})}{\partial q_{ijtk}} * \frac{q_{ijtk}}{p^S_{jtk}}$; and $1/\epsilon^{Buy}_{kt} = \frac{\partial p^B_{kt}(q_{ijtk}+q_{ihtk})}{\partial q_{ihtk}} * \frac{q_{ihtk}}{p^B_{kt}} = \frac{\partial p^B_{kt}(q_{ijtk}+q_{ihtk})}{\partial q_{ihtk}} * \frac{q_{ijtk}}{p^B_{kt}}$

5.3.2 Selling Market Entry Conditions

Traders enter selling market m if their expected profits from selling in market m are positive. The entry condition for home market and for alternative market are such that expected profits from selling in markets h and j exceed cost of entry (see Appendix Section A for derivations).

5.3.3 Solving for Quantities

Using the price function (1), (2) and the optimal price expressions from the optimization (A4), I solve for quantities, including market entry conditions (A6):

$$q_{ihtk} = [\frac{1}{\alpha\omega_{htk}} * \frac{1}{1+1/v} * [\zeta E[b_{kt}]Q^B_{kt}](1+\frac{2}{\epsilon^{Buy}_{kt}}) + \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) + \delta_4(\sigma^{BC}_{ikt})^2 + d_{ikt} + c_{iht} + \delta_1(\sigma^B_{ikt})^2]^v \tag{6}$$

with $\alpha\omega_{ht}q^{1/v}_{htk} - \zeta E[b_{kt}]Q^B_{kt} - \delta_1(\sigma^B_{ikt})^2 - \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) - \delta_4(\sigma^{BC}_{ikt})^2 - \mu d_{ikt} \geq c_{iht}$

$$q_{ijtk} = \begin{cases} 0 \text{ if } E[\omega_{jt}]\alpha_{jt}q_{ijtk}^{1/v} - [\zeta E[b_{kt}]Q_{kt}^{B}] - \delta_1(\sigma_{ikt}^{B})^2] - \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) - \delta_4(\sigma_{ikt}^{BC})^2 - \mu d_{ikt} - \delta_2(\sigma_{ijt}^{\omega})^2 < c_{ijt} \\ \\ [\frac{1}{\alpha E[\omega_{jt}]} * \frac{1}{1+1/v} * [\zeta E[b_{kt}]Q_{kt}^{B}](1+\frac{2}{\epsilon_{kt}^{Buy}}) + \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) + \delta_4(\sigma_{ikt}^{BC})^2 + \mu d_{ikt} \\ \qquad + c_{ijt} + \delta_1(\sigma_{k}^{B})^2 + \delta_2(\sigma_{ijt}^{\omega})^2]]^{v} \\ \text{if } E[\omega_{jt}]\alpha_{jt}q_{ijt}^{1/v} - [\zeta E[b_{kt}]Q_{kt}^{B}] - \delta_1(\sigma_{ikt}^{B})^2 - \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) - \delta_4(\sigma_{ikt}^{BC})^2 - \mu d_{ikt} - \delta_2(\sigma_{ijt}^{\omega})^2 \geq c_{ijt} \end{cases} \tag{7}$$

5.4 Step 2: Choosing Buying Market and Route

5.4.1 Choice model

Trader i will compare her utility across each market route, taking the optimal quantity for each route as given.

Trader i will pick buying market route k' iff $V_{ik't} \geq V_{ikt}$ (See Appendix Section A for derivations). The intuition is that increased profits from lower marginal costs in a new buying market route need to be larger than the lost utility from switching market routes $\lambda_{ik} - \lambda_{ik'}$.

There is a $\bar{\lambda}_i$, at which $V_{ik't} = V_{ikt}$. And if $\lambda_{ik} - \lambda_{ik'} \leq \bar{\lambda}_i$, trader i switches to k'. $\lambda_{ik} = \hat{\lambda_k} + \lambda'_{ik}$ with λ'_{ik} being an unobserved/random term that follows an extreme value distribution.

5.4.2 Choice Probabilities

Using a Mixed Logit Model, the probability of choosing buying market route k is :

$Prob(Y_{it=k}) = \int \frac{exp(V_{ikt}(\beta))}{\Sigma exp(V_{ikt}(\beta))} * f(\beta|\theta) * d\beta$ with β coefficients in V and θ parameters for the mixing distribution, estimated through simulations.

5.5 Predictions and Comparative Statics

The model will be estimated in the last section of the paper. In this section, I derive how quantities, prices and choice of market-trade route vary with marginal changes in costs. I specifically look at the effect of the following costs (as they are directly related to information frictions):

- $E[p^B_{kt}(q_{ihtk} + q_{ijtk})]$ as variable purchasing cost for route k
- $(\sigma^B_{ikt})^2$ as purchasing cost uncertainty for route k
- $VC_{ikt} = \delta_3 E[BC_{ikt}](1 + \gamma_{ikt}) + \delta_4(\sigma^{BC}_{ikt})^2 + \mu d_{ikt} + c_{ijt}$ as other variable cost for route k (including mean and variance of border costs, distance and selling market specific marginal costs)
- $(\sigma^\omega_{ijt})^2$ as selling price uncertainty

Table 2, Panels (A) and (B) show the marginal effect of a change in purchasing costs, purchasing costs uncertainty, other variable costs and selling price uncertainty on quantity and prices. Note that those marginal changes are conditional on using route k and assume entry conditions are met. Since $\upsilon \leq -1$ and $\epsilon^{Buy}_{kt} \geq 0$; all marginal price changes are ≥ 0 and marginal quantity changes ≤ 0. I will describe in the next section that reducing information frictions (decreasing the four types of costs outlined above) theoretically leads to a reduction in equilibrium prices and an increase in quantities traded.

Choice of supplier market route:

- $\frac{\partial V_{ikt}}{\partial E[p^b_{kt}]} \leq 0 \implies \frac{\partial ProbY_{it}=k}{\partial E[p_{kt}]} \leq 0$
- $\frac{\partial V_{ikt}}{\partial (\sigma^B_{ikt})^2} \leq 0 \implies \frac{\partial ProbY_{it}=k}{\partial (\sigma^B_{kt})^2} \leq 0$
- $\frac{\partial V_{ikt}}{\partial E[BC_{ikt}]} \leq 0 \implies \frac{\partial ProbY_{it}=k}{\partial E[BC_{ikt}]} \leq 0$
- $\frac{\partial V_{ikt}}{\partial (\sigma^{BC}_{ikt})^2} \leq 0 \implies \frac{\partial ProbY_{it}=k}{\partial (\sigma^{BC}_{ikt})^2} \leq 0$

An increase in market route price (mean or variance), border costs (mean or variance) reduces the probability of choosing that market route.

5.6 Effect of Reducing Information Frictions

A reduction in information frictions about market prices and official border costs (tariffs) implies:
E$[p^B_{kt}] = p^B_{kt}$ & reduces variance $(\sigma^B_{ikt})^2$ for buying markets [Marginal Cost Effect] (a)
E[ω] = $\bar{\omega}$ & reduces variance $(\sigma^{\omega}_{ijt})^2$ for selling markets [Marginal Revenue Effect] (b)
E$[BC_{ikt}] = BC_{ikt}$ & reduces $(\sigma^{BC}_{ijt})^2$ for k = Formal [Border Cost Effect] (c)
A reduction in γ_{ikt} for k = Formal [Bargaining Effect] (d)

I describe below how the treatment's four effects impact equilibrium market prices and trader's quantities in home selling market, alternative selling market and buying markets (according to the model). As an extreme case, let's assume treatment removes all uncertainty.

(a) MARGINAL COST EFFECT: $E[p^B_{kt}] + \delta_1(\sigma^B_{ikt})^2 = p^B_{kt} \implies MC_{ikt} \downarrow$

- Home selling market: $\Delta p_{htk} < 0$ and $\Delta q_{htk} > 0$
- Other selling market: $\Delta q_{jtk} \geq 0$ and $\Delta p_{jtk} \leq 0$ as
  - If entry condition already satisfied pre-treatment $E[p^S_{jtk}(q_{ijtk}) - \delta_2(\sigma^{\omega}_{ijt})^2] - E[p^B_{kt}(q_{ihtk} + q_{ijtk}) + \delta_1(\sigma^B_{ikt})^2] - BC_{ikt} * (1 + \gamma_{ikt}) + d_{ikt} \geq c_{ijt} \implies \Delta E[p_{jtk}] < 0$ and $\Delta q_{jtk} > 0$
  - If entry condition not satisfied pre-treatment and still not satisfied post-treatment: $q_{ijtk} = 0 \implies \Delta q_{jtk} = 0$ and $\Delta P_{jtk} = 0$
  - If entry condition not satisfied pre-treatment and becomes satisfied post-treatment: $\Delta q_{jtk} > 0$
- Buying market: Probability of switching buying market $\uparrow$
  - If same buying market [based on λ] ($k* = k_0$): $\Delta p_{ik*t} > 0$ as $\Delta q_{ik*t} > 0$
  - If new buying market [based on λ] ($k* \neq k_0$): $\Delta p_{ik*t} > 0$ as $q_{ik*t} > 0$ and $\Delta p_{ik_0t} < 0$ as $\Delta q_{ik_0t} < 0$

(b) MARGINAL REVENUE EFFECT: E[ω_{ijt}] + $\delta_2(\sigma^{\omega}_{ijt})^2 = \bar{\omega}_{jt} \implies MR_{ijt} \uparrow$

- Other selling market: $\Delta q_{jtk} \geq 0$ and $\Delta p_{jtk} \leq 0$ as
  - If entry condition already satisfied pre-treatment: $\Delta p_{jtk} < 0$ and $\Delta q_{jtk} > 0$
  - If entry condition not satisfied pre-treatment and still not satisfied post-treatment: $q_{ijtk} = 0 \implies \Delta q_{jtk} = 0$ and $\Delta p_{jtk} = 0$
  - If entry condition not satisfied pre-treatment and becomes satisfied post-treatment: $\Delta q_{jtk} > 0$
- Buying market: $\Delta q_{itk*} \geq 0$

(c) BORDER COSTS EFFECT $E[BC_{ikt}] + \delta_4(\sigma^{BC}_{ikt})^2 = BC_{ikt}$

- Same conclusions as $E[p^B_{kt}] + \delta_2(\sigma^B_{ikt})^2 = p^B_{kt} \implies MC_{ikt} \downarrow$ but only for $k = F$, i.e., for market routes that are formal

(d) BARGAINING EFFECT γ_{ikt} is reduced

- Same conclusions as $E[p^B_{kt}] + \delta_2(\sigma^B_{ikt})^2 = p^B_{kt} \implies MC_{ikt} \downarrow$ but only for $k = F$, i.e., for market routes that are formal

Overall model predictions about reducing information frictions about market prices and official border costs

(1) *Reducing information frictions leads to more markets connected by trade.*

A reduction in information frictions leads to traders buying in new markets[17]. They also sell in new markets (in addition to their home market), thereby increasing the number of markets in which they sell.

[17] The number of buying markets also increases if the model is expanded across multiple time periods.

(2) *Reducing information frictions leads to higher trade volumes, higher sales and profits for traders.*

(3) *Reducing information frictions increases cross-border trade and formalization (both incidence and trade volumes).*

(4) *Reducing information frictions has ambiguous effects on bribes.*
Demand for cross-border trade increases (higher likelihood of corruption), but demand for informal crossing decreases. Moreover, bargaining at the border increases (by assumption, lower likelihood of corruption).
(5) *Reducing information frictions leads to cheaper prices for the consumer and more supply.*
Traders decrease prices and increase quantity in their home market to account for the reduction in marginal cost. Passthrough is non-zero.

(6) *Reducing information frictions leads to higher buying prices in new buying markets and may lead to cheaper buying prices in initial buying markets.*
Overall quantity purchased and sold increases, leading to an increase in price in new buying markets. Prices in initial buying markets are ambiguous, as overall quantity bought increases (putting upward pressure on the price) but the probability of switching to a new buying market increases too (putting downward pressure on the price). Prices decrease for markets that face significant switching-out, while markets with little switching-out face an increase in prices.

6 Empirical Strategy

In May 2022, I carried out a Randomized Controlled Trial based on an information intervention. Treatment traders received access to trade and market information through a phone platform, while Control traders did not.

6.1 Intervention: Access to Information

Treated traders received free access to a mobile-based trade and market information platform developed by Sauti East Africa[18]. Sauti East Africa empowers women-led small and medium-sized enterprises to trade legally, safely and profitably across East Africa's borders. The platform is accessible on any phone through USSD[19] and offers multiple features (Figure A5). First, it provides information about market prices for each product in main markets across East Africa, encouraging traders to seek out profitable opportunities in terms of goods and markets. Second, it gives traders information about exchange rates, helping them decide when to trade cross-border and to better negotiate exchange rates. Third, traders can request information on taxes, tariffs and procedures applicable to traded products, informing them of cross-border procedures and increasing their bargaining power at the border to reduce corruption and harassment. Fourth, traders can get access to weather forecast for the next day in locations of their choice. Examples of weather forecast include "Partly Cloudy", "Very Cloudy", "Rainy", "Sunny". Traders are interested in weather forecast for the business and it both gives them information about the market conditions in potential markets on specific days (e.g., fewer customers on a rainy day) as well as transport costs (e.g., longer public transport waiting time).

"Now, at the comfort of my couch or kitchen, I can get all the business and customs information I need right in my cheap old phone. I'm now more confident to pass through the gazetted route and not scared of personally clearing my goods. It is like a secret partner in my business. Before I even leave my house I know the price of groundnuts in Gulu and Lira, the current exchange rate and the amount of tax I will pay." Interview collected by Sauti East Africa in Busia Uganda, 2016.

The platform can be accessed by all traders through an access code (i.e., traders would, for example, text #1234*). Usage was not restricted to my sample; however, my implementation partner had not targeted Busia or carried out marketing campaigns in the area, implying that the initial adoption rate at baseline was relatively low (as confirmed by screening ques-

[18] https://sautiafrica.org

[19] Similar technology to text messages (SMS).

tions in the baseline survey). Treated traders received an invitation to a workshop where they were given the access code and shown how to use the platform. Workshops were held in 3 locations, over the period of 10 days.

6.2 Randomization

The randomization is at the trader level: 50% of traders received access to the platform. In addition, the treatment intensity was varied at the market x industry level to control for spillovers and estimate general equilibrium results at the market level. Industry is defined as agriculture or shoes and clothing; I therefore have approximately 60 market x industry clusters. The intensity of treatment at the market x industry level ranged from 0 to 75% of the market.

Trader-level randomization was stratified by market, gender and trader type (domestic, informal crossings, official crossings); while market-level randomization was stratified by market size and location area.

Table A4 shows that treatment and control traders are balanced across covariates before implementation. Table A5 shows that survey attrition post-implementation was balanced across treatment and control groups.

6.3 Take Up

Take-up is characterized in two steps: first, attendance to the workshop, and second, usage of the platform. The analysis in the paper focuses on ”Intent to Treat” effects, and therefore includes traders who did not attend the workshops.

Eighty-five percent of treatment traders attended the workshops and take-up of the platform averaged 70%, i.e., 59% of treatment traders (irrespective of whether they attended the workshops) accessed the platform at least once.

The workshops were organized in April 2021 and the endline survey was carried out in November 2021. In this paper, I look at usage data from May 2021 to November 2021, i.e., 7 months of usage. Traders access Sauti East Africa’s platform through sessions. In each session they can request as many features (market prices, weather, trade procedures or exchange rates) as they want and multiple alternatives for each features, e.g., multiple markets or goods if they request market prices, multiple locations if they request weather forecasts, multiple products and values if they request tax procedures and multiple amounts if they request exchange rates. I highlight below 3 main insights on traders' search process using the platform.

Traders continue to use the platform after implementation. Figure 7 shows the distribution of number of months of usage per trader. 40% of traders never use the platform. Conditional on using the platform at least once, the mean number of months of usage is 2.8 months. Indeed, 67.5% of users use the platform up to 3 months. This however does not mean that for these 67.5% of users, the 3 months of usage necessarily are the first 3 and that traders stop using the platform after the first 3 months. Figure A7 shows that more than 50% of traders use the platform both within the first 3 months and within the last 4 months. Figure 8 shows the distribution of users (Panel A), sessions (Panel B) and sessions by user (Panel C) across the 7 months. Conditional on using the platform in a given month, traders use the platform on average for 3 sessions a month.

Traders are interested in using the 4 features, query different features at different times and prioritize features that inform them of high frequency shocks to market conditions, i.e., market prices, weather and exchange rates. Figure 9 (left column) shows that amongst users, traders tend to look up a single feature per session but over 50% of users are interested in 3 or 4 features across the 7 months. Figure 9's right column shows that weather forecasts, market prices and exchange rates are the most demanded features, reaffirming that consistent with the model, information frictions seem to come from a lack of information on high frequency shocks that affect buying and selling markets i.e., weather (affecting demand and supply), market prices and exchange rates.

Over time, traders look up different markets and alternatives. Table A6 shows the number of alternative market prices, exchange rate amounts, trade policies (tariffs) and weather locations requested by session, day, month and overall. Table A6 shows that traders look up 3 markets over time and those markets are different from each other (see alternative per month versus unique alternatives per month). On the other extreme, weather forecasts are asked for multiple locations repeatedly.

The patterns highlighted here show that the workshops and the platform did not simply play the role of nudging traders to look elsewhere. Instead traders repeatedly request different markets, locations or alternatives to help them make informed decisions for their business.

6.4 Spillovers

The platform is accessible by all traders, conditional on having the access code. Spillovers in this context could be of two types: (1) control traders could have access to the code and use the platform and (2) treatment traders could tell control traders about the information included in the platform, without traders in the control group having to access the platform. In the first case, I can control for non-compliers as I have access to the usage data. However, this is not the case for the second type of spillovers. This is why I varied the intensity of treatment at the market x industry level to test for spillovers. Only 1.5% (9 traders) of control group traders accessed the platform.

6.5 Empirical Strategy

I run 3 types of regressions to assess the effect of treatment on outcomes for trader i, in round t and market m. $Treat_i$ is a dummy variable for whether the trader is in the treatment group, $TreatxPost_{it}$ and $IntensityTreatxPost_{mt}$ the interaction between the treatment variable and a dummy $Post$ relating to the outcome being measured after the intervention. T_t are rounds fixed effects and X_i are trader level characteristics/strata. I run 3 types of regressions to assess the effect of treatment on outcomes for trader i, in round t and market m. $Treat_i$ is a dummy variable for whether the trader is in the treatment group and $IntensityTreat_m$ the market intensity of treatment defined by the ratio of the number of treated traders over all traders, either buying or selling (depending on the specification) in market m at baseline. $TreatxPost_{it}$

and $IntensityTreatxPost_{mt}$ the interaction between the treatment variable and a dummy $Post$ relating to the outcome being measured after the intervention. T_t are rounds fixed effects and X_i are trader level characteristics/strata.

$Outcome_i = \alpha + \beta_2 Treat_i + X_i + \epsilon_i$

for a specific round t, with robust standard errors.

$Outcome_{it} = \alpha + \beta_1 Treat_i + \beta_2 TreatxPost_{it} + T_t + X_i + \epsilon_{it}$

for all rounds t including baseline, with standard errors clustered at the trader level.

$Outcome_{mt} = \alpha + \beta_1 IntensityTreat_m + \beta_2 IntensityTreatxPost_{mt} + T_t + \epsilon_{mt}$

for all rounds/month t including baseline, with standard errors robust or clustered at the market level.

The coefficient of interest is β_2.

7 Results

7.1 Main Results

Table 3 (Panel A) shows that information has a direct effect on trading. Treatment increases the likelihood of being in business by 3.5 to 4.6 percentage points and increases the probability of relying on trading as the main source of income by 3.5 percentage points. Moreover, treated traders also diversify by increasing the number of goods in which they trade by nearly 10% .

Table 3 (Panel B) shows that information led to an increase in the number of buying markets by 7% and an 11% increase in the number of selling markets (Model Prediction 1). This means traders expanded their set of markets and potentially switched away from their initial markets. Table A7 shows that, after the intervention, an average control trader sold in 82% of the markets he/she used to sell in pre-intervention and 86% of control traders sold in at least one of their initial markets. However, treatment traders were significantly less likely to sell in the same market. This points to the fact that traders tend to stick to their selling markets but that the intervention both increased the number of markets sold in and induced a fraction of traders to switch out of their initial markets for new markets. On the other hand, only 40%

of control traders report buying in the same markets pre- and post-intervention, pointing to the fact that switching costs are higher for selling markets than buying markets (this is not surprising, as traders have to pay fees to have a selling spot in a market). Information did increase the number of markets from which traders buy, but did not have an effect on whether or not traders switched out of their initial buying markets for other markets.

Relaxing information frictions improved treated traders' business by increasing both sales and profits by 17-18% at endline (Table 4 Panel A) (Model Prediction 2). As per the model, the positive effect on profits can stem from (i) buying cheaper quality-adjusted goods, (ii) selling goods at a higher price (increasing markups), (iii) reducing transport and border costs and/or (iv) increasing quantity. I am unable to assess the effect on quality; however, Table 4 (Panel B) shows that treated traders purchase higher quantities, leading to increased purchasing costs (Column 1). However, once I control for the increased quantity purchased, there is no effect on markups[20] (Columns 3 and 4). Either treatment isn't allowing traders to purchase goods at a lower price or they buy better quality-adjusted goods and have a near 100% passthrough. Equally I do not find treatment effects when I include other costs (in addition to purchasing costs) to the calculation of markups or significant treatment effects on profit margins[21]. Treatment does, however, seem to reduce transport and border costs by 11-13% (Columns 4 and 5 of Table 4 Panel C), meaning that information allowed traders to negotiate better. Note that, despite finding no effect on bribes paid, bribes are often lumped with transport and taxes, as traders are not aware of how much they should be paying for transport and taxes across the border. The negative impact on transport and border costs points in the direction of reduced corruption and bribes paid at the border.

Table 3 (Panel C) focuses on trade routes and shows that treatment pushed traders to become cross-border traders, resulting in a 20% increase in the incidence of cross-border traders (Model Prediction 3). This is a meaningful result as (i) domestic traders becoming cross-border traders implies both buying from new markets and navigating importing procedures;

[20]Here I am looking at an approximation of reversed markups: purchasing price over selling price. I do not have marginal costs and am therefore assuming here marginal cost equals average costs.

[21]Note that another explanation for finding no treatment effect on markups and profit margins is that measures of profits and costs tend to be noisy and I may not have the power to detect any effect

(ii) cross-border trade was relatively low at the time of the intervention due to the trade restrictions imposed during the pandemic (only 24% of control traders in my sample were cross-border traders post-implementation of Covid restrictions, a stark reduction from the 55% at the beginning of 2020). Moreover, the treatment helped formalize trade, increasing formal trade by 25%, which implies that domestic traders switching to cross-border trade opted to use the formal border crossing. Interestingly, the results on cross-border trade are concentrated in the first few months after implementation. Which traders became cross-border traders? Table 5 (Panel A) shows that traders who become cross-border traders due to the experiment are not traders who switched from cross-border trading to domestic during the border closure and did not switch back (called ”Sticky” in the table).

Table 6 shows that there are no effects on reports of corruption or harassment (Model Prediction 4).

7.2 General Equilibrium Effects on Market Prices

Reducing information frictions has general equilibrium effects on market prices. Reducing information frictions has general equilibrium effects on market prices. I use the variation in treatment intensity to look at how market prices changed due to the intervention. I use two sets of data: (i) the market price data from the platform and (ii) reported buying/selling price data from surveys of traders in my sample. They both have advantages and drawbacks. The data in the platform is more complete and does not rely on sample traders actually buying or selling in markets; however, markets on the platform do not perfectly match those in my sample (geographically) and are more numerous. I therefore assign to each market on the platform the treatment intensity of the closest treated sample market. The markets included are located within 25 km of the study site.

Table 7 (Panel A) shows that reducing information frictions reduces aggregate consumer market prices. Indeed, markets that were more intensively treated have lower retail consumer prices (Model Prediction 5). In Columns 1 and 2, the regression is at the market price level and I control for product fixed effects. Goods included are agriculture goods and goods sold by traders in my sample. In Column 3 (my preferred specification) I build a consumer price index over all targeted goods, at the market level. Markets where more traders were treated experienced a relative decrease in consumer prices. Related to the model predictions, traders now buy goods at cheaper prices and pass the cost reduction through to consumers. Table 7 (Panel B) shows that reducing information frictions also affects market prices on the buying side. Treatment reduces market prices in markets in which traders used to buy (Model Prediction 6). Again Columns 3 and 6 show that markets that were more intensively experienced a larger reduction in prices, both for retail and wholesale prices. Related to the model, traders now buy in new markets, lowering demand in initial buying markets.

Table A12 and A13 find similar results when I use reported prices from traders' surveys, although the result is less obvious for the buying markets. Note that the results are robust to different ways of constructing the CPI variable.

As robustness checks, I first include markets that are farther away from the study site and control for distance to the border and the interaction of distance and treatment intensity. Table in Online Appendix shows that the treatment effect declines as distance from the study site increases. This implies that there is no effect of treatment on markets outside the study site. Second, instead of only looking at the effect on prices for goods and industries in which traders traded, I look at the effect of treatment on goods which the project does not focus on. I find no effect of treatment (Table in Online Appendix).

8 Magnitudes, Welfare Analysis and Counterfactuals

8.1 Magnitude of Treatment Effect and Information Frictions

Table 8 shows that the closure of the border increased market prices but that the increased costs differentially affected markets closer to the border, who are more likely to rely on cross-border trade. More generally, the coefficient on the interaction between Closure and Distance can be interpreted as a clean estimate of the cost of being a km farther away from the border.

Along those lines, comparing the treatment effect on prices (-21.55) in Table 7 to the cost of distance, treatment was equivalent to pushing markets closer to the border by about 150 km.

8.2 Cost Effectiveness

As a reminder, the key results from reducing information frictions are:

- Reduction in consumer prices in selling markets (initial and new selling markets)
- Increased quantity sold
- Reduction in purchasing prices in initial buying markets; increase in purchasing prices in new buying markets
- Increase in profits for treated traders
- Increase in official cross-border trade flows

Consumers' Welfare Gains Consumer prices decreased by 6.6% due to the intervention. Based on average sales of USD 9148.3 per year at baseline, this is equivalent to an increase in USD 604 in consumer surplus. In this welfare calculation, I focus on the first-order components and do not include the benefit for consumers of increased demand. This means that my analysis will be a lower bound.

Suppliers' Welfare Gains: I assume the decrease in prices in treated markets is compensated for by the increase in prices in new purchasing markets[22], leading to no change in welfare for suppliers. Again, this is underestimating the welfare gains, as it does not include the increase in purchased quantity (treated traders increase purchasing costs by 6-17%)

Traders' Welfare Gains: I assume the increased profits for treated traders are compensated for by a reduction in profits for other traders.

Governments' Welfare Gains: Treated traders' probability of using the official border increases by 20%. This is equivalent to an increase in USD 246 of trade flows over three

[22]The model assumes iso-elastic supply curves, with the same elasticity across markets; which goes in the direction of my argument.

months (based on USD 1229 per month of purchasing costs). Due to seasonality, and taking the fact that monthly sales during those three months needs to be 16x to get to yearly sales (USD 1634 for 3 months in February 2022, USD 9148 for the year), I assume official trade flow increases by USD 3936 by year, leading to an increase in USD 79 in tax revenues. Note that I do not include any potential effect on bribes in this analysis.

Intervention Costs: Sauti East Africa estimates their usage cost to be USD 7 per user. I do not include costs related to price data collection.

Welfare and Cost Effectiveness: Reducing information frictions leads to an increase in welfare of USD 683 per trader per year (USD 604 from consumer surplus, USD 79 from government surplus). At a cost of USD 7 per user, this is equivalent to a cost-benefit ratio of 1%.

8.3 Estimating the Model

Following the model described above, I estimate the parameters α and v in the model. I estimate the parameters first by simply matching means (which I refer to Simple Mean Matching method) and then by a two-step Generalized Method of Moment (GMM) estimation with Gauss-Newton optimization. I rely only on the updated baseline (February 2021) to (i) avoid contamination from the treatment after baseline and (ii) allow myself to do a out of sample test of the model for the 2020 data (see next sections). For the GMM method I either use markups (referred to as GMM with markups) or profit margins (referred to as GMM with profit margins). Table 9 shows the results.

I use the following equilibrium relationship[23]:

$$p_m = \alpha \omega_m q_m^{\frac{1}{v}} \tag{8}$$

I add the following equilibrium results from the model :

[23]The time subscript is removed as I only rely on one round of data.

$$p_m = \frac{1}{1 + 1/v} * M_i \tag{9}$$

with M_i being marginal costs for trader i[24].

From (8) and (9)

$$Markup_i = \frac{p_m * q_i}{M_i * q_i} = \frac{1}{1 + 1/v} \tag{10}$$

$$ProfitMargin_i = \frac{Profits_i}{Sales_i * q_i} = -\frac{1}{v} \tag{11}$$

The general idea (for either method) is that equations 10 or 11 can be used to estimate v and equation 8 can then be used to estimate α, using estimated v.

8.3.1 Simple Mean Matching

In this very simple method, I simply match means. v is computed from using the mean of trader level markups in the data (using purchasing costs only for costs) and assigning estimated v to the mean. Panel A of Table 9 shows the means from the data used for each method. For the Simple Mean Matching, I match average $Sales_i$, $nmarkets_i$, $Markups_i$ and p_m to the data. Only one α is computed by estimating the average quantity per market q_m taking traders' average total sales (corrected for the average number of markets sold in) and dividing this average by the average price index across markets (see equation 12 and 13). Note that I use Sauti East Africa's back-end data to get an average price per market. Panel B of Table 9 shows the estimated α and v.

[24]Note that is assumes that each trader has the same markups and profit margins across the different markets they sell in.

$$Sales_m = \frac{Sales_i}{nmarkets_i} = \alpha\omega_m q_m^{\frac{v+1}{v}} \tag{12}$$

$$q_m = \frac{Sales_i}{p_m} * \frac{1}{nmarkets_i} \tag{13}$$

8.3.2 Generalized Method of Moment

I also estimate parameters using a two-step generalized method of moment estimation (GMM), with Gauss-Newton optimization. For v, I continue to use trader level markups but use them as instruments in a GMM estimation. For α, I estimate a specific α per good g, using the data at the transaction level. For each trader, I know the quantity of good sold in what market and at what price. The coefficient and SE in Panel B of Table 9 are therefore the average of all 30 estimated α and the respective standard error of the average. Each good level demand curve is estimated using prices per kg and quantities in kg. For this reason, in the GMM estimations (both GMM using markups[25] or profit margins) restrict the sample to agriculture goods for more consistent prices per kg.

Lastly, in the GMM estimation with profit margins, instead of using markups that only relies on purchasing costs for costs, I use trader level profit margins (dividing trader's profits by sales).

8.3.3 Results of Estimated Parameters

Panel B of Table 9 shows the estimated parameters and corresponding standard errors, using the three different methods. All methods end up estimating relatively similar parameters. v is estimated to be between -5.76 and -4.4 (depending on the methods) and is relatively precisely estimated. The average α across all goods varies between 273 and 353. Note that the large standard errors here do not mean α's are not precisely estimated, rather that there are (un-

[25] Again, I use average costs rather than marginal costs.

surprisingly) a large variation in α's across each good. Indeed, standard errors around each estimated α per good are on average 31.63 (not shown in Table).

8.4 Counterfactual Simulations

Using the estimated model, I now run a few counterfactuals. First, I use the model to predict prices in a scenario where formal crossings are closed. I compare my model predictions to the reduced form effect of the official border closure on prices. The data used to estimate my model (updated baseline) is different than the rounds of data used to estimate the reduced form effect of the official border closure. This implies that the comparison between my model predictions and reduced form results is valid. Then, I run a second counterfactual analysis and look at what would happen to market prices if the informal crossings were also shut down.

8.4.1 Out-of-Sample Prediction: No Formal Route

Using a Panel Mixed Logit model with route-specific random intercept (correlated), I estimate the mean and variance of the normal distribution of route-specific preferences (or fixed costs) as well as their covariance. That allows me to estimate the predicted choice probabilities, using control traders. Table 10 (Panel A), Row 1 shows choice probabilities averaged across the study period.

Table 10 (Panel A), Row 2 shows how, based on estimated route-specific preferences and covariance, the predicted choice probabilities change when a formal route is no longer an option. When the formal route closes, 81% of traders who used to use the official crossing are predicted to switch to domestic trade, 8% to informal border crossings, and 10% to exit[26]. Table 10 (Panel B) then highlights the model's predictions in terms of market prices. The model predicts that closing the formal border leads to a 7.5% increase in prices, which is comparable to the 8.7% increase estimated in the reduced form analysis of the effect of the

[26]Note that the large share of domestic traders comes from the fact that I am using the updated baseline to estimate the model.

closure of the official border (Table 8).

8.4.2 No Informal Route

A similar exercise can be carried out, now assuming the informal crossings are also closed. Table 10 (Panel A), Row 3 shows that 86% of informal traders who can no longer cross the border become domestic traders, while 14% exit. This means that, without the existence of informal crossings, 14% more traders would have stopped trading. Table 10 (Panel B) shows that, according to the model, having informal crossings prevented prices from going up by another 11.5%. This points to the importance of informal crossings in smoothing shocks. Without the existence of informal crossings, the closure of the border (and the consequences from Covid-19-related restrictions) would have led to significantly higher consumer prices.

8.5 Discussion about Formalization

As described above, reducing information frictions leads to welfare improvements stemming from trade formalization (governments' welfare increase from more tax revenues). However, the majority of the welfare gains come from consumers being able to buy cheaper goods. My results, taken together, do not advocate for a complete formalization of trade (i.e., closing informal crossings) as a way to maximize welfare. To the contrary, the different counterfactual analysis presented in this section show that closing informal crossings would lead to a reduction in welfare, especially during border shocks. Indeed, we would see gains from formalization but a larger loss from increased consumer prices. Reducing information frictions leads to increased welfare, however policies that push for a complete formalization of trade may not.

9 Conclusion

This paper shows that information frictions play a significant role in informal trade, which is an under-studied but important segment of trade. Using the closure of the official border as a shock, the paper first documents key insights about informal trade that point toward the existence of informal frictions. I develop and estimate a model that embeds informal frictions taking the form of uncertainty about and randomness in market conditions in other buying and selling markets. I test the model using a Randomized Controlled Trial that gave traders access to information about market prices and formal border costs. I provide evidence that information frictions play a large role: reducing information frictions improves traders' profits, increases formalization of trade, and reduces equilibrium market prices for consumers, leading to a large increase in welfare. It is important to keep in mind that, despite the potential welfare improvements of switching to formal routes (due to increased tax revenues), informal routes significantly help smooth prices in the event of shocks at the formal border.

In future work, I hope to disentangle the role played by traders' increased bargaining power and reduction in uncertainty in the effects observed due to reducing information frictions. In addition, insights on whether the results highlighted by this paper continue to hold long-term seems crucial. More rigorous and experimental work should also be done on understanding market structures and how information frictions affect those. Lastly, while this paper focuses on small-scale informal traders, more research is needed on understanding the role of scale such as the inter-dependencies between informal small-scale traders and formal larger traders and whether there is a transition from one to the other.

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Tables

Table 1: Traders' characteristics

	mean
Panel A. Socio-economic characteristics - Baseline	
CB-Official Crossing	0.19
CB-Informal Crossing	0.36
Domestic trader	0.45
Ag	0.79
Men	0.19
Age	40.81
Kenyan	0.94
Trade is main income	0.95
Has other source of income	0.40
N goods sold in past 3 months	2.51
Panel B. Traders' Costs - Updated baseline	
Total sales (3M, 00 Kshs)	1633.73
Total purchase costs (3M, 00 Kshs)	1228.83
Total costs (3M, 00 Kshs)	103.98
Total profits (3M, 00 Kshs)	288.20
Panel C. Information Environment - Baseline	
Market Prices	
Knows market price for main goods in other markets	0.38
Informs themselves about market prices	0.51
Echange Rates	
Informs themselves about exchange rates	0.18
Types of info shared	
Traders share info about market prices	0.77
Traders share info about exchange rates	0.29
Traders share info about taxes/tariffs	0.20
Observations	1166

Panel A shows means of traders' socio-economic characteristics. Panel B shows means of traders' profitability measures "in the past 3 months" (sales, costs and profits) measured in hundreds of Kenyan Shillings (Kshs) and over all goods traded. Traders who did not trade were assigned values of 0. Panel C describes means of variables related to traders' information environment and are all ratios or shares (i.e., total is 1). Panels A and C come from the baseline data (February 2020) and panel B comes from the updated baseline in February 2021.

Table 2: Model's Comparative Statics of Treatment Effect on Quantities and Prices

Panel A. Comp. Statics on Q	q_{ijtk}	q_{ihtk}
Purchasing Costs ($E[p^B_{kt}]$)	$(1+\frac{2}{\epsilon^{Buy}_{kt}})\frac{1}{\alpha E[\omega_{jt}]}\frac{1}{1+1/v}v[\frac{1}{\alpha E[\omega_{jt}]}\frac{1}{1+1/v}*Z_j]^{v-1}$	$(1+\frac{2}{\epsilon^{Buy}_{kt}})\frac{1}{\alpha\omega_{jt}}\frac{1}{1+1/v}v[\frac{1}{\alpha\omega_{jt}}\frac{1}{1+1/v}*Z_h]^{v-1}$
Purch Costs Uncert ($(\sigma^B_{ikt})^2$)	$\frac{\delta_1}{\alpha E[\omega_{jt}]}\frac{1}{1+1/v}v[\frac{1}{\alpha E[\omega_{jt}]}\frac{1}{1+1/v}*Z_j]^{v-1}$	$\frac{\delta_1}{\alpha\omega_{ht}}\frac{1}{1+1/v}v[\frac{1}{\alpha\omega_{ht}}\frac{1}{1+1/v}*Z_h]^{v-1}$
Other Variable Costs	$\frac{1}{\alpha E[\omega_{jt}]}\frac{1}{1+1/v}v[\frac{1}{\alpha E[\omega_{jt}]}\frac{1}{1+1/v}*Z_j]^{v-1}$	$\frac{1}{\alpha\omega_{ht}}\frac{1}{1+1/v}v[\frac{1}{\alpha\omega_{ht}}\frac{1}{1+1/v}*Z_h]^{v-1}$
Selling P Uncert ($(\sigma^\omega_{ijt})^2$)	$\frac{\delta_2}{\alpha E[\omega_{jt}]}\frac{1}{1+1/v}v[\frac{1}{\alpha E[\omega_{jt}]}\frac{1}{1+1/v}*Z_j]^{v-1}$	0

Panel B. Comp. Statics on P	p_{jtk}	p_{htk}
Purchasing Costs ($E[p^B_{kt}]$)	$\frac{1}{1+1/v}(1+\frac{2}{\epsilon^{Buy}_{kt}})$	$\frac{1}{1+1/v}(1+\frac{2}{\epsilon^{Buy}_{kt}})$
Purch Costs Uncert ($(\sigma^B_k)^2$)	$\frac{1}{1+1/v}\delta_1$	$\frac{1}{1+1/v}\delta_1$
Other Variable Costs	$\frac{1}{1+1/v}$	$\frac{1}{1+1/v}$
Selling Price Uncert ($(\sigma^S_\omega)^2$)	$\frac{1}{1+1/v}\delta_2$	0

Panel A shows how traders' quantities derived in the model change with a one unit change in the following: (i) Expected Purchasing Costs (line 1), (ii) Purchasing Costs Uncertainty (line 2), Other variable Costs which include Border Costs (means and variance), distance and market specific marginal cost (line 3) and (iv) Selling Price Uncertainty (line 4). The comparative statics are done for quantities in alternative market (Column 2) and home market (Column 3). In Panel B, the same structure is repeated for prices, i.e., Panel B shows comparative statics for the equilibrium market prices derived in the model. Note that $Z_j = E[p^B_{kt}(q_{iht}+q_{ijt})](1+\frac{2}{\epsilon^{Buy}_{kt}}) + \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) + \delta_4(\sigma^{BC}_{ikt})^2 + \mu d_{ikt} + c_{ijt} + \delta_1(\sigma^B_{ikt})^2 + \delta_2(\sigma^\omega_{ijt})^2$ and

$Z_h = E[p^B_{jt}(q_{iht}+q_{ijt})](1+\frac{2}{\epsilon^{Buy}_{kt}}) + \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) + \delta_4(\sigma^{BC}_{ikt})^2 + \mu d_{ikt} + c_{iht} + \delta_1(\sigma^B_{ikt})^2$.

Table 3: RCT Results: Trade, Supply Chain and Trade Route Choice

Panel A: RCT Results: Trade Outcomes

	Traded		N Goods		Trade Main Income
	(1) Rounds 1-3	(2) Endline	(3) Rounds 1-3	(4) Endline	(5) Endline
Treatment	-0.007	0.035*	-0.061	0.007	0.035**
	[0.008]	[0.021]	[0.140]	[0.188]	[0.014]
Post x Treatment	0.046***		0.230**		
	[0.016]		[0.103]		
Dep Var Mean (Control)	0.964	0.873	2.784	2.690	0.936
R-Squared	.037	.003	.013	0	.007
Pre-Period	X		X		
Observations	4952	915	4951	914	894

Panel B: RCT Results: Supply Chain Outcomes

	N Supp. Markts		N Selling Markets		N Trips	
	(1) Rounds 1-3	(2) Endline	(3) Rounds 1-3	(4) Endline	(5) Rounds 1-3	(6) Endline
Treatment	-0.029	0.085**	-0.105	0.105	0.410**	1.863
	[0.042]	[0.041]	[0.072]	[0.076]	[0.178]	[1.236]
Post x Treatment	0.078*		0.181***			
	[0.044]		[0.060]			
Dep Var Mean (Control)	1.172	1.017	1.593	1.424	2.610	20.435
R-Squared	.033	.005	.01	.002	.005	.003
Pre-Period	X		X			
Observations	3653	912	3766	914	2832	913

Panel C: RCT Results: Choice of Trade Routes

	Cross Border			Formal		Informal	
	(1) Rounds 1-3	(2) Endline	(3) Rounds 1-2	(4) Rounds 1-3	(5) Endline	(6) Rounds 1-3	(7) Endline
Treatment	0.020	0.024	0.047*	-0.026	-0.002	0.042**	0.018
	[0.024]	[0.030]	[0.026]	[0.016]	[0.018]	[0.021]	[0.025]
Post x Treatment	0.015			0.035**		-0.008	
	[0.022]			[0.017]		[0.021]	
Dep Var Mean (Control)	0.399	0.279	0.247	0.150	0.083	0.246	0.162
R-Squared	.072	.001	.003	.02	0	.052	.001
Pre-Period	X			X		X	
Observations	4947	914	1886	4947	914	4947	914

This table shows the treatment effects of the Randomized Controlled Trial on trade outcomes (Panel A), supply chain outcomes (Panel B) and route choice outcomes (Panel C). In Panel A, Traded is measured by a binary variable switching to 1 if traders traded in the past two weeks (Column 1) and in the past month (Column 2). Columns labeled "Rounds 1-3" include follow-up surveys 1, 2 and 3; Columns labeled "Rounds 1-2" include follow-up surveys 1 and 2; while Columns labeled "Endline" focus on the endline. Columns that include "Pre-period" means that the specification included baseline and updated baseline. When that's the case, the variable of interest is "Post x Treatment". Columns labeled "Rounds 1-3" include rounds fixed effects. Standard errors (reported in brackets) are clustered at the trader level for specifications labeled "Rounds 1-3" and robust otherwise. * p<0.1, ** p<0.05, *** p<0.01.

Table 4: RCT Results: Sales, Profits and Costs

Panel A: RCT Results: Sales and Profits

	Sales		Profits		Stock	
	(1) Rounds 1-3	(2) Endline	(3) Rounds 1-3	(4) Endline	(5) Rounds 1-3	(6) Endline
Treatment	0.556***	0.455*	0.483***	0.353*	0.175	0.138
	[0.192]	[0.250]	[0.172]	[0.214]	[0.230]	[0.292]
Dep Var Mean (Control)	8.751	10.028	7.059	8.456	6.421	6.576
R-Squared	.009	.004	.008	.003	.001	0
RoundFE	X		X		X	
Observations	2790	898	2792	895	2806	906

Panel B: RCT Results: Main Costs

	Total		Per Sales		Per Trip	
	(1) Purch. Costs	(2) Oth. Costs	(3) Purch. Costs	(4) Oth. Costs	(5) Purch. Costs	(6) Oth. Costs
Treatment	0.292**	0.039	0.009	-0.010*	0.133	-0.034
	[0.123]	[0.081]	[0.018]	[0.006]	[0.085]	[0.087]
Dep Var Mean (Control)	9.738	7.701	0.827	0.117	9.265	6.801
R-Squared	.007	.008	.001	.003	.006	.005
Observations	2430	2434	2402	2398	2076	2072

Panel C: RCT Results: Deep Dive in Other Costs

	Total			Per Sales			Per Trip		
	(1) Formal Taxes	(2) Transport	(3) Bribes	(4) Formal Taxes	(5) Transport	(6) Bribes (E)	(7) Formal Taxes	(8) Transport	(9) Bribes
Treatment	30.944	-315.911	107.014**	-0.002*	-0.011**	0.000	-5.563	-16.940	4.001
	[20.320]	[367.111]	[52.939]	[0.001]	[0.005]	[0.000]	[8.789]	[197.730]	[2.888]
Dep Var Mean (Control)	219.849	2238.009	78.128	0.018	0.081	0.001	111.202	860.783	5.826
R-Squared	.005	.001	.005	.002	.004	.001	.002	.001	.003
Observations	2832	2463	894	2416	2412	809	2102	2098	783

This table shows the treatment effects of the RCT on sales, profits and stock value (Panel A), costs (Panel B) and specific costs (Panel C). Values are in Kshs. In Panel A and B, they are transformed to inverted hyperbolic sine. B and in Panel C, they are in levels and in Kshs (transformations into IHS do not change the results). In Panel A, Columns labeled ”Rounds 1-3” include follow-up surveys 1, 2 and 3, while columns labeled ”Endline” focus on the endline. None of the specifications include baseline or updated baseline controls. Columns labeled ”Rounds 1-3” include rounds fixed effects. Standard errors (reported in brackets) are clustered at the trader level for specifications labeled ”Rounds 1-3” and robust otherwise. In Panel B and C, all specifications include rounds 1-3, except for Columns 3, 6 and 9 of Panel C, which includes the endline. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 5: RCT Results: Heterogeneity by Trader Type

Panel A: Treatment Effect Heterogeneity on Probability of Crossing the Border

	Prob of being Cross-border Trader
Treatment × Sticky (CB-Dom-Dom)	0.002
	[0.059]
Treatment × Adaptors (CB-Dom-CB)	0.126*
	[0.066]
Treatment × Domestic (Dom-Dom-Dom)	0.022
	[0.044]
Treatment × CB (CB-CB-CB)	0.230*
	[0.125]
Treat	-0.006
	[0.041]
Sticky (CB-Dom-Dom)	0.116***
	[0.042]
Adaptors (CB-Dom-CB)	0.436***
	[0.048]
Domestic (Dom-Dom-Dom)	-0.163***
	[0.031]
CB (CB-CB-CB)	0.527***
	[0.110]
Dep Var Mean (Control)	0.312
R-Squared	.295
Round FE	X
Observations	1845

Panel B: Treatment Effect Heterogeneity on Route Choice

	(1) Formalization-Init.Formal	(2) Formalization-Init.Inf	(3) Formalization-Init.Domestic
Treatment	-0.082	-0.077*	-0.033**
	[0.060]	[0.044]	[0.015]
Post x Treatment	0.034	0.053	0.044**
	[0.097]	[0.061]	[0.019]
Dep Var Mean (Control)	0.799	0.781	0.297
R-Squared	.181	.035	.021
Pre-Period	X	X	X
Round FE	X	X	X
Observations	319	675	4661

This table looks at heterogeneity of treatment on the probability of crossing the border to trade (Panel A) and on probability of choosing the official route (Panel B). In Panel A, heterogeneity groups are defined by status at baseline-updated baseline-endline. Rounds included in the analysis are follow-up 1 and 2. Standard errors (reported in brackets) are robust. Panel B runs separate specifications for each type of traders: those who were initially cross border traders crossing officially (Column 1), initial cross border traders crossing unofficially (Column 2) and initial domestic traders (Column 3). The specifications focus on baseline, updated baseline, follow-up surveys 1, 2 and 3 and endline and include rounds fixed effects. Standard errors (reported in brackets) are clustered at the trader level. * p<0.1, ** p<0.05, *** p<0.01.

Table 6: RCT Results: Non Tariff Barriers

	Corruption		Harassment		Corruption (CB Sample)		Harassment (CB Sample)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Rounds 1-3	Endline	Rounds 1-3	Endline	Rounds 1-3	Endline	Rounds 1-3	Endline
Treatment	0.009	0.023	0.000	-0.001	0.020	0.068	-0.001	-0.008
	[0.010]	[0.018]	[0.005]	[0.006]	[0.023]	[0.062]	[0.013]	[0.023]
Post x Treatment	0.002		0.004		0.003		0.011	
	[0.012]		[0.007]		[0.037]		[0.023]	
Dep Var Mean (Control)	0.046	0.067	0.013	0.008	0.137	0.339	0.036	0.036
R-Squared	.01	.002	.003	0	.085	.005	.012	.001
Pre-Period	X		X		X		X	
Observations	4905	915	4905	915	1465	226	1465	226

This table looks at the effect of the RCT on non tariff barriers such as corruption and harassment. The outcome variables are incidence of corruption and harassment, defined as the probability of traders reporting facing corruption (Columns 1-2 and 5-6) or harassment (Columns 3-4 and 7-8). Columns 1-4 look at the whole sample, while Columns 5-8 restrict the sample to traders who cross the border (note these are traders who cross the border at the time of the survey, not those who initially crossed the border at baseline; which therefore implies selection issues). In Columns 1, 3, 5 and 7, rounds included in the analysis are baseline, updated baseline and follow-ups 1, 2 and 3. The specifications include rounds fixed effects. The coefficient of interest is Post x Treatment. Standard errors (reported in brackets) are clustered at the trader level. In Columns 2, 4, 6 and 8, the only round included in the analysis is the endline. The coefficient of interest is Treatment. Standard errors (reported in brackets) are robust. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 7: GE Effects of RCT: Market prices

Panel A: Selling Market Prices ("App Data")

	Retail (Sell)		
	(1)	(2)	(3)
	Price Levels	Price Logs	CPI (Log)
Intensity Treat x Post	-21.558***	-0.038*	-0.282**
	[3.369]	[0.023]	[0.116]
Intensity Treat	14.819***	-0.013	0.174
	[3.333]	[0.022]	[0.114]
Post	22.448***	0.106***	0.226**
	[2.713]	[0.016]	[0.094]
Dependent Variable Control Mean	117.252	4.471	4.271
R-Squared	.728	.744	.067
Product FE	X	X	
Observations	21965	21965	323

Panel B: Buying Market Prices ("App Data")

	Retail (Buy)			Wholesale (Buy)		
	(1)	(2)	(3)	(4)	(5)	(6)
	Price Levels	Price Logs	CPI (Log)	Price Levels	Price Logs	CPI (Log)
Intensity Treat x Post	-6.489	-0.144***	-0.246***	-15.643***	-0.128***	-0.291***
	[5.145]	[0.012]	[0.063]	[2.041]	[0.012]	[0.063]
Intensity Treat	2.754	0.036***	0.137***	8.091***	0.018*	0.142***
	[2.496]	[0.010]	[0.048]	[2.026]	[0.011]	[0.052]
Post	6.299**	0.123***	0.089**	-13.957***	-0.011	-0.147***
	[2.709]	[0.008]	[0.038]	[1.294]	[0.008]	[0.040]
Dependent Variable Control Mean	90.846	4.247	4.243	83.367	4.117	4.122
R-Squared	.157	.607	.078	.375	.622	.224
Product FE	X	X		X	X	
Observations	62184	62184	1064	56339	56339	1013

This table looks at the effect of treatment intensity on aggregate market prices, using back-end data from the phone platform. Goods included are agriculture goods and the types of goods sold by traders in my sample. Panel A describes selling prices and Panel B buying prices (Columns 1-3 are retail, Columns 4-6 are wholesale). Variable Intensity of Treatment is constructed using the intensity of treatment of a buying or selling market based on baseline randomization. As the platform markets do not perfectly match the randomization, the randomization value of the closest sample market is assigned to the platform market. I only include markets that are less than or equal to 25kms to a sample market. Data ranges from 2019 to 2021. Post in a binary variable taking the value of 1 if the data is after implementation. Specifications control for countries and currency fixed effects. Columns 1 and 4 run a specification that includes all data and controls for product fixed effects. Columns 2 and 5 run the same specification in logs. Columns 3 and 6 run a market level specification after creating a standard consumer price index (average of log prices). The CPI here is flatly weighted (see Appendix for weighted CPIs). Standard errors (reported in brackets) are clustered at the market level. * p<0.1, ** p<0.05, *** p<0.01.

Table 8: Comparing treatment effect to cost of distance

	Retail		Wholesale	
	(1) Price Levels	(2) CPI (Log)	(3) Price Levels	(4) CPI (Log)
Closure x Dist to Border	-0.146*	-0.002**	-0.110	-0.002**
	[0.085]	[0.001]	[0.069]	[0.001]
Distance to border (Kms)	0.143*	0.001*	0.103	0.002***
	[0.085]	[0.001]	[0.072]	[0.001]
Closure of Off Border	6.979	0.093*	4.124	0.072
	[7.264]	[0.051]	[6.368]	[0.053]
Dep Var Mean (Control)	79.273	4.208	64.857	3.872
R-Squared	.401	.238	.718	.18
Year FE	X	X	X	X
SE Clustered	X		X	
Selected Goods	X	X	X	X
Dist from Border	100	100	100	100
Observations	28534	457	25335	441

This table regresses market prices from the platform's back-end data on distance to the border, a dummy variable for whether the official border was closed and the interaction of both of these variables. The specification also includes country fixed effects, currency fixed effects and year fixed effects. Distance is calculated as a straight line from the border and is in kms. Market prices used are prices from markets located within 100 kms from the border in Busia. Goods included are agriculture goods and types of goods sold by traders in my sample. I only include goods that were easily convertible to a price per kg. Columns 1-2 report retail prices and Columns 3-4 report wholesale prices. Columns 1 and 3 use all prices in Kenyan Shillings per kg (Ugandan prices were transformed to Kshs using the average exchange rates) and Columns 2 and 4 use a standard consumer price index (average of log prices). The CPI here is flatly weighted. Standard errors (in bracket) are clustered at the market level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 9: Estimating Model's Parameters

Panel A: Sample data used for moments	Mean	SE
Simple Mean Matching		
$Sales_i$ (Kshs)	24616	
$nmarkets_i$	1.6	
$Markup_i$	1.21	
p_m (index)	117	
Computed $Sales_m$ (Kshs)	15385	
Computed q_m (index bundle)	131.5	
GMM		
$Markup_i$	1.53	2.02
$ProfitMargin_i$	0.22	0.23
q_{igm} (Kg)	4587.73	21955.89
p_{igm} (Kshs per kg)	81.42	86.45

Panel B: Parameter Estimates	Coefficient	SE
Simple Mean Matching		
v	-5.76	
α	273	
GMM with markups		
v	-4.40	0.2
α_g	353.02	243.58
GMM with profit margins		
v	-4.86	0.12
α_g	306.73	204.94

This table shows the estimates of the model parameters. Panel A shows the summary statistics taken from the data and used to estimate the parameters. Panel B shows the resulting parameter estimates and Standard Errors when relevant. I use 3 methods to estimate the parameters. First, the Simple Mean Matching simply matches means. v is computed from trader level markups (using purchasing costs only). Only one α is computed using traders' average sales (corrected for the average number of markets sold in) and the average price index across markets. Second I use a generalized method of moment estimation, using sample data variables as instruments and a Gauss-Newton optimization in a 2 step estimation. Here, a α per good g is estimated. The coefficient and SE in Panel B are therefore the average of all 30 estimated α and the respective SE of the average. v is computed from trader level markups (using purchasing costs only) or from trader level profit margins (using profit data). The data used is the updated baseline and Sauti's price data (for the Simple Mean Matching method) while the GMM estimations restrict the sample to agriculture goods for more consistent prices per kg.

Table 10: Counterfactual Model Simulations: Closure of trade routes

Panel A: Choice Probabilities: Substitution Patterns

	Domestic	**Exit**	**Formal**	**Informal**
Initial Model (4 routes)	0.769	0.129	0.038	0.063
	(0.012)	(0.010)	(0.041)	(0.008)
No Formal	0.8	0.133	0	0.066
	(0.013)	(0.010)	(0.000)	(0.008)
No Formal, No Informal	0.857	0.142	0	0
	(0.011)	(0.011)	(0.000)	(0.000)

Panel B: Counterfactual Simulations: Model Predictions on Prices

	Mean
Initial quantity by trader (Kg)	131
Initial $p_{mtk}(Kshs)$	114
No Formal Route	
Total Quantity exited (Kg)	554
Quantity exited by market (Kg)	41
New quantity by trader (Kg)	90
New p_{mtk} (Kshs)	122
Δp_{mtk}	7.5%
No Informal Route, No Formal Route	
Total Quantity exited (Kg)	1183
Quantity exited by market (Kg)	82
New quantity by trader (Kg)	49
New p_{mtk} (Kshs)	136
Δp_{mtk}	19%

This table shows the results of the counterfacutal analysis. Panel A shows how the shares in route choice vary in each scenario. Taking these shares into consideration, Panel B shows how aggregate market prices would change in each scenario.

Figures

Figure 1: Data Collection and Intervention Timeline

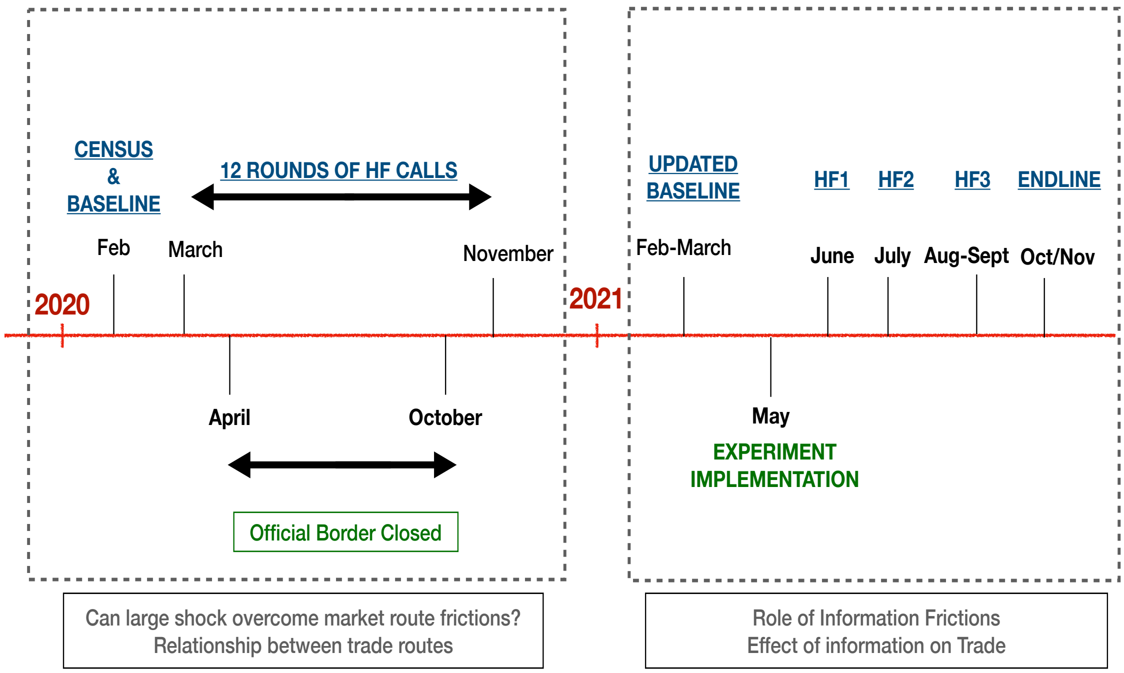


Figure 2: Market prices across time

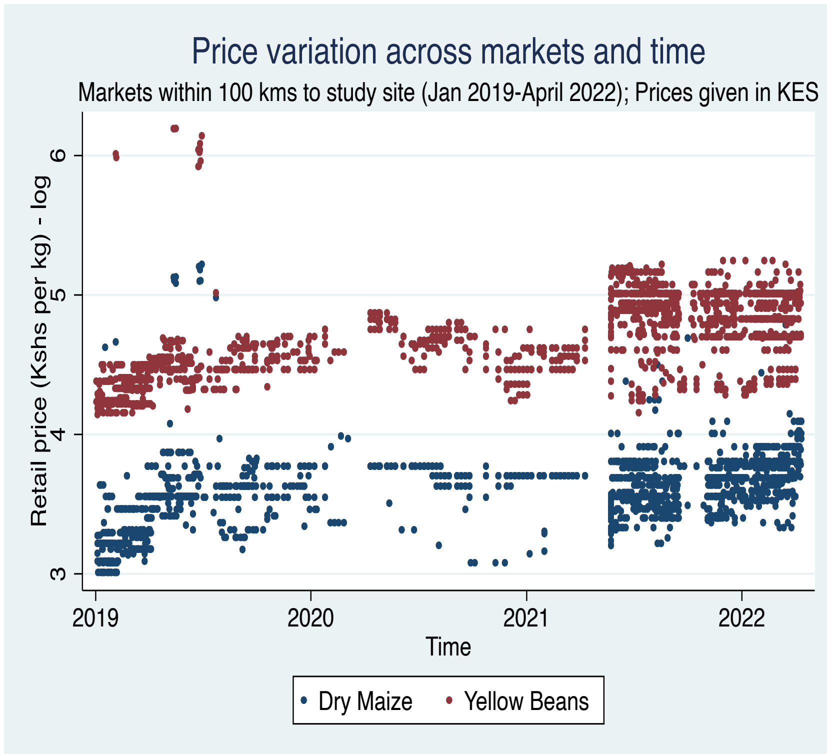
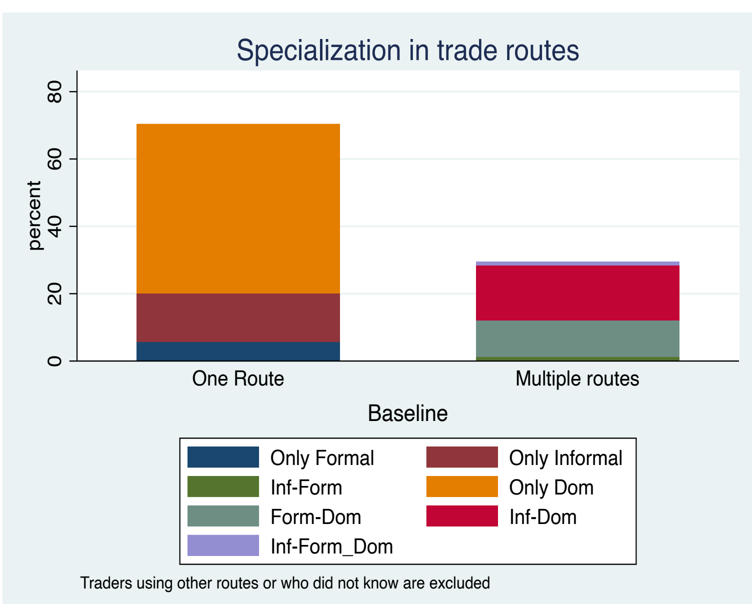


Figure 3: Market and Route Specialization



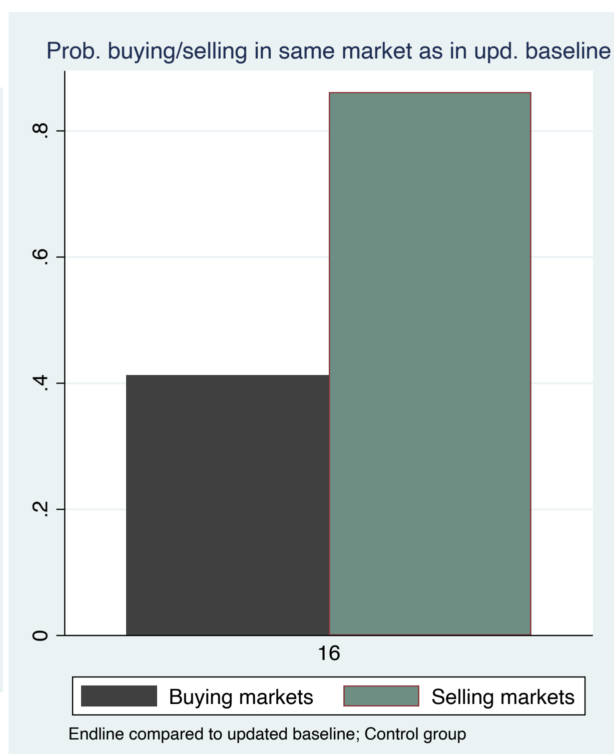
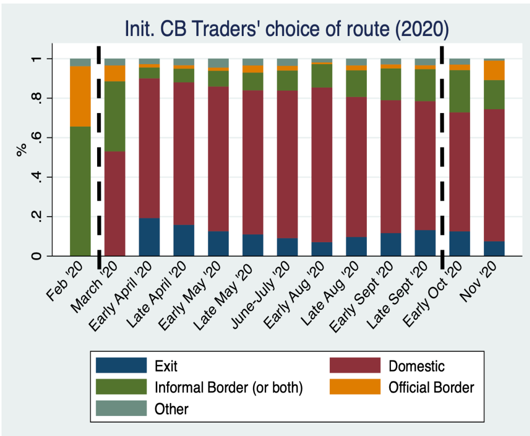


Figure 4: Border Closure effect on route choice - CB and Domestic traders



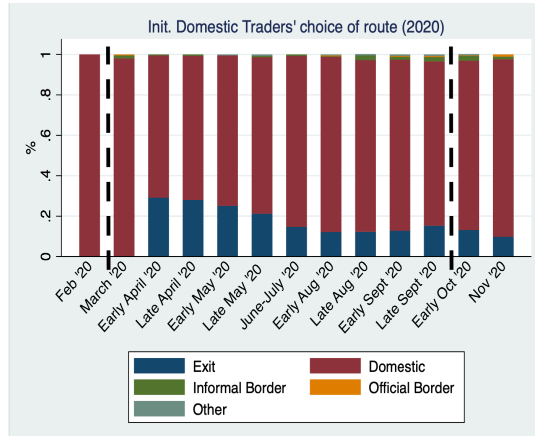


Figure 5: Route choice when border re-opens

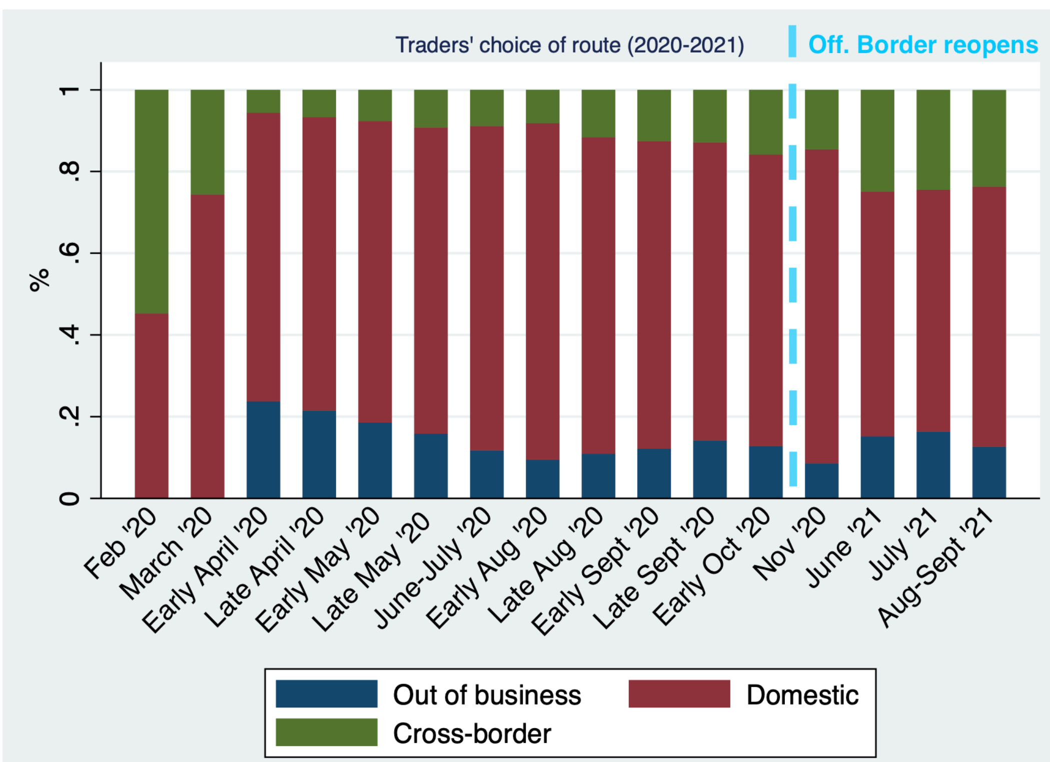


Figure 6: Overview of Model

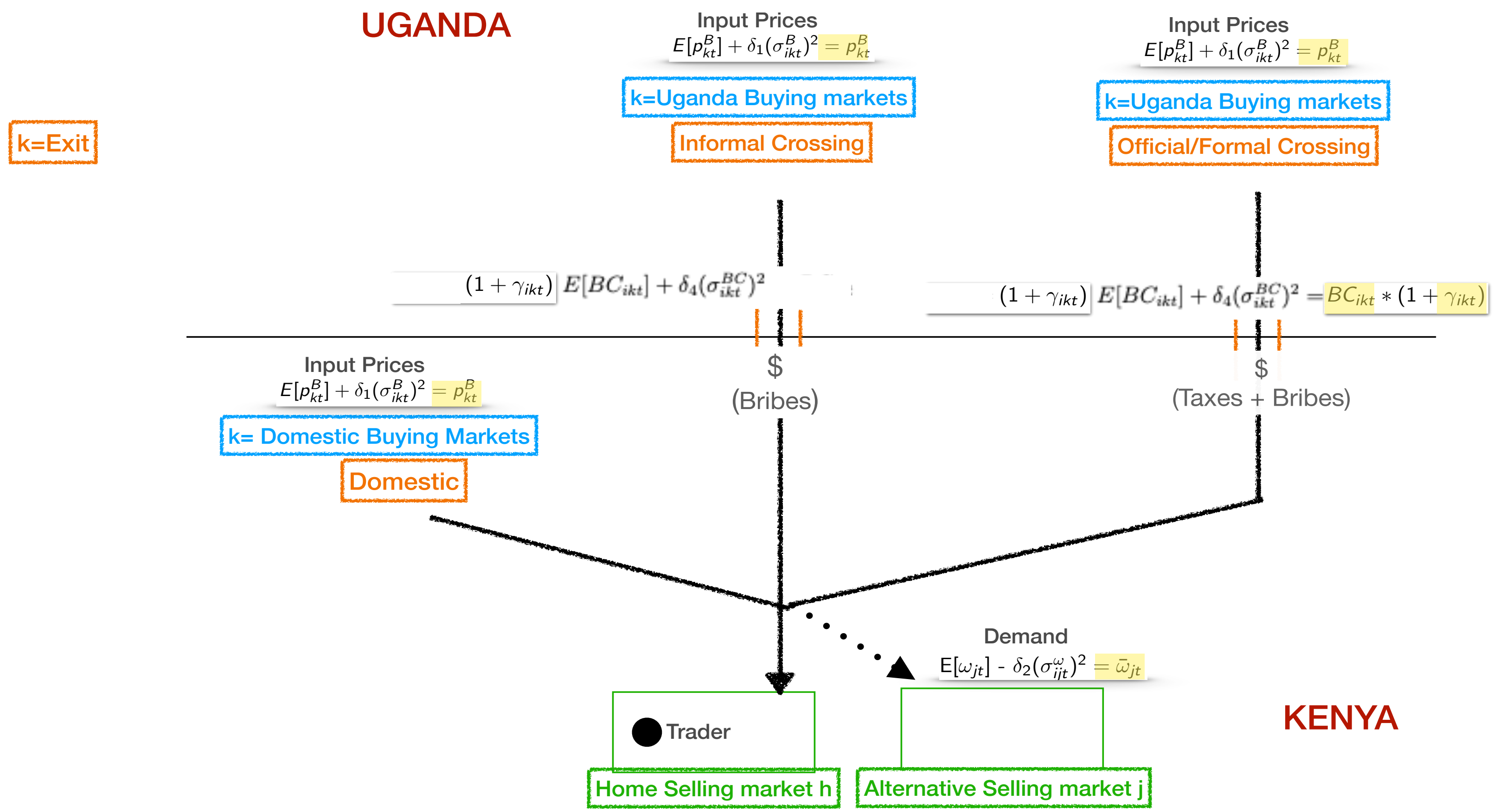


Figure 7: First Stage: Distribution of number of months of usage (Treatment Group)

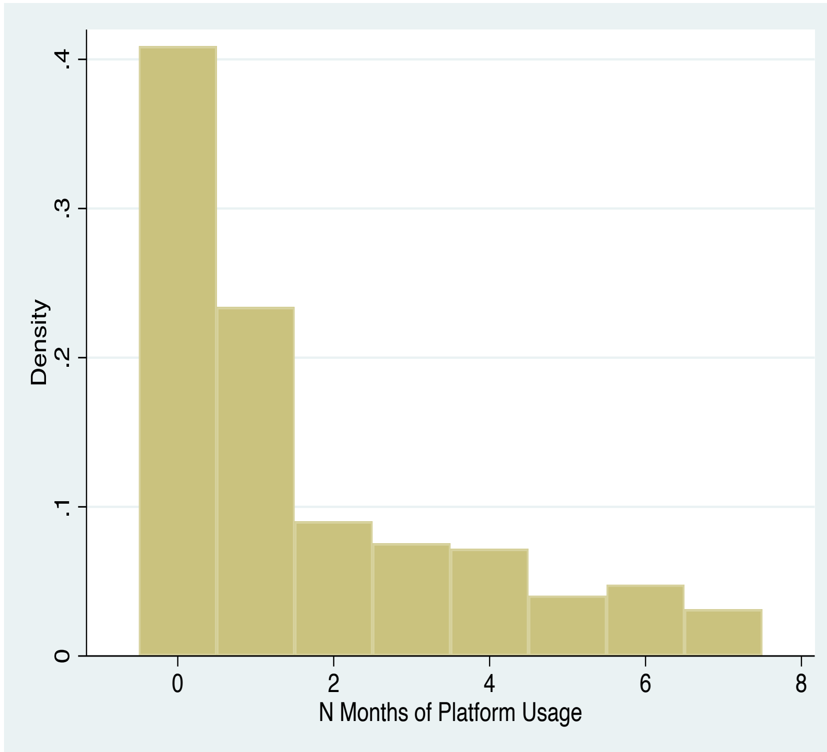


Figure 8: First Stage: N users, sessions and sessions per user (Treatment Group, conditional on usage)

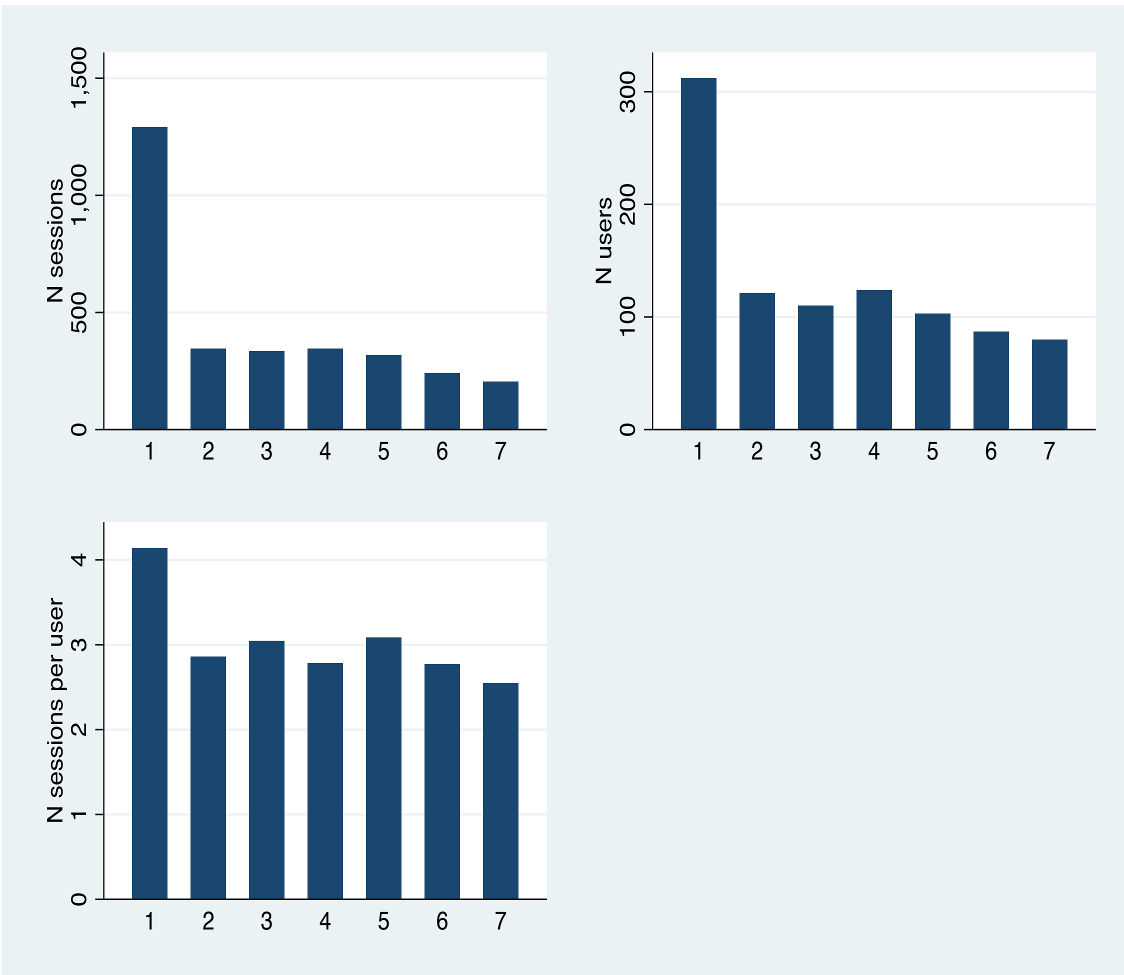
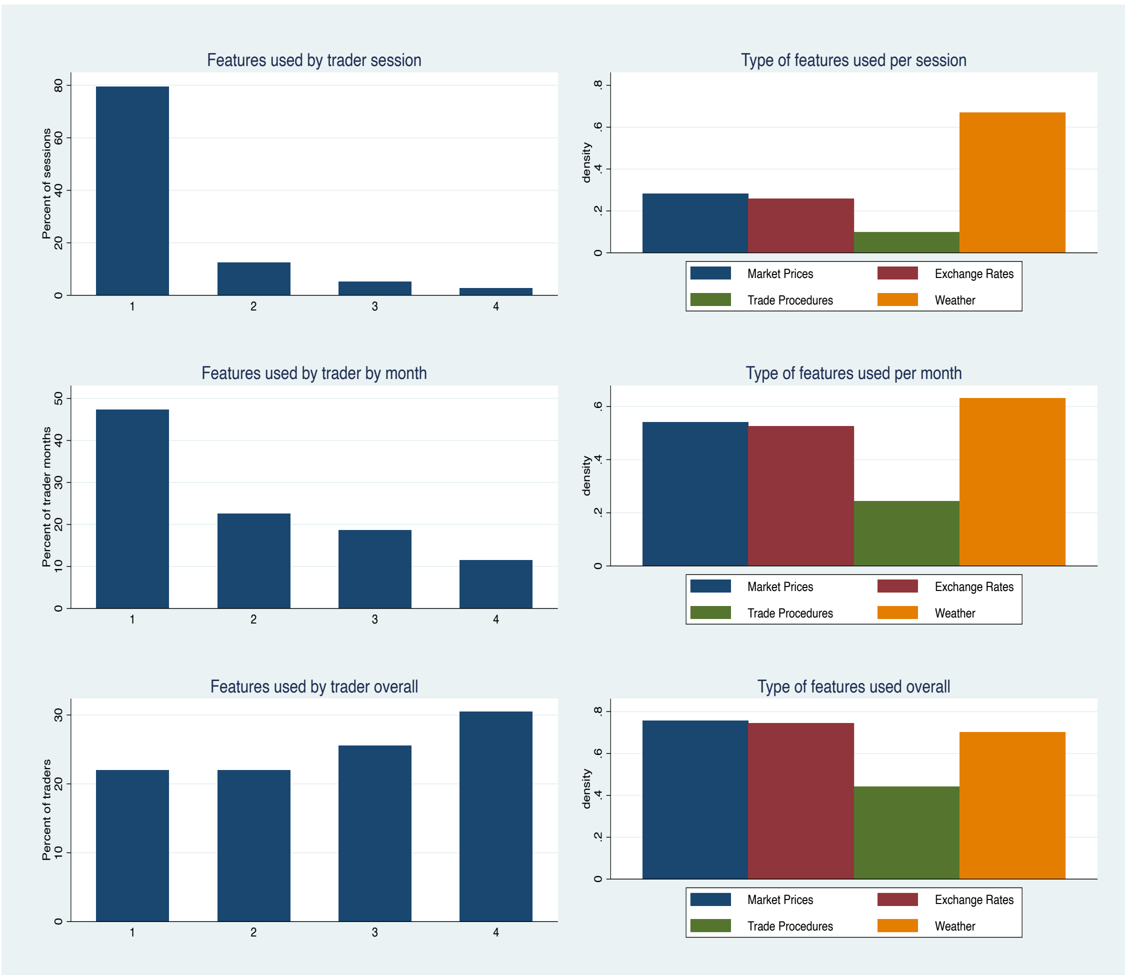


Figure 9: First Stage: Type of features requested (Treatment Group, conditional on usage)



Appendix

Appendix Section A: Model

9.1 Trader's Maximization Problem

9.1.1 Trader's Utility

Trader i maximizes her (risk-averse) utility by maximizing expected revenues and minimizing expected costs. Her utility is a standard profit function including a quadratic term in price gaps between selling and buying markets and in border costs. The utility for trader i, using market route k at time t, is as follows. Note that trader i's utility for market route k at time t includes quantities sold in home market h and alternative market j, conditional on using market route k (which is why quantities vary by market route k).

$$
\begin{aligned}
&MaxV_{ikt} = \\
&E[\sum_{m=h,j}\{[p^S_{mtk}(q_{imtk}) - p^B_{kt}(q_{ijtk}+q_{ihtk})] * q_{imtk} + \delta[p^S_{mtk}(q_{imtk}) - p^B_{kt}(q_{ijtk}+q_{ihtk})]^2 * q_{imtk}\} - \\
&[\delta_3 BC_{ikt}(1+\gamma_{ikt}) + \delta_4 BC^2_{ikt} + \mu d_{ikt}] * (q_{ihtk}+q_{ijtk}) + c_{iht}q_{ihtk} + c_{ijt}q_{ijtk} + \lambda_{ik} + u_{ikt}]
\end{aligned}
\tag{A1}
$$

Trader i has full information about random demand shocks ω_{ht} in her home market h but faces uncertainty about random demand shocks ω_{jt} in the other selling market j. Passing through the expectations, expected prices become $E[p_{jtk}] = \alpha E[\omega_{jt}]q_{ijtk}^{\frac{1}{v}}$ and $p_{htk} = \alpha\omega_{ht}q_{ihtk}^{\frac{1}{v}}$ and trader i's utility simplifies to the following:

$$
\begin{aligned}
&MaxV_{ikt} = \\
&[\alpha E[\omega_{jt}]q_{ijtk}^{\frac{1}{v}} - \delta_2(\sigma^{\omega}_{ijt})^2] * q_{ijtk} + \alpha\omega_{ht}q_{ihtk}^{\frac{1}{v}} * q_{ihtk} - [E[p^B_{kt}(q_{ijtk}+q_{ihtk})] + \delta_1(\sigma^B_{ikt})^2] * (q_{ihtk}+q_{ijtk}) - \\
&[\delta_3 E[BC_{ikt}](1+\gamma_{ikt}) + \delta_4(\sigma^{BC}_{ikt})^2 + \mu d_{ikt}] * (q_{ihtk}+q_{ijtk}) + c_{iht}q_{ihtk} + c_{ijt}q_{ijtk} + \lambda_{ik} + u_{ikt}
\end{aligned}
\tag{A2}
$$

with

- Expected revenues from selling in market h and j, conditional on using market route k: $[\alpha E[\omega_{jt}]q_{ijtk}^{\frac{1}{v}} - \delta_2(\sigma_{ijt}^{\omega})^2] * q_{ijtk} + \alpha\omega_{ht}q_{ihtk}^{\frac{1}{v}} * q_{ihtk}$

- Expected costs split between (i) purchasing costs $E[p_{kt}^B] * (q_{ihtk} + q_{ijtk})$, (ii) border costs $\delta_3 E[BC_{ikt}] + \delta_4(\sigma_{ikt}^{BC})^2$ (Tariffs if k = Uganda/Formal and Bribes if k = Uganda/Informal), (iii) bargaining power $1+\gamma_{ikt}$ (with $\gamma_{ikt} \geq 0$) (iv) distance μd_{ikt} and (v) selling market-specific marginal cost for home market c_{ijt} and alternative market c_{iht}

- λ_{ik} utility associated with using buying market-route k. λ_{ik} includes supplier relationship, experience/comparative advantage, access to information or fixed costs

- $\delta_1 \geq 0$, $\delta_2 \geq 0$, $\delta_3 \geq 0$, $\delta_4 \geq 0$

9.1.2 Order of Maximization

Order of maximization (backwards induction):

Step 1: For each possible market-route k, trader chooses optimal quantities q_{ihtk}^* and q_{ijtk}^* to sell in home market h and alternative selling market j, conditional on using market route k

Step 2: Taking optimal quantity for market route k as given $q_{ikt} = q_{ihtk} + q_{ijtk}$, trader i chooses which market route k^* to use (Uganda/Formal, Uganda/Informal, Kenya/Domestic, Exit) to maximize utility V

9.2 Step 1: Solving for Prices and Quantities in Selling Markets

9.2.1 Solving for Prices

Trader i chooses q_{ihtk} and q_{ijtk} by maximizing V_{ikt}. Trader i therefore computes an optimal pair of quantities sold in home and alternative market q_{ihtk} and q_{ijtk} for each of the four alternative market routes k.

Following standard FOCs :

$$\frac{\partial V_{ikt}}{\partial q_{ijtk}} = \alpha E[\omega_{jt}]q_{ijtk}^{\frac{1}{v}} - \delta_2(\sigma_{ijt}^S)^2 + \frac{\partial \alpha E[\omega_{jt}]q_{ijtk}^{\frac{1}{v}}}{\partial q_{ijtk}} * q_{ijtk} - E[p_{kt}^B(q_{ihtk} + q_{ijtk}, q_{-ikt})] - \delta_1(\sigma_{ik}^B)^2 -$$
$$\frac{\partial E[p_{kt}^B(q_{ihtk} + q_{ijtk}, q_{-ikt})]}{\partial q_{ijtk}} * (q_{ijtk} + q_{ihtk}) - \delta_3 E[BC_{ikt}](1 + \gamma_{ikt}) - \delta_4(\sigma_{ikt}^{BC})^2 - \mu d_{ikt} - c_{ijt} = 0$$
$$\frac{\partial V_{ikt}}{\partial q_{ihtk}} = \alpha \omega_{ht} q_{ihtk}^{\frac{1}{v}} + \frac{\partial \alpha \omega_{ht} q_{ihtk}^{\frac{1}{v}}}{\partial q_{ihtk}} * q_{ihtk} - E[p_{kt}^B(q_{ihtk} + q_{ijtk}, q_{-ikt})] - \delta_1(\sigma_{ik}^B)^2 -$$
$$\frac{\partial E[p_{kt}^B(q_{ihtk} + q_{ijt}, q_{-ikt})]}{\partial q_{ihtk}} * (q_{ihtk} + q_{ijtk}) - \delta_3 E[BC_{ikt}](1 + \gamma_{ikt}) - \delta_4(\sigma_{ikt}^{BC})^2 - \mu d_{ikt} - c_{iht} = 0$$
(A3)

Solving for p_{jtk} and p_{htk}:

Following the standard monopoly optimal pricing strategy, setting the mark-up over marginal costs as a function of the price elasticity of demand in the selling market, I solve for price[27] as a function of the price elasticity of demand in selling market v and price elasticity of supply (elasticity of marginal cost)[28] ϵ_{kt}^{Buy}

$$E[p_{jtk}^S] = \frac{1}{1+1/v} * [E[p_{kt}^B(q_{ihtk} + q_{ijtk})](1 + \frac{2}{\epsilon_{kt}^{Buy}}) + \delta_3 E[BC_{ikt}](1 + \gamma_{ikt}) + \delta_4(\sigma_{ikt}^{BC})^2 + \mu d_{ikt} + c_{ijt} + \delta_1(\sigma_{ikt}^B)^2 +$$
$$\delta_2(\sigma_{ijt}^{\omega})^2]$$
$$p_{htk}^S = \frac{1}{1+1/v} * [E[p_{kt}^B(q_{ihtk} + q_{ijtk})](1 + \frac{2}{\epsilon_{kt}^{Buy}}) + \delta_3 E[BC_{ikt}](1 + \gamma_{ikt}) + \delta_4(\sigma_{ikt}^{BC})^2 + \mu d_{ikt} + c_{iht} + \delta_1(\sigma_{ikt}^B)^2]$$
(A4)

Using the structure imposed in buying markets (equation 2):

[27] See appendix for derivations of the model without demand structure and for full derivations with demand structure

[28] Again, I am assuming the partial effect on expectation of price is the same as the partial effect on price

$$E[p^S_{jtk}] = \frac{1}{1+1/v} * [\zeta E[b_{kt}]Q^B_{kt}(1+\frac{2}{\epsilon^{Buy}_{kt}}) + \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) + \delta_4(\sigma^{BC}_{ikt})^2 + \mu d_{ikt} + c_{ijt} + \delta_1(\sigma^B_{ikt})^2 + \delta_2(\sigma^\omega_{ijt})^2]$$

$$p^S_{htk} = \frac{1}{1+1/v} * [\zeta E[b_{kt}]Q^B_{kt}(1+\frac{2}{\epsilon^{Buy}_{kt}}) + \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) + \delta_4(\sigma^{BC}_{ikt})^2 + \mu d_{ikt} + c_{iht} + \delta_1(\sigma^B_{ikt})^2] \tag{A5}$$

with $1/v = 1/\epsilon^{Sell}_{htk} = \frac{\partial p^S_{htk}(q_{ihtk})}{\partial q_{ihtk}} * \frac{q_{ihtk}}{p^S_{htk}}$ = $1/\ \epsilon^{Sell}_{jtk} = \frac{\partial p^S_{jtk}(q_{ijtk})}{\partial q_{ijtk}} * \frac{q_{ijtk}}{p^S_{jtk}}$ as I am assuming partial effect on expectation of price is the same as partial effect on price $\frac{\partial E[p^S_{jtk}(q_{ijtk})]}{\partial q_{ijtk}} * \frac{q_{ijtk}}{E[p^S_{jtk}]} = \frac{\partial p^S_{jtk}(q_{ijtk})}{\partial q_{ijtk}} * \frac{q_{ijtk}}{p^S_{jtk}}$; and $1/\epsilon^{Buy}_{kt} = \frac{\partial p^B_{kt}(q_{ijtk}+q_{ihtk})}{\partial q_{ihtk}} * \frac{q_{ihtk}}{p^B_{kt}} = \frac{\partial p^B_{kt}(q_{ijtk}+q_{ihtk})}{\partial q_{ihtk}} * \frac{q_{ijtk}}{p^B_{kt}}$

9.2.2 Selling Market Entry Conditions

Traders enter selling market m if their expected profits from selling in market m are positive. The entry condition for home market and for alternative market:

$$\begin{aligned} p^S_{htk}(q_{ihtk}) - E[p^B_{kt}(q_{ihtk}+q_{ijtk})] - \delta_1(\sigma^B_{ikt})^2 - \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) - \delta_4(\sigma^{BC}_{ikt})^2 - \mu d_{ikt} \geq c_{iht} \\ E[p^S_{jtk}(q_{ijtk})] - \delta_2(\sigma^\omega_{ijt})^2 - E[p^B_{kt}(q_{ihtk}+q_{ijtk})] - \delta_1(\sigma^B_{ikt})^2 - \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) - \delta_4(\sigma^{BC}_{ikt})^2 - \mu d_{ikt} \geq c_{ijt} \end{aligned} \tag{A6}$$

9.2.3 Solving for Quantities

Using the price function (1) and the optimal price expressions from the optimization (A4), I solve for quantities, including market entry conditions (A6):

$$q_{ihtk} = [\frac{1}{\alpha\omega_{htk}} * \frac{1}{1+1/v} * [E[p^B_{kt}(q_{ihtk}+q_{ijtk})](1+\frac{2}{\epsilon^{Buy}_{kt}}) + \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) + \delta_4(\sigma^{BC}_{ikt})^2 + d_{ikt} + c_{iht} + \delta_1(\sigma^B_{ikt})^2]^v \tag{A7}$$

$$\text{with } \alpha\omega_{ht}q_{htk}^{1/v} - E[p_{kt}^B(q_{ihtk}+q_{ijtk})] - \delta_1(\sigma_{ikt}^B)^2 - \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) - \delta_4(\sigma_{ikt}^{BC})^2 - \mu d_{ikt} \geq c_{iht}$$

$$q_{ijt} = \begin{cases} 0 \text{ if } E[\omega_{jt}]\alpha_{jt}q_{ijtk}^{1/v} - E[p_{kt}^B(q_{ijtk}+q_{ihtk})] - \delta_1(\sigma_{ikt}^B)^2] - \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) - \delta_4(\sigma_{ikt}^{BC})^2 - \mu d_{ikt} - \delta_2(\sigma_{ijt}^{\omega})^2 < c_{ijt} \\ \\ [\frac{1}{\alpha E[\omega_{jt}]} * \frac{1}{1+\frac{1}{v}} * [E[p_{kt}^B(q_{ihtk}+q_{ijtk})](1+\frac{2}{\epsilon_{kt}^{Buy}}) + \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) + \delta_4(\sigma_{ikt}^{BC})^2 + \\ \mu d_{ikt} + c_{ijt} + \delta_1(\sigma_k^B)^2 + \delta_2(\sigma_{ijt}^{\omega})^2]^v \\ \qquad \text{if } E[\omega_{jt}]\alpha_{jt}q_{ijt}^{1/v} - E[p_{kt}^B(q_{ihtk}+q_{ijtk})] - \delta_1(\sigma_{ikt}^B)^2 - \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) - \delta_4(\sigma_{ikt}^{BC})^2 - \mu d_{ikt} - \delta_2(\sigma_{ijt}^{\omega})^2 \geq c_{ijt} \end{cases} \tag{A8}$$

Using structure put on selling markets in equation 2:

$$q_{ihtk} = [\frac{1}{\alpha\omega_{htk}} * \frac{1}{1+1/v} * [\zeta E[b_{kt}]Q_{kt}^B](1+\frac{2}{\epsilon_{kt}^{Buy}}) + \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) + \delta_4(\sigma_{ikt}^{BC})^2 + d_{ikt} + \\ c_{iht} + \delta_1(\sigma_{ikt}^B)^2]^v \tag{A9}$$

$$\text{with } \alpha\omega_{ht}q_{htk}^{1/v} - [\zeta E[b_{kt}]Q_{kt}^B] - \delta_1(\sigma_{ikt}^B)^2 - \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) - \delta_4(\sigma_{ikt}^{BC})^2 - \mu d_{ikt} \geq c_{iht}$$

$$q_{ijt} = \begin{cases} 0 \text{ if } E[\omega_{jt}]\alpha_{jt}q_{ijtk}^{1/v} - [\zeta E[b_{kt}]Q_{kt}^B] - \delta_1(\sigma_{ikt}^B)^2] - \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) - \delta_4(\sigma_{ikt}^{BC})^2 - \mu d_{ikt} - \delta_2(\sigma_{ijt}^{\omega})^2 < c_{ijt} \\ \\ [\frac{1}{\alpha E[\omega_{jt}]} * \frac{1}{1+1/v} * [\zeta E[b_{kt}]Q_{kt}^B](1+\frac{2}{\epsilon_{kt}^{Buy}}) + \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) + \delta_4(\sigma_{ikt}^{BC})^2 + \mu d_{ikt} + c_{ijt} + \delta_1(\sigma_k^B)^2 + \delta_2(\sigma_{ijt}^{\omega})^2]]^v \\ \qquad \text{if } E[\omega_{jt}]\alpha_{jt}q_{ijt}^{1/v} - [\zeta E[b_{kt}]Q_{kt}^B] - \delta_1(\sigma_{ikt}^B)^2 - \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) - \delta_4(\sigma_{ikt}^{BC})^2 - \mu d_{ikt} - \delta_2(\sigma_{ijt}^{\omega})^2 \geq c_{ijt} \end{cases} \tag{A10}$$

9.3 Step 2: Choosing Buying Market and Route

9.3.1 Choice model

Trader i will compare her utility across each market route, taking the optimal quantity for each route as given.

Trader i will pick buying market route k' iff $V_{ik't} \geq V_{ikt}$

$$\begin{aligned}
&[E[p^S_{jtk'}(q_{ijtk'})] - \delta_2(\sigma^{\omega}_{ijt})^2] * q_{ijtk'} + p^S_{htk'}(q_{ihtk'}) * q_{ihtk'} - E[p^B_{k't}(q_{ihtk'} + q_{ijtk'})] - \delta_1(\sigma^B_{ik't})^2 - \\
&\delta_3 BC_{ik't}(1 + \gamma_{ik't}) - \delta_4(\sigma^{BC}_{ik't})^2 - \mu d_{ik't} + \lambda_{ik'} \geq \\
&[E[p^S_{jtk}(q_{ijtk})] - \delta_2(\sigma^{\omega}_{ijt})^2] * q_{ijtk} + p^S_{htk}(q_{ihtk}) * q_{ihtk} - E[p^B_{kt}(q_{ihtk} + q_{ijtk})] - \\
&\delta_1(\sigma^B_{ikt})^2 - \delta_3 BC_{ikt}(1 + \gamma_{ikt}) - \delta_4(\sigma^{BC}_{ikt})^2 - \mu d_{ikt} + \lambda_{ik}
\end{aligned} \tag{A11}$$

So, increased profits from lower marginal costs in a new buying market route need to be larger than the lost utility from switching market routes $\lambda_{ik} - \lambda_{ik'}$.

There is a $\bar{\lambda}_i$, at which $V_{ik't} = V_{ikt}$. And if $\lambda_{ik} - \lambda_{ik'} \leq \bar{\lambda}_i$, trader i switches to k'. $\lambda_{ik} = \hat{\lambda_k} + \lambda'_{ik}$ with λ'_{ik} being an unobserved/random term that follows an extreme value distribution.

9.3.2 Choice Probabilities

Using a Mixed Logit Model, the probability of choosing buying market route k is :

$Prob(Y_{it=k}) = \int \frac{exp(V_{ikt}(\beta))}{\Sigma exp(V_{ikt}(\beta))} * f(\beta|\theta) * d\beta$ with β coefficients in V and θ parameters for the mixing distribution, estimated through simulations.

Appendix Section B: Model under Cournot competition

In this section, I relax the assumption of firms being monopolies and instead solve for Cournot competition (and perfect competition). I also relax the second order effect of the increase in quantity in market h on the marginal cost of purchasing goods for market j (the direct effect of an increase in quantity in market h on the cost of purchasing goods for market j remains).[29]

In this setting, there are N identical firms selling a homogeneous good. $P_{mtk} = \alpha * Q_{mtk}^{1/v}$ with Q being the sum of all individual firms quantities sold in market m. Each firm chooses quantity, taking as given the quantity of other firms (i.e. taking into account other firms' maximized quantity).

Following standard FOCs :

$$\begin{aligned}
\frac{\partial V_{ikt}}{\partial q_{ijtk}} &= \alpha E[\omega_{jt}] Q_{jtk}^{\frac{1}{v}} - \delta_2(\sigma_{ijt}^S)^2 + \frac{\partial \alpha E[\omega_{jt}] q_{ijtk}^{\frac{1}{v}}}{\partial Q_{jtk}} * q_{ijtk} - E[p_{kt}^B(q_{ihtk} + q_{ijtk}, q_{-ikt})] - \delta_1(\sigma_{ik}^B)^2 - \\
&\frac{\partial E[p_{kt}^B(q_{ihtk} + q_{ijtk}, q_{-ikt})]}{\partial q_{ijtk}} * (q_{ijtk}) - \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) - \delta_4(\sigma_{ikt}^{BC})^2 - \mu d_{ikt} - c_{ijt} = 0 \\
\frac{\partial V_{ikt}}{\partial q_{ihtk}} &= \alpha \omega_{ht} Q_{htk}^{\frac{1}{v}} + \frac{\partial \alpha \omega_{ht} Q_{htk}^{\frac{1}{v}}}{\partial q_{ihtk}} * q_{ihtk} - E[p_{kt}^B(q_{ihtk} + q_{ijtk}, q_{-ikt})] - \delta_1(\sigma_{ik}^B)^2 - \\
&\frac{\partial E[p_{kt}^B(q_{ihtk} + q_{ijt}, q_{-ikt})]}{\partial q_{ihtk}} * (q_{ihtk}) - \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) - \delta_4(\sigma_{ikt}^{BC})^2 - \mu d_{ikt} - c_{iht} = 0
\end{aligned} \tag{A12}$$

Since $q_1^* = q_{*2} = ... = q_N^* \implies Q_{htk} = Nq_i$ and $Q_{jtk} = Nq_i$

Substituting this in the first order conditions to get optimal quantities:

$q_{ijtk}^* = \frac{1}{N}[MC(q_{ijtk}) * \frac{1}{\alpha} * \frac{1}{1+\frac{1}{Nv}}]^v$

$q_{ihtk}^* = \frac{1}{N}[MC(q_{ihtk}) * \frac{1}{\alpha} * \frac{1}{1+\frac{1}{Nv}}]^v$

with $MC(q_{ijtk}) = \delta_2(\sigma_{ijt}^S)^2 + E[p_{kt}^B(q_{ihtk} + q_{ijtk}, q_{-ikt})] + \delta_1(\sigma_{ik}^B)^2 + \frac{\partial E[p_{kt}^B(q_{ihtk}+q_{ijtk}, q_{-ikt})]}{\partial q_{ijtk}} * (q_{ijtk})$
$+ \delta_3 E[BC_{ikt}](1+\gamma_{ikt}) + \delta_4(\sigma_{ikt}^{BC})^2 + \mu d_{ikt} + c_{ijt}$

[29]This simplification was done to simplify the algebra but does not affect the predictions or results.

and $MC(q_{ihtk}) = E[p^B_{kt}(q_{ihtk} + q_{ijtk}, q_{-ikt})] + \delta_1(\sigma^B_{ik})^2 + \frac{\partial E[p^B_{kt}(q_{ihtk}+q_{ijt},q_{-ikt})]}{\partial q_{ihtk}} * (q_{ihtk})$
$+ \delta_3 E[BC_{ikt}](1 + \gamma_{ikt}) + \delta_4(\sigma^{BC}_{ikt})^2 + \mu d_{ikt} + c_{iht} = 0$

Solving for market quantities:

$Q_{jtk} = N * q^*_{ijtk} = [MC(q_{ijtk}) * \frac{1}{\alpha} * \frac{1}{1+\frac{1}{Nv}}]^v$

$Q_{htk} = N * q^*_{ihtk} = [MC(q_{ihtk}) * \frac{1}{\alpha} * \frac{1}{1+\frac{1}{Nv}}]^v$

Solving for the associated market prices :

$P_{jtk} = MC(q_{ijtk}) * \frac{1}{1+\frac{1}{Nv}}$

$P_{htk} = MC(q_{ihtk}) * \frac{1}{1+\frac{1}{Nv}}$

Comparing Cournot solutions to monopolies

Not surprisingly, each firm's quantity under Cournot is smaller than the monopoly's quantity. However, market level quantity under Cournot is larger than the monopoly's quantity. Prices in Cournot are lower than under the monopoly's assumption.

Perfect competition

As N become large, the Cournot solution approximates perfect competition. Indeed as N increases:

Solving for market quantities:

$Q_{jtk} = [MC(q_{ijtk}) * \frac{1}{\alpha}]^v$

$Q_{htk} = [MC(q_{ihtk}) * \frac{1}{\alpha}]^v$

Solving for the associated market prices :

$P_{jtk} = MC(q_{ijtk})$

$P_{htk} = MC(q_{ihtk})$

Note that we find that MC equals price, common to a competitive equilibrium.

Appendix Section C: Tables

Table A1: Business Registration

	mean
Personal KRA Pin Number	0.40
Business KRA Pin Number	0.02
Personal and Business KRA Pin Number	0.01
No KRA Pin Number	0.57
Observations	954

Table A2: Traders' Costs by crossing type - Audit Study Experiment

	Official Crossing mean	Informal Crossing (Marachi) mean
Value of good (Kshs '00)	107.79	144.53
Costs (Kshs '00)		
Crossing Bribes	1.09	1.57
Total Crossing Costs (excl.transport)	1.94	1.81
Crossing Transport Costs	0.08	0.65
Experience		
Waiting Time	20.66	6.81
N border agents faced	1.76	1.72
N trucks at crossing	10.61	0.51
N traders at crossing	16.74	8.12
Filled certificate	0.03	0.00
Observations	38	209

Table A3: Costs by trader size

	(1) Sales Kshs
Total purchase costs	1.135***
	[0.026]
Total costs	0.728**
	[0.351]
Constant	12997.709***
	[3491.072]
Dep Var Mean	1.63e+05
R-Squared	.835
Observations	826

Note: Standard errors robust (reported in brackets).
* p<0.1, ** p<0.05, *** p<0.01.
Data from second baseline

Table A4: RCT: balance table

	Control	Treatment	P-value of Diff
Baseline			
Gender	0.20	0.18	0.406
Age	39.58	37.09	0.380
N formal associations	0.56	0.61	0.313
N informal associations	1.24	1.22	0.847
Trading main source of income (past 12 months)	0.96	0.94	0.178
Inventory	0.44	0.42	0.637
Value of Inventory	16626.14	16048.02	0.851
Domestic	0.46	0.44	0.417
Official	0.21	0.17	0.055*
Informal	0.32	0.39	0.015**
Updated Baseline			
Attrition Midline	0.17	0.20	0.183
Out of business Midline	0.04	0.04	0.965
Domestic (Midline)	0.73	0.70	0.265
Official (Midline)	0.08	0.08	0.684
Informal (Midline)	0.16	0.20	0.113

Note: * p<0.1, ** p<0.05, *** p<0.01.

Table A5: Attrition Balance

	(1) Midline	(2) Round 1	(3) Round 2	(4) Round 3	(5) Endline
Treatment	-0.029 [0.023]	0.015 [0.023]	0.001 [0.023]	0.027 [0.023]	0.027 [0.024]
Dep Var Mean	0.818	0.811	0.808	0.810	0.785
Observations	1166	1165	1166	1166	1166

* p<0.1, ** p<0.05, *** p<0.01.

Table A6: First Stage: Number of alternatives looked up in platform

	Market Prices		Exchange Rates		Trade Procedure		Weather	
	mean	sd	mean	sd	mean	sd	mean	sd
N alternatives by session	1.75	1.50	1.34	0.65	1.16	0.53	1.25	0.87
N alternatives by day	1.87	1.70	1.44	0.78	1.23	0.67	1.40	1.11
N alternatives by month	2.71	3.35	2.21	2.02	1.49	1.22	4.18	6.11
N alternatives overall	4.67	7.61	3.86	5.39	2.01	2.25	9.16	15.85
N unique alternatives by session	1.75	1.50	1.34	0.65	1.16	0.53	1.25	0.87
N unique alternatives by day	1.85	1.65	1.41	0.74	1.19	0.57	1.30	0.99
N unique alternatives by month	2.46	2.58	1.96	1.55	1.31	0.73	1.87	2.21
N unique alternatives overall	3.75	4.61	2.90	3.55	1.50	0.92	2.77	3.53

Table A7: RCT Results: Switching to new markets

	Ratio upd. baseline selling markets		Ratio upd. baseline buying markets	
	(1) Round 1-3	(2) Endline	(3) Round 1-3	(4) Endline
Treatment	-0.032*	-0.067**	0.032	0.019
	[0.019]	[0.026]	[0.023]	[0.033]
Dep Var Mean (Control)	0.697	0.798	0.368	0.383
R-Squared	.305	.008	.093	0
Pre-Period				
Round FE	X		X	
Observations	7963	846	7579	837

Note: Standard errors robust or clustered as trader level (reported in brackets).
* p<0.1, ** p<0.05, *** p<0.01.

Table A8: RCT: Sales - Levels

	Sales		Profits		Stock	
	(1) Rounds 1-3	(2) Endline	(3) Rounds 1-3	(4) Endline	(5) Rounds 1-3	(6) Endline
Treatment	4984.250**	14402.266**	712.951**	2283.362*	-618.428	927.209
	[2068.393]	[6614.729]	[356.012]	[1177.428]	[863.044]	[1213.227]
Dep Var Mean (Control)	24616.063	68568.821	4270.341	11376.329	8883.181	8897.763
R-Squared	.008	.005	.007	.004	.001	.001
Pre-Period						
RoundFE	X		X		X	
Observations	2790	898	2792	895	2806	906

Note: Standard errors robust or clustered as trader level (reported in brackets).
* p<0.1, ** p<0.05, *** p<0.01.

Table A9: RCT: Costs - Levels

	Total		Per Sales	
	(1) Purch. Costs	(2) Oth. Costs	(3) Purch. Costs	(4) Oth. Costs
Treatment	3759.665**	196.612	0.038	-0.010
	[1760.577]	[146.113]	[0.046]	[0.007]
Dep Var Mean (Control)	22003.278	1904.950	1.033	0.120
R-Squared	.006	.004	.001	.002
Pre-Period				
Round FE	X	X	X	X
Observations	2795	2799	2402	2398

Note: Standard errors robust or clustered as trader level (reported in brackets).
Similar results with costs in levels
* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A10: Reasons for staying domestic : Updated Baseline and Endline

	Updated Baseline mean	Endline mean
Lack of contacts	0.14	0.18
Better prices in dom. markets	0.47	0.44
Expensive tarrifs and fees	0.16	0.09
Difficult Importing/Exporting process	0.20	0.27
Not enough knowledge on procedures	0.16	0.11
Covid 19	0.12	0.12
Border Closure	0.09	0.04
Existing ties with suppliers	0.19	0.36
Observations	613	297

Table A11: Types of traders: baseline-updated baseline-endline

CB-CB-CB	0.02
CB-Dom-CB	0.06
CB-DomCB-CB	0.09
CB-CB-Dom	0.00
CB-Dom-Dom	0.19
CB-DomCB-Dom	0.04
Dom-CB-CB	0.00
Dom-Dom-CB	0.01
Dom-DomCB-CB	0.01
Dom-CB-Dom	0.00
Dom-Dom-Dom	0.30
Dom-DomCB-Dom	0.01
Complete Exit During/Post BC	0.27
Observations	1137

Table A12: Selling market prices (Reported Data)

	(1) Price Levels	(2) Price Logs	(3) CPI	(4) Log CPI	(5) CPI	(6) Log CPI
Intensity Treat x Post	-13.312	-0.234***	-15.527	-0.623	-2.335*	-0.193***
	[10.398]	[0.076]	[16.115]	[0.639]	[1.386]	[0.067]
Intensity Treat	9.988	0.174**	15.063	0.358	1.799	0.044
	[11.491]	[0.080]	[15.428]	[0.600]	[1.206]	[0.043]
Post	4.925	0.116***	-0.307	-0.222	1.048	0.110**
	[3.928]	[0.031]	[6.636]	[0.304]	[0.878]	[0.049]
Dependent Variable Control Mean	77.419	4.035	22.874	1.532	2.497	0.191
R-Squared	.711	.716	.024	.049	.01	.041
Market Cluster	X	X				
Product FE	X	X				
Market Weight			X	X		
Area Weight			.		X	X
Observations	1223	1266	232	232	250	250

Note: Standard errors robust or clustered at market level (reported in brackets).
* p<0.1, ** p<0.05, *** p<0.01.
Markets outside sampleframe included, updated baseline, HF rounds and endline used.

Table A13: Buying market prices (Reported Data)

	(1) Price Levels	(2) Price Logs	(3) CPI	(4) Log CPI	(5) CPI	(6) Log CPI
Intensity Treat x Post	-2.926	0.011	0.570	0.066	-0.468	-0.123
	[10.101]	[0.132]	[8.087]	[0.581]	[1.457]	[0.139]
Intensity Treat	3.656	-0.017	9.723	0.642	-1.100	-0.019
	[12.498]	[0.150]	[7.396]	[0.522]	[1.345]	[0.123]
Post	3.356	0.087	0.559	0.132	0.297	0.090
	[4.275]	[0.067]	[3.279]	[0.255]	[0.856]	[0.068]
Dependent Variable Control Mean	58.326	3.734	12.733	1.215	3.750	0.318
R-Squared	.71	.715	.073	.052	.036	.026
Market Cluster	X	X				
Product FE	X	X				
Market Weight			X	X		
Area Weight					X	X
Observations	797	812	236	236	263	263

Note: Standard errors robust or clustered at market level (reported in brackets).
* p<0.1, ** p<0.05, *** p<0.01.
Markets outside sampleframe included; updated baseline, HF rounds and endline used.

Appendix Section D: Figures

Figure A1: Definition of informal traders

		Type of Routes		
		Domestic	Informal Crossings	Official Crossings
Status of Trader	Unregistered			
	Registered			

Figure A2: Attrition across rounds

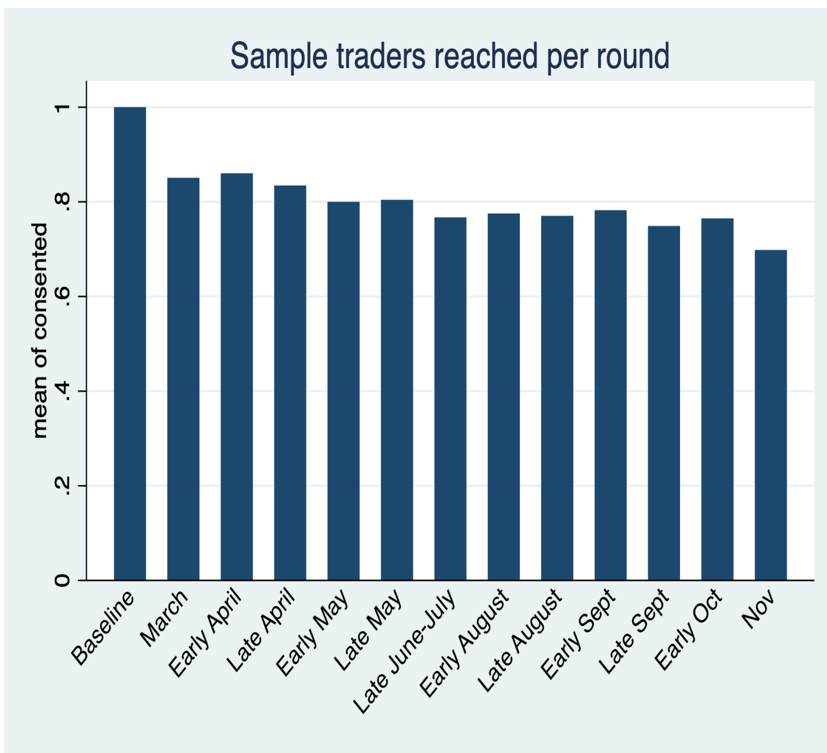


Figure A3: Sample Composition

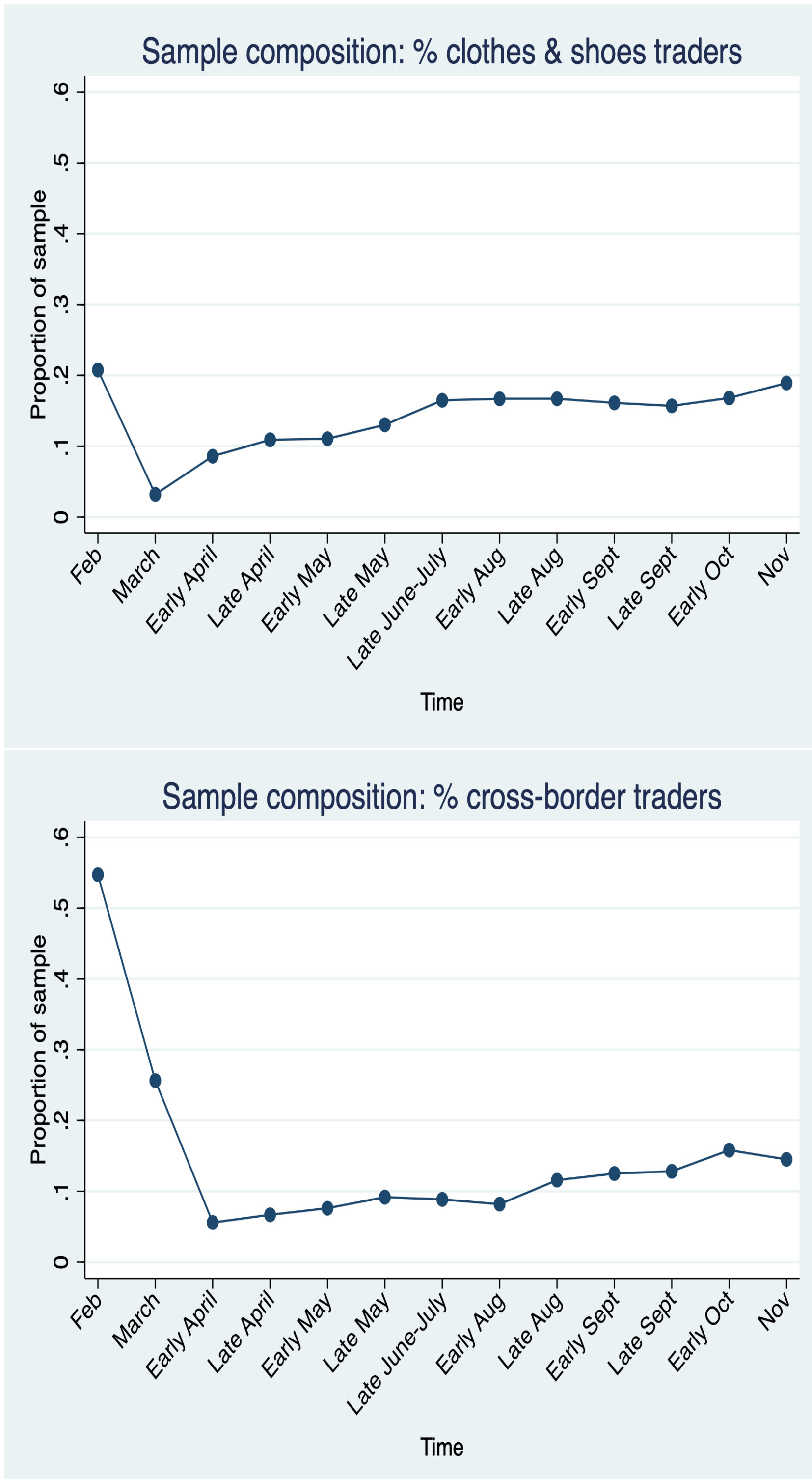


Figure A4: Determinants of being Out of business by industry and trader type

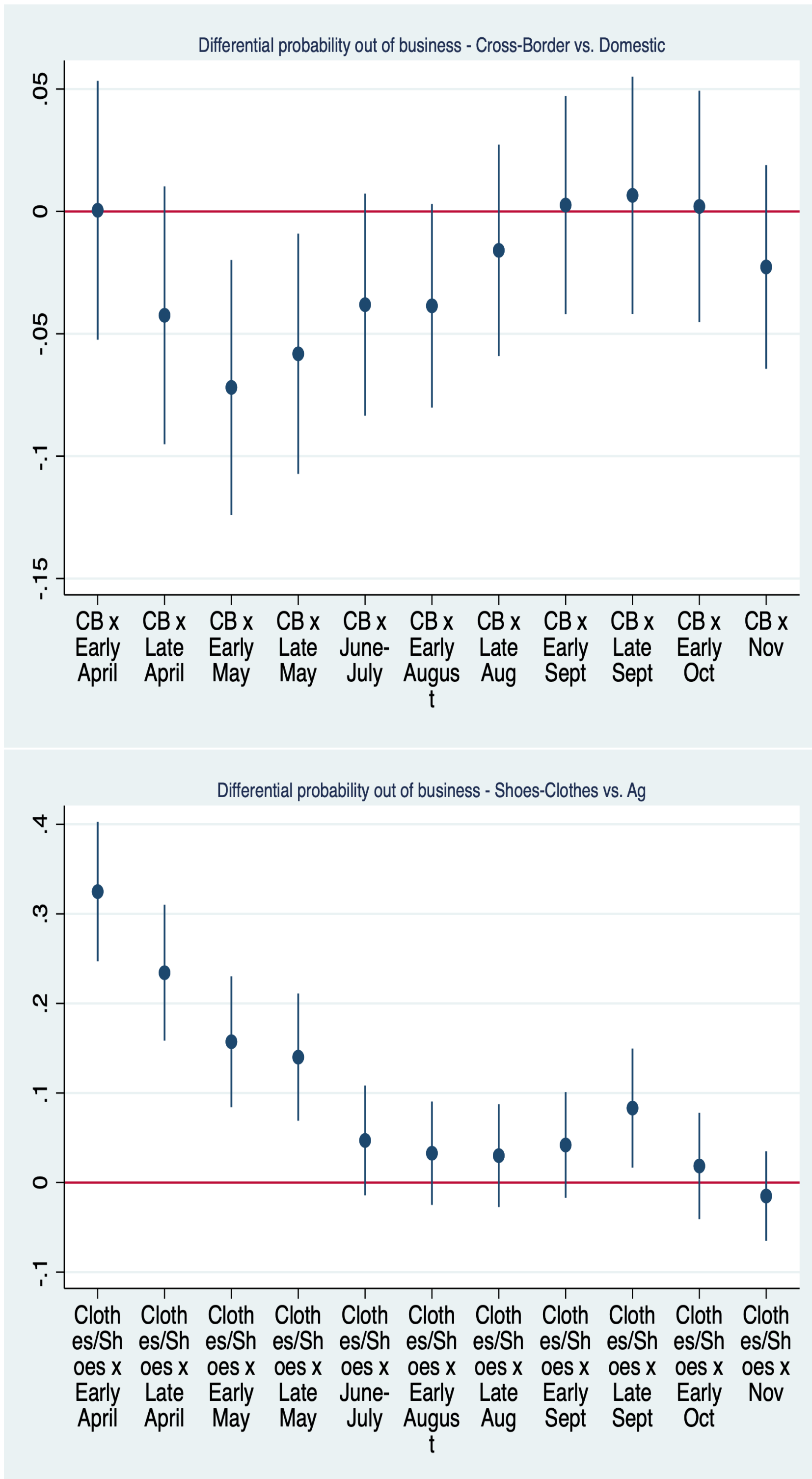


Figure A5: Platform

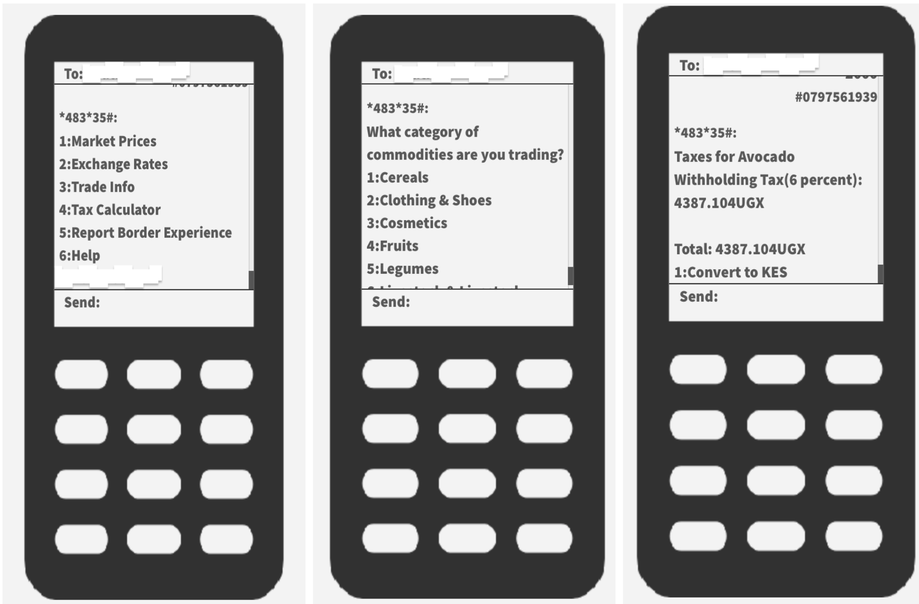


Figure A6: Increase in corruption and harassment during border closure

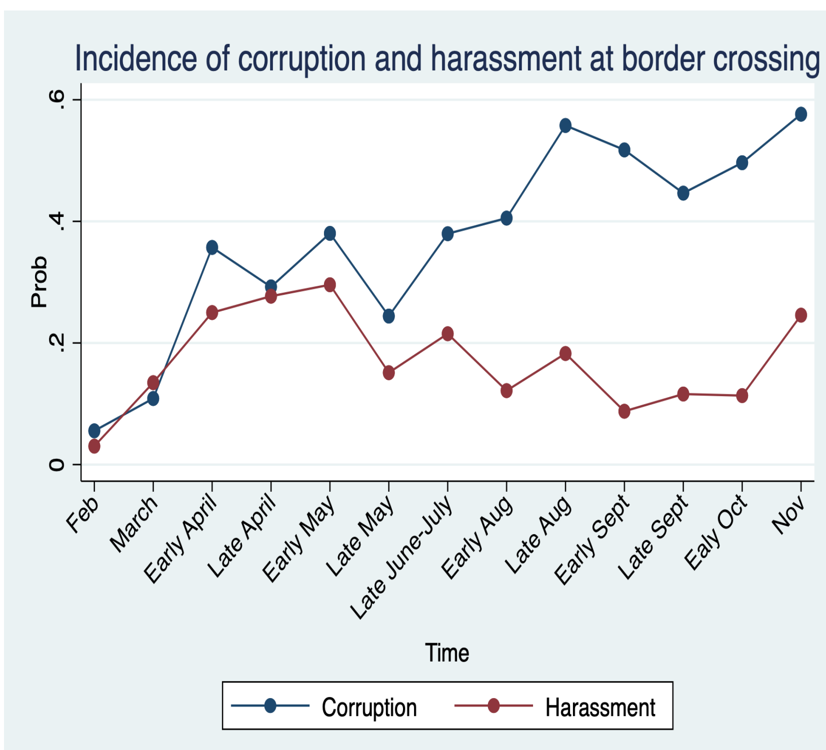


Figure A7: First Stage: Distribution of usage early months versus late months