Search Externalities in Firm-to-Firm Trade

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Abstract I develop a model of firm-to-firm search and matching to show that the impact of falling trade costs on firm sourcing decisions and consumer welfare depends on the relative size of search externalities in domestic and international markets. These externalities can be positive if firms share information about potential matches, or negative if the market is congested. Using unique firm-to-firm transaction-level data from Uganda, I show empirical evidence consistent with positive externalities in international markets and negative externalities in domestic markets. I then build a dynamic quantitative version fo the model and show that, in Uganda, a 25% reduction in trade costs led to a 5.2% increase in consumer welfare, 15% of which was due to search externalities.

Keywords Firm-to-Firm Trade, VAT Data, Search-and-Matching, Importing

JEL Classification F14, F15, O19

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1. Introduction

In a developing country, finding and maintaining an efficient and reliable supplier can be a costly and a time consuming process (Allen, 2014; Macchiavello and Morjaria, 2015; Startz, 2016). One factor which can make this process more difficult, is if many other firms are simultaneously searching for a supplier (Arnosti et al., 2018). This *congestion externality* will occur when trading frictions mean supply cannot instantaneously meet demand from multiple buyers. This is plausibly a large concern in developing countries where contracting frictions cause high adjustment costs (Macchiavello and Morjaria, 2019), and a lack of access to credit can cause firm supply-constraints (Manova, 2012). One policy response is to open to international trade, giving firms access to a large pool of suppliers which are less inhibited by these trading frictions.[1]

In this paper, I show that reducing international trade costs will lead to a greater number of matches in the international market, alongside an important and novel secondary benefit - the alleviation of the consequences of congestion in the domestic supplier market. I formalise this new mechanism for a domestic market consumer welfare gain from trade and consider its effects in Uganda. I show empirical evidence consistent with the Ugandan supplier market suffering from greater congestion than the international supplier market. I then demonstrate through model simulations that, for the case of Uganda, the impact of this channel on consumer welfare is quantitatively significant; a 25% reduction in international trade costs in 2011 has led to a 5.2% increase in consumer welfare, 15% of which is accrued to the difference in congestion between the two markets. Finally, I show that the presence of search externalities lends support to policy interventions to reduce search costs, but that these should be targeted at sectors less inhibited by congestion.

This analysis requires a unique combination of data on firm-to-firm domestic and international transactions. I use Ugandan administrative Value Added Tax (VAT) data

[1] These firms are likely to be less inhibited given international exporters tend to be larger (Bernard and Jensen, 2004) and with better access to credit (Manova, 2012). Indeed this channel should exist in any two markets, where one is more congested due to firms being supply-constrained.

that includes information on every transaction between domestic tax-paying firms. I also use the government's import customs dataset which includes details on both the buyer in Uganda and the foreign seller. The combination of these datasets amounts to a dynamic transaction-level firm-to-firm input-output matrix. Using the firm's unique ID, I link this dataset with other tax administration datasets: firm balance-sheet data, firm employment information and detailed firm geographic location. Together, this constitutes a dynamic picture of the entire Ugandan formal economy from 2010 to 2016. To the best of my knowledge, this is the first paper to combine this breadth of administrative firm-level transaction-data in a developing country.

I start by developing a simple model of optimal search in two markets with different search externalities. The model serves to highlight the key mechanism proposed in this paper - after a trade cost reduction, firms increase search in international markets as these goods become relatively lower-cost to source. This is mitigated by two forces. First, as firms move into the import market, this increases aggregate import market-tightness, thus decreasing the probability of an import match. Second, as firms move out of the domestic-market, domestic market-tightness decreases, therefore increasing the probability of a domestic match. The scale of these congestion effects depends on the relative size of positive and negative search externalities in each market. These parameters also determine the welfare consequences of a reduction in international trade costs. If there is a greater positive externality to search in international markets compared to domestic markets, then a reallocation of search towards international markets not only leads to more matches in the international market, but also alleviates congestion in the domestic market. This will lead to a greater number of overall matches which benefits consumers with taste-for-variety.[2]

Motivated by the simple model, I undertake two empirical exercises. In the first

[2] An alternative way of thinking about the model is through a lens of trading frictions. In this sense, buyers may be aware of the existence of suppliers, however, there is no centralized market where buyers and suppliers meet and trade at a single price (Rogerson et al., 2005). In order to form a partnership they must undertake costly investments which involve externalities.

empirical exercise, I study the impact of a 25% reduction in international transport costs that Uganda implemented in 2010-2011.[3] I test the model's predictions on number and type of matches and show that: (i) there was a 80% increase in the number of new importing firms; (ii) the firms that began importing in 2011 simultaneously adjusted their supply-chain by dropping domestic suppliers; (iii) the suppliers that were dropped as a consequence of this readjustment re-matched primarily with firms which were not importers.

In the second empirical exercise, I look for evidence of search externalities in a reduced-form setting. In the case of Uganda and consistent with previous literature,[4] I show that firms located in the same building adopt sequentially the same import suppliers. I then show that this effect is substantially larger for firms located in the same building compared to firms located in a next-door building. This is consistent with information diffusing among firms about suppliers at a very local level. When looking at domestic suppliers, however, this effect is not significantly different from zero. By contrast, in the domestic market, a buyer adding a specific new supplier actually reduces the probability of buyers in a different region of the country matching with that supplier. This is consistent with geographically distant firms not benefiting from the information externality, but still subject to the congestion externality, and has not been tested in the literature to date.

The results are in line with qualitative evidence that I collected through structured interviews with firms in East Africa.[5] I interviewed 25 managers from firms in a variety of sectors[6] who reported that: (i) it is common for buyers to share information about international suppliers; (ii) international suppliers have the size or the ability to scale up to service multiple buyers; (iii) domestic suppliers are limited in their ability to service

[3]The reforms are discussed in detail in Section 3.2.3. Given the reforms were exclusively conducted outside Uganda or on the border crossing, I assume they had no impact on domestic trade costs.

[4]See for instance Bisztray et al. (2018) and Kamal and Sundaram (2016)

[5]Interviews were conducted with firms in Kampala in Uganda and in Kigali in Rwanda which has a very similar structure of firm market.

[6]I interviewed firms in logistics, retail and wholesale, coffee and tea, hotels and tourism, agribusiness, service input sectors. A full list of firms is available on request.

multiple buyers and this means that sometimes there is wasted search effort.[7]

Having identified evidence consistent with there being a difference in externalities between domestic and international markets, I structurally estimate the quantitative model by simulated method of moments in order to quantify the impacts of a search channel on consumer welfare. However, in order to match the data, I extend the simple model substantially. I build a dynamic quantitative version of the model where both buyers and suppliers choose optimal search intensity and the proportion of search in each market. The model builds on existing work by Eaton, Jinkins, Tybout and Xu (2016) (hereafter EJTX (2016)), adding both a domestic and an international search decision and market-specific matching functions, as well as adding firm heterogeneity and additional structure to search costs.

The most important structural parameters are those which govern the returns to scale in the matching function. I find that there are decreasing returns to scale to searching in domestic markets and increasing returns to scale to searching in international markets, as is consistent with the reduced-form results. I then test the external validity of the model by simulating the effect of a reduction in international trade costs and comparing the results to what is observed in the data. The proportion of firms that import increases from 20% to 23%, the average number of import suppliers increases by 20% and the average number of domestic suppliers decreases by 6.5%. The change observed in the data is the same direction and of a similar magnitude to that seen in the simulation.

Finally, I run two counterfactual experiments. In the first experiment, I consider how much the increase in consumer welfare is due to differences in search externalities between markets. I again simulate the reduction in trade costs, but assume both markets have the same constant returns to scale matching function. The average number of import suppliers increases by a smaller amount (11.1% vs. 20.1%), as there is a larger increase

[7] For instance, in one interview I undertook with a firm they stated that they had asked another firm in the same business park about their input supplier for imported packaging. In another interview a firm had stated that they had tried to find a domestic transport firm but that another similar firm had already taken the contract.

in import market tightness. There is also a larger decrease in the average number of domestic suppliers (-9.8% vs. -6.5%), this is because the reduction in search domestically does not have the mitigating effect of reducing congestion in the domestic market. This results in an increase in consumer welfare which is 15% smaller than when I allow there to be differences in externalities between markets, demonstrating that allowing for search externalities has a quantitatively important impact on welfare.

Second, I simulate the government of Uganda's goal of a "25% reduction in search costs for suppliers" as one of its four goals in trade (Government of Uganda, 2019).[8] I show that this leads to a 3-5% increase in consumer welfare, depending on where the reduction is targeted. If the government reduces international search costs, then this will significantly increase the number of matches in the same manner as the trade cost reduction. If, however, the government reduces domestic search costs then the impact, albeit still positive, is dampened by the increase in domestic congestion caused by a greater number of searching firms.

This paper relates to three main strands of the literature. This paper contributes to the literature on firm-to-firm search. The literature has shown that the competitive equilibrium does not necessary result in the socially optimal level of search (Krolikowski and McCallum, 2017), that search frictions explain firm's export market decisions (Chaney, 2014), and that search influences predictions on gains from trade (Antras and Costinot, 2011). I build on work by Eaton, Jinkins, Tybout and Xu (2016), who write a dynamic quantitative model of optimal two-sided buyer-supplier search which is rich enough to take to the data.[9] This paper's contribution is to separately model search in domestic and international markets and incorporating different matching technologies in either market, providing new predictions on a search channel for consumer welfare gains following a

[8]The specific sub targets are i) establishing a internet platform support programme (e.g. organize quarterly trainings on the use of Ali Baba), ii) encourage firms peer-to-peer learning (e.g. organize quarterly peer groups with Uganda business groups), iii) target key firms in supplier development programmes (e.g. establish anchor firm support unit and annual public-supplier meetings).

[9]Other important contributions on sourcing include Rauch (2001), Rauch and Trindade (2002), Rauch and Watson (2003). A parallel literature also exists on exporter search for buyer markets (See for instance Eaton et al. (2017), Allen (2014), Albornoz et al. (2012)).

reduction in international trade costs and using novel data.

In addition, this paper relates to the literature on the firm supply-chain impacts following a trade liberalization in the absence of search frictions. Arkolakis et al. (2012) show that gains from trade are higher in models with intermediate goods. Tintelnot et al. (2018) and Fieler et al. (2018) build quantitative models to show that the gains from trade depend on domestic firm-to-firm linkages and how firms are directly or indirectly connected to the international market. Antras et al. (2017) build a quantitative model of global sourcing.[10] I build on this literature by incorporating intermediate goods into a model of domestic and international sourcing whilst also including a search channel. Moreover, I consider not only firms' international sourcing decisions but also the interdependencies between this and domestic sourcing decisions.

Finally, the paper contributes to the empirical literature on firm-to-firm search externalities. The closest paper to the reduced-form work is Bisztray et al. (2018), which has extremely detailed geographic data on firms in Hungary. The authors show that firms in the same building sequentially add imports from the same country and in the same product category. The paper also relates to Kamal and Sundaram (2016), who show a similar effect for matched importer-exporter data but without detailed geographic data. Cai and Szeidl (2017) show that when firms are randomly allocated into different business groups they refer each other leading to a 9% increase in the number of suppliers.[11] I build on this literature in four ways. First, the Ugandan dataset contains details on both the geographic location of firms and the matched supplier which gives more detail than the existing literature. Second, I compare firms searching domestically to firms searching internationally, providing evidence of the comparative size of domestic and international externalities for the first time. Third, in addition to looking for a positive search externality, I also show results consistent with a negative search externality. Fourth, besides

[10] A connected literature considers the role of production networks in firm performance and the propagation of shocks (Lim (2017), Carvalho (2014), Carvalho (2014), Bernard and Moxnes (2018), Bernard et al. (2018a)).

[11] A number of related empirical papers highlight additional aspects of the search frictions among firms (Bernard et al. (2015), Startz (2016), Steinwender (2018), Fafchamps and Quinn (2016)).

providing reduced-form evidence of search externalities, I also provide structural evidence of search externalities which differ between markets, which I use to show welfare consequences of different counterfactual experiments.

The remainder of this paper is organized as follows: Section 2 sets out a simple two-period model of firm-to-firm search and shows comparative statics; Section 3 describes the dataset and the context of the trade cost reduction, it also provides descriptive statistics on how firms responded to the trade cost fall; Section 4 provides empirical empirical evidence of search externalities in Uganda; Section 5 presents the quantitative model; Section 6 structurally estimates the model; Section 7 provides counterfactual simulations; and Section 8 concludes.

2. A Simple Model of Firm-to-Firm Search in Two Markets

To illustrate the key mechanisms in this paper, I build a simple model of buyers purchasing intermediary goods from suppliers in international and domestic markets.

The simple model is shown graphically in Figure 1. Buyers sell a single differentiated product to consumers in a frictionless retail market. Buyers purchase these products from suppliers, who are either domestic or international,[12] and each produces one differentiated product. International suppliers produce a higher quality product, but must pay a higher transportation cost. Buyers and suppliers cannot costlessly match, but must instead undertake search to find a match. In both markets, a match between a buyer and a supplier depends on the intensity of search effort and the equilibrium market tightness. In order to incorporate differences in search externalities between markets, I allow the matching technology to differ when looking for domestic or international suppliers.

I demonstrate the main mechanisms of the model by showing comparative statics of a reduction in trade costs leading to a reallocation of search between markets, but with some mitigation due to congestion.[13]

[12] International here implies a foreign exporter

[13] The simple model, however, misses some salient features observed in the data. In order to make the model match key moments from the Ugandan data, I extend the framework in Section 5 to include a

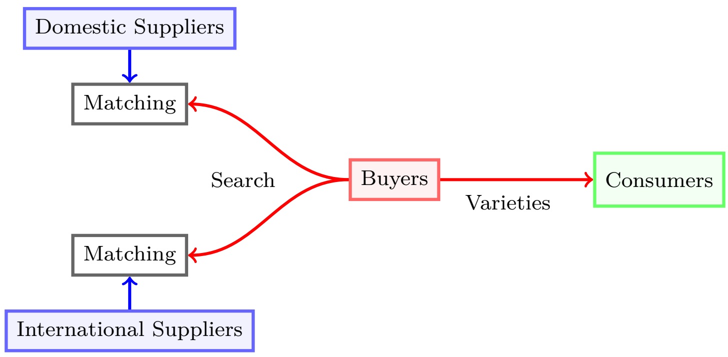


Figure 1: Model Environment

2.1. Buyers, Suppliers and Consumers

There is a measure B continuum of buyers, measure S_D continuum of domestic suppliers and measure S_I continuum of international suppliers. For simplicity, I assume for the simple model that $S_D = S_I = S$.

Suppliers produce differentiated products which they sell to buyers once they match. Let $B(s_I)$ denote the set of buyers who match with international suppliers. Similarly, let $B(s_D)$ denote the set of buyers who match with domestic suppliers. For simplicity I assume all suppliers have the same marginal cost.

Buyers pay an iceberg trade cost τ_I on each unit of international goods and iceberg trade cost τ_D on each unit of domestic goods, where I normalize $\tau_D = 1$.

Buyers begin with marginal cost c and no matches. Buyers have a fixed search intensity σ but choose the proportion of search they exert domestically, a such that $a \in [0, 1]$, and internationally, $1 - a$.

Consumers demand differentiated products from buyers b with a CES utility function, which shows their taste-for-variety over products sold by buyers

$$C = \left[\int_{b \in B(s_I)} \psi_I C_b^{\frac{\eta-1}{\eta}} + \int_{b \in B(s_D)} C_b^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}, \tag{1}$$

where I assume all international products have the same demand shifter, ψ_I, and all

number of these features and estimate the quantitative model in Section 6.

domestic products have the same demand shifter, ψ_D, which I normalize to 1. If imports are higher quality products, we might expect $\psi_I > 1$ for imported goods, although I do not impose this. $\eta > 1$ is the elasticity of substitution between goods which does not vary between imports and domestic products.

2.2. Pricing and Division of Profits

In period one, buyers search and matches materialize. In period two, buyers compete using Bertrand competition in the retail market. This leads to the standard CES constant mark-up rule

$$\frac{p_b - c_b}{p_b} = \frac{1}{\eta}, \tag{2}$$

where p_b is the price charged by buyer b.

Substituting the mark-up into the profit function yields the instantaneous profit flow for a buyer and a matched supplier which depends on whether the supplier is domestic or international

$$\pi(s_L) = \frac{E}{\eta P^{1-\eta}} \left[\left(\frac{\eta}{\eta - 1} \right) \frac{\tau_L c}{\psi_L} \right]^{1-\eta} \quad \text{for } L \in \{D, I\}, \tag{3}$$

where P is the standard CES aggregate price index and E is household expenditure. Once I make the standard CES assumption that the elasticity of substitution $\eta > 1$, the profit function behaves as one would expect - increasing in the aggregate price index, decreasing in marginal cost. If there is a domestic good then $\tau_D = \psi_D = 1$. For higher international trade costs (τ_I) or smaller international demand shifter (ψ_I) profits from matching with an international supplier are smaller.

I assume profits are split via Nash bargaining where $\Lambda \in [0, 1]$ is the bargaining coefficient for the seller and $1 - \Lambda$ is the bargaining coefficient for the buyer. This assumption means I do not need to consider inefficiencies lost due to double marginalization.[14]

[14] In practice, Bernard and Dhingra (2015) show this assumption may not hold, but it is a necessary simplification for the purposes of this paper as firm pricing is not a main feature of the paper's focus.

2.3. Search and Matching

I assume two aggregate matching functions which are homogeneous of degree one in the search of buyers and sellers, respectively. In the simple model, all sellers search such that their aggregate search is simply given by their mass S. The aggregate buyers' search in each market is given by the mass of buyers multiplied by the amount they search in each market, such that

$$\begin{aligned} B_D &= a\sigma B \\ B_I &= (1-a)\sigma B. \end{aligned} \tag{4}$$

Following the labor literature, I assume that the aggregate measure of matches per unit time (X^D, X^I) is homogeneous of degree one and increasing in the aggregate search of buyers and suppliers

$$\begin{aligned} X^D &= S^{\gamma_S} B_D^{\gamma_B} \\ X^I &= S^{\beta_S} B_I^{\beta_B}. \end{aligned} \tag{5}$$

The matching function exponents are key objects in the model. A positive externality to search would be indicated by high γ_S, γ_B and β_S, β_B. This is because, at the margin, an increase in buyers or sellers will lead to a large increase in the number of matches. There are increasing returns to scale in domestic matching if $\gamma_S + \gamma_B > 1$, in which case an increase in the mass of firms by 10% would have a greater than 10% increase in the number of matches.[15] By contrast, a congestion externality to search would be indicated by low γ_S, γ_B and β_S, β_B, as more firms entering leads to very few new matches. There are decreasing returns to scale in domestic matching if $\gamma_S + \gamma_B < 1$. A low γ_S would indicate that congestion is largely on the domestic supplier-side. Whereas, a low γ_B would

[15] Allowing for the matching function to not be constant returns to scale generates a possibility for multiple equilibria (Petrongolo and Pissarides, 2001). For simplicity, I assume that firms obtain an equilibrium with the highest level of search.

indicate that there is high congestion among domestic buyers. It is common in the labor literature to assume a constant returns to scale matching function, as this guarantees a single equilibrium and has some empirical support (Petrongolo and Pissarides, 2001). However, this has not been as extensively tested in firm-to-firm search. In Section 4, I show reduced-form evidence on the relative size of search externalities between markets. In Section 6, I structurally estimate the exponents in a richer version of the simple model to verify reduced-form results and to demonstrate further mechanisms within the model.

The match flow per unit of buyer search θ is a measure of market tightness and is defined separately in the domestic and international markets, given by

$$\theta_D = \frac{S^{\gamma_S} B_D^{\gamma_B}}{B_D} \qquad \theta_I = \frac{S^{\beta_S} B_I^{\beta_B}}{B_I}. \tag{6}$$

A higher value of θ simply indicates that the hazard-rate of finding a match is higher.

2.4. Optimal Search

Buyers solve a maximization problem by picking an optimal search intensity in the domestic market a to maximize profits

$$\max_a \left\{ a\sigma\theta_D \pi(s_D) + (1-a)\sigma\theta_I \pi(s_I) - k(a) \right\}, \tag{7}$$

where $a\sigma\theta_D$ and $(1-a)\sigma\theta_I$ are the endogenous hazard rates of making a domestic and international match, respectively. k is a convex search cost on the amount that buyers search in each market such that $\frac{\partial^2 k}{\partial a^2} > 0$ and k is minimized at $a = \frac{1}{2}$.[16] The rationale for this assumption is that it is relatively easy to undertake a light search in either market by, for instance, browsing the internet. However, undertaking a comprehensive search might involve travel or hiring a consultant, which would increase costs rapidly.

Taking the first order condition of Equation 7 yields a policy function which determines

[16]Picking the minimum point at $\frac{1}{2}$ is based on the assumption that searching equally in both markets is the minimum cost. Changing this to an alternative minimum would not alter results.

the optimal level of domestic search depending on the relative market tightness, the difference in profit from a domestic and an international supplier, and the change in search costs.

$$\sigma\theta_D\pi(s_D) - \sigma\theta_I\pi(s_I) - \frac{\partial k}{\partial a} = 0 \tag{8}$$

The intuition behind Equation 8 is that the firm wishes to choose their proportion of domestic search to equate the profit from matching with a domestic supplier multiplied by the probability of a domestic match with the profit from matching with a international supplier multiplied by the probability of a international match.

2.5. Comparative Statics

To demonstrate the main search channel in the model, I present comparative statics of how firms respond to a reduction in transportation costs.

2.5.1. Buyer search decisions

The first comparative static shows how the proportion of search intensity in the domestic market changes when international trade costs change. In order to obtain this comparative static, I totally differentiate equation 8 as shown in Appendix B, which yields equation 9.

$$\begin{aligned}\frac{\partial a}{\partial \tau_I} &= \frac{-\sigma\theta_I\frac{\partial\pi(s_I)}{\partial\tau_I}}{\sigma\frac{\partial\theta_I}{\partial a}\pi(s_I) - \sigma\frac{\partial\theta_D}{\partial a}\pi(s_D) + \frac{\partial^2 k}{\partial a^2}} \\ &= \frac{-\sigma\theta_I\frac{\partial\pi(s_I)}{\partial\tau_I}}{\sigma^2(1-\beta^B)\theta_I B_I\pi(s_I) + \sigma^2(1-\gamma^B)\theta_D B_D\pi(s_D) + \frac{\partial^2 k}{\partial a^2}}\end{aligned} \tag{9}$$

For the purposes of exposition, I discuss the case of a fall in transport costs to match the case study of Uganda. The numerator of equation 9 shows the direct effect of a change in trade costs; when trade costs decrease, the proportion of domestic search (a) falls as returns to importing increases.

This is mitigated by two main forces. First, as firms increase import search, the international market becomes tighter driven by international congestion $\frac{\partial\theta_I}{\partial a}$. Second, as firms move out of the domestic market, domestic market-tightness decreases $\frac{\partial \theta_D}{\partial a}$. Together, these forces reduce the amount of reallocation towards imports following the international trade cost reduction.[17]

To reinforce the idea, consider a positive search externality in the international market (β_B is large). Assuming that $\beta_B < 1$, then each additional buyer entering the international market reduces the probability of other firms matching, but only by a small amount. Therefore, a substantial volume of buyers can be absorbed by the international market before market-tightness increases sufficiently to stop this flow.

If $\beta_B > 1$, then each additional buyer joining the international market actually increases the chance of existing buyers matching. Even in this case, the model predicts that not all firms will search internationally, as buyers have convex search costs and there would be a reduction in market-tightness in the domestic market, as discussed below.

If there is a negative externality in the domestic market then γ would be small. When buyers leave the domestic market, this causes a large reduction in market tightness in the domestic market. Consequently, it becomes easier for firms to match domestically, causing a smaller reallocation towards imports following the trade cost reduction.

2.5.2. Consumer Welfare and Matching Efficiency

The second comparative static concerns consumer welfare. Given all buyers are ex-ante identical, I can rewrite consumer welfare as the consumption from each buyer (C) multiplied by the matching probability of each type (A). A is made up of the probability of a domestic match ($a\sigma\theta_D$) plus the probability of an international match ($(1-a)\sigma\theta_I$)

[17] In addition to these two forces there is a third force coming from the convexity of the search costs

multiplied by the international match demand shifter ψ_I.

$$\begin{aligned} W(a) &= \left[\int_{b \in B(s_I)} \psi_I C_b^{\frac{\eta-1}{\eta}} + \int_{b \in B(s_D)} C_b^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} \\ &= \underbrace{\left[a\sigma\theta_D + \psi_I(1-a)\sigma\theta_I \right]}_{A} \underbrace{\left[\int_{b \in B} C_b^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}}_{C} \end{aligned} \tag{10}$$

The impact on welfare is therefore split into two parts. The first part is due to a reduction in trade costs leading to higher consumption acting through lower marginal costs $\frac{\partial C}{\partial \tau_I} < 0$. Meanwhile, the second part considers how the matching probability changes as trade costs change $\frac{\partial A}{\partial \tau_I}$. As shown in Appendix B.1.2, the change in welfare from matching following a fall in trade costs will be greater than zero if and only if the inequality in equation 11 holds.

$$\frac{\partial A}{\partial \tau_I} < 0 \iff \gamma_B a^{\gamma_B - 1} < \beta_B \psi_I (1-a)^{\beta_B - 1} S^{\beta_S - \gamma_S} B^{\beta_B - \gamma_B} \tag{11}$$

Equation 11 shows that for sufficiently large a and $\psi_I \geq 1$, the change in welfare due to matching depends on the relative size of the matching exponents. If $\gamma_B < \beta_B$ and $\gamma_S < \beta_S$ then the returns to search are higher in the international market. Consequently, a fall in trade cost will increase welfare, given firms will move from matching in the decreasing returns to scale domestic market to the increasing returns to scale international market. The intuition for this result is that a reallocation of search leads to more matches for the same search intensity. Given consumers have a taste-for-variety, this generates an increase in consumer welfare.[18]

In summary, following a fall in trade costs, both the level of reallocation between

[18] An alternative consideration is to compare welfare in the decentralized market economy to the level of welfare should a social planner pick the optimal level of search in the presence of search frictions. This is similar to the Hosios (1990) condition, which shows in a wide array of search models that the socially optimal level of search occurs when buyers' share of the joint match surplus equals the elasticity of the matching function with respect to buyers (Mangin and Julien, 2018). However, the model does not fall into this class of models given the matching function is not constant returns to scale and there are two search markets.

markets and the degree to which consumer welfare increases depend on the relative size of search externalities in domestic and international markets.

3. Data, Context and Descriptive Statistics

Having demonstrated the main mechanism in the simple model, I now look for empirical evidence of reallocation in firm supply-chains following a reduction in international trade costs. In this section, I first describe the datasets I use in this study, present descriptive statistics on firms and their connections in Uganda, and discuss the context and consequences of a reduction in trade costs.

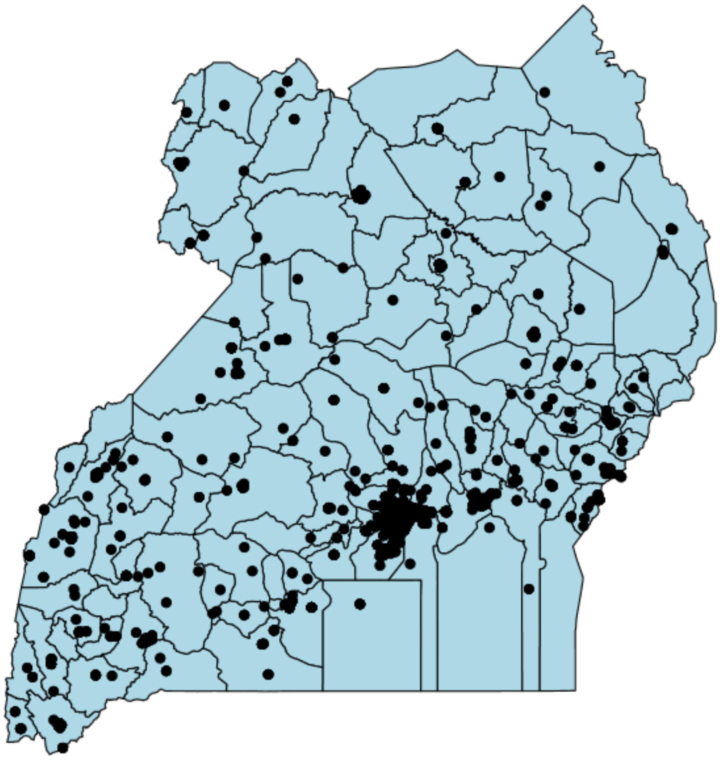
3.1. Datasets

The data used in this paper comes from four linked datasets collected by the Ugandan Revenue Authority (URA) which are administered for taxation purposes and cover the period 2010-2016. This data is confidential and is made available for the purposes of this research. Each tax dataset contains a unique tax identification number which allows the datasets to be linked across firms and time. The datasets contain the universe of firms paying tax in Uganda; consequently they are representative of the entire formal sector. It also contains the universe of importing firms in Uganda, as all firms choosing to import must go through a customs office and must be registered to pay tax. Inference on the informal sector is outside the scope of this study.[19]

The first dataset contains details on domestic firm transactions. Ugandan firms are required to record every transaction with any other tax-paying firm alongside the transacting firm's unique tax ID for Value-Added-Tax (VAT) purposes. This gives a line-by-line

[19]While I do not observe non-tax paying firms, this is not a major concern given tax paying firms in Uganda are much larger and more technically adept (Kathage, 2018) and represent the sample of firms I am most interested in. Between 2009-2011, 58% of Uganda's workforce was working in the informal sector, 13% of informal-sector workers were paid employees, 23% were unpaid helpers and 63% were working proprietors (mainly subsistence farmers) (Overseas Development Institute, 2015). There is a possibility that there is greater missed data domestically to internationally given import customs checks are likely to be more thorough.

Figure 2: Locations of firms in Uganda



Notes: Each point on the graph represents a unique location, although there are likely to be multiple firms in each location. There are a small number of firms located on islands in lake Victoria located in the bottom right.

account of the good transacted, the value of the transaction, the date it took place, and the tax identification number of the linked firm. This dataset, therefore, constitutes a dynamic input-output matrix for the entire Ugandan formal economy.[20]

The second dataset contains transaction-level international trade data. The dataset includes variables of import origin, value, product and the matched foreign exporter on the other side of the transaction.[21]

The third dataset is monthly balance-sheet data from VAT records from 2010-2016. Ugandan firms are required to report on their total sales and total inputs each month. I

[20]It also allows a product-specific calculation of inputs, although this is not done for the time being given the complexity of the data management process since records are manually entered without product codes.

[21]There is also data on firm exports, although I do not use this for the purpose of this project given I am primarily interested in firm sourcing behaviour.

Table 1: Descriptive Statistics

Variable	**Import Sample**	**Domestic Sample**
Number of buyers	6788	12984
Number of suppliers	24133	86689
Number of buyers (> 3 matches)	3373	7294
Number of suppliers (> 3 matches)	3451	17293
Firm-to-firm connections	71,000	420,000
Transactions	1.3m	11m
Mean Age	8.7	8.5
Median Wage Bill (USH)	100900	40100
Median Sales (USH)	1468800	972800

Notes: Data combined from Uganda administrative tax datasets from 2010-2016. The import sample comes from import trade data and the domestic sample comes from the VAT transaction dataset. Mean age comes from the firm registration dataset. Mean wage and sales comes from the firm balance sheet dataset.

winsorize these variables at the 5% level and collapse to annual frequency.

The fourth dataset is a firm registration dataset and contains descriptive details on the firm itself. This includes the ISIC industrial sector classification[22] and a more general description of its main operations. It also includes firms' addresses which I show on a map of Uganda in Figure 2.[23]

Descriptive statistics are presented in Table 1. The consolidated dataset contains 7,000 import buyers 13,000 domestic buyers, 24,000 import suppliers and 86,000 domestic suppliers. There are in total over 12 million transactions and over 490,000 firm-to-firm connections.

To the best of my knowledge, this is the first paper to link VAT transaction level data with firm employee and importer-exporter matched customs data. This allows observations on the complete and dynamic picture of the formal economy of Uganda. As research using tax data remains rare, one potential concern might be that the data is inconsistent with other datasets. In Appendix A.2, I address this concern by comparing the tax data used in this study to other freely-available data sources on firms in Uganda.

[22]Standard industrial classification of economic activities (ISIC) is a classification system for industry categories. The URA classifies firms at a 4 digit level.

[23]Address geo locations were mapped using google maps API

3.2. Context and Trade Cost Reduction Stylized Facts

3.2.1. Ugandan Economy

Uganda is a landlocked country in East Africa which has experienced high and sustained growth driven by high investment levels and strong international trade performance. The economy is made up of a large services sector (56.6%); agriculture, forestry and fishing (24.2%); and industry (19.2%) (World Bank, 2019).

Uganda is open to the external sector with imports reaching 25.9% as a share of GDP in 2016/17 (International Monetary Fund, 2019). The largest components of imports are consumables and capital goods for investment (World Bank, 2019).

As shown in Figure 4, only a small proportion of Ugandan firms import. As shown in Table 1, importers are on average larger than firms who only source domestically, with median sales and wage bill 1.5 and 2.5 times higher, respectively. This is consistent with previous research on this topic (e.g. Bernard and Jensen (1999)).

On average, each Ugandan firm has 2.7 domestic suppliers. The sectors with the largest number of connections are in service and manufacturing industries including construction services, telecommunication services, accounting services, and the manufacturing of plastic products, metals, and paper products.[24]

3.2.2. Buyer-Supplier Search and Search Externalities in Uganda

Finding a buyer or supplier in Uganda is a costly process. Sen (2018) argues that a lack of information about Ugandan suppliers is one of the main reasons behind a lack of oil and gas sector supplier development. Steenbergen and Sutton (2017), in neighboring Rwanda, suggest that "international firms often do not have extensive local networks, and so are unfamiliar with all the inputs that domestic suppliers may be able to provide." Buyers also have limited information about international suppliers given that the cultural, language and/or knowledge barriers are difficult for Ugandan firms to navigate. Moreover, as few

[24] This topic is covered in detail in Spray and Wolf (2016)

firms in Uganda import, there are a limited number of firms to approach for importing advice.[25] This has led the Ugandan Government to target reducing search costs by 25% in 2019 (Government of Uganda, 2019).[26]

If information about potential new suppliers diffuses among firms, either deliberately due to firms sharing knowledge or through buyers and suppliers meeting for instance in the same business location, then this would imply a positive search externality.[27] Qualitative interviews I undertook with firms in East Africa suggest that in some instances knowledge about new import suppliers is, indeed, passed among businesses.[28]

By contrast, it may be difficult for firms to make matches if there is a congestion externality. Congestion occurs when one firm's search reduces another firm's chance of matching. For instance, a buyer may spend resources looking for a supplier only to match with a firm who is unable to meet the demand because they have recently matched with another buyer (Arnosti et al., 2018). This effect has been shown to occur in multiple contexts where there is a search friction. For instance, Fradkin (2015) shows congestion in online platform AirBnB and Horton (2010) shows congestion in online labor markets.[29]

Given Ugandan suppliers are characterized by being small and with limited access to credit (Spray and Wolf, 2016), one might expect that congestion effects are larger among these firms compared to foreign importers. In an interview with a hotel in Uganda, the CEO stated that they had tried to find a domestic fruit and vegetable supplier, but that another similar hotel had recently signed up the supplier to an exclusive contract. In Section 4, I look for evidence for both of these effects empirically.

[25]Indeed, making new connections internationally has been shown in other countries to be easier if other firms in the same location are already importing (Bisztray et al., 2018).

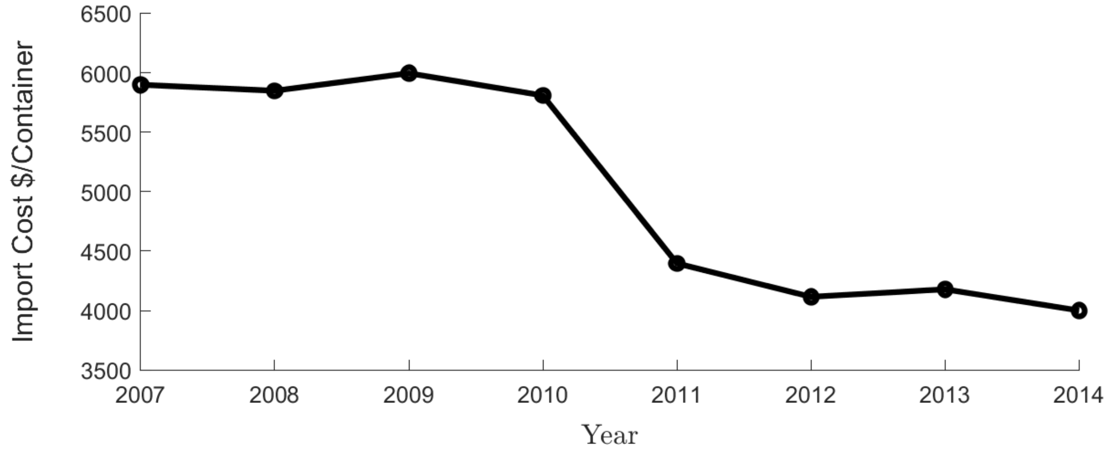
[26]A similar goal is being targeted by the government of Rwanda through the Made in Rwanda policy via establishing a publicly available supplier database to make information about firms operating in Rwanda easier to find Spray and Steenbergen (2017).

[27]If this information is priced then it would no longer represent an externality, however, this was never mentioned by firms.

[28]For instance, one tea processor explained that to find a foreign supplier of packaging products they would speak to multiple other business owners to obtain advice before purchasing. This was recounted to me in an interview with a tea factory CEO

[29]Fradkin (2015) shows a congestion effect for matches made on the online platform AirBnB, where 49% of inquiries are rejected or ignored by the host, and only 15% of inquiries lead to a transaction. An initial rejection decreases the probability that the guest eventually books any listing by 50%.

Figure 3: Transport costs for a 20’ container



Notes: Data comes from the World Bank Trading Across Borders Index. The y-axis shows the import cost in US dollars per 20-foot container. The reform took place between 2010 and 2011.

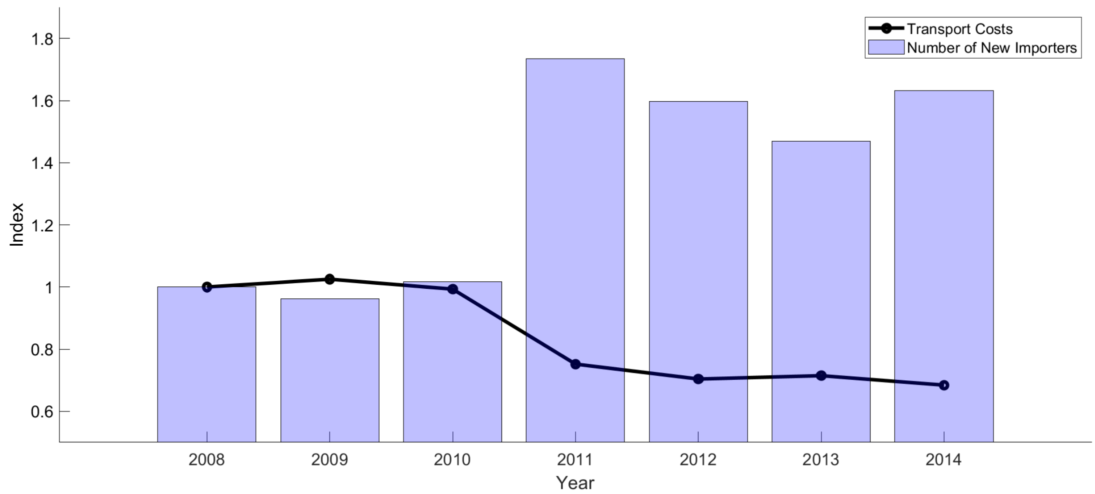
3.2.3. Trade Cost Reduction and Descriptive Statistics

Despite having a high import volume, Uganda has some of the highest transportation costs in the world. In 2017, Uganda ranked 136 out of 190 countries on World Bank’s Trading Across Border Index (World Bank, 2016). The majority of goods entering Uganda must first transit through the port of Mombasa in Kenya. In 2010, 68% of Ugandan imports arrived from the Kenyan border.[30] In 2010, the Mombasa port was described as having “persistent congestion”, being “behind international standards” and facing issues of “corruption and incompetence” (Bulzomi et al., 2014). Once goods are cleared from the port, they are required to be transported over 1000km by road through Kenya, before crossing the border into Uganda. A map of the main trade corridor, and location of the six weighbridge truck stops is shown in Figure 17 in Appendix A.1.

High transport costs have been shown in other research in Africa to severely constrict international trade (see Donaldson et al. (2017) for summary). Given Uganda’s high trade costs, the effects of reducing transportation costs may be substantial.

[30]Based on customs dataset. 25% of imports arrived through the airport, and the remainder came through the Tanzanian, Rwandan, Congolese borders or through the lake port in Jinja.

Figure 4: Transport Costs and Imports



Notes: The black line shows transport cost in USD per 20-foot container from the World Bank's Trading Across Border Index between 2007-2014, the bars show the number of new importers. The data for the bars comes from customs dataset. Reforms took place between 2010 and 2011.

In 2011, Uganda implemented reforms to reduce the cost of importing. The main reforms were longer border opening hours and improved port infrastructure at the main port in Mombasa (World Bank, 2011). In addition, Uganda rehabilitated roads thanks to a large grant from the European Union and removed several weighbridges along the route (Bulzomi et al., 2014). These reforms were negotiated at the East African Community (EAC) level and so can be thought to be outside the direct control of the Ugandan government, thus making them quasi-exogenous. The combination of these reforms led to a 25% fall in transport costs in 2011, which then reduced the cost of importing a 20-foot container from USD5807 to USD4396 (-24.3%). As shown in Figure 3, this effect happened rapidly over one year and was later stable.

I present three descriptive statistics on how firms responded to the reduction in trade costs.

(i) Falling transport costs corresponded with an increase in importers

As shown in Figure 4, the fall in transport costs corresponded with an increase in the number of new importers. The fall in transport costs was very rapid between 2010 and 2011, and was then followed by a period of flat costs. Similarly, the increase in importing also happened very rapidly followed by a corresponding period of zero growth. I show in Appendix Figures 20 and 21 that the total number of importers, the average number of suppliers and the proportion of firms which import also increase in line with the falling transport costs.[31] Although I do not observe a counterfactual of what would have happened in the absence of falling trade costs, this fits with what one would expect based on the previous literature in Africa (Donaldson et al., 2017).

(ii) Falling transport costs corresponded with new importers reducing domestic suppliers relative to other firms

To demonstrate that the change in transportation costs also corresponded with firms making readjustments to their domestic supply-chains, I compare the number of domestic suppliers used by firms who first imported in 2011 to all other buyers in a difference-in-difference specification as shown in equation 12. Note, that I do not have domestic transaction data prior to 2010, so I can not look for pre-trend differences in treatment and control groups.

$$DomesticSuppliers_{it} = \sum_t \beta_t(\delta_t \times FirstImportIn2011_i) + \alpha_i + \delta_t + u_{it} \tag{12}$$

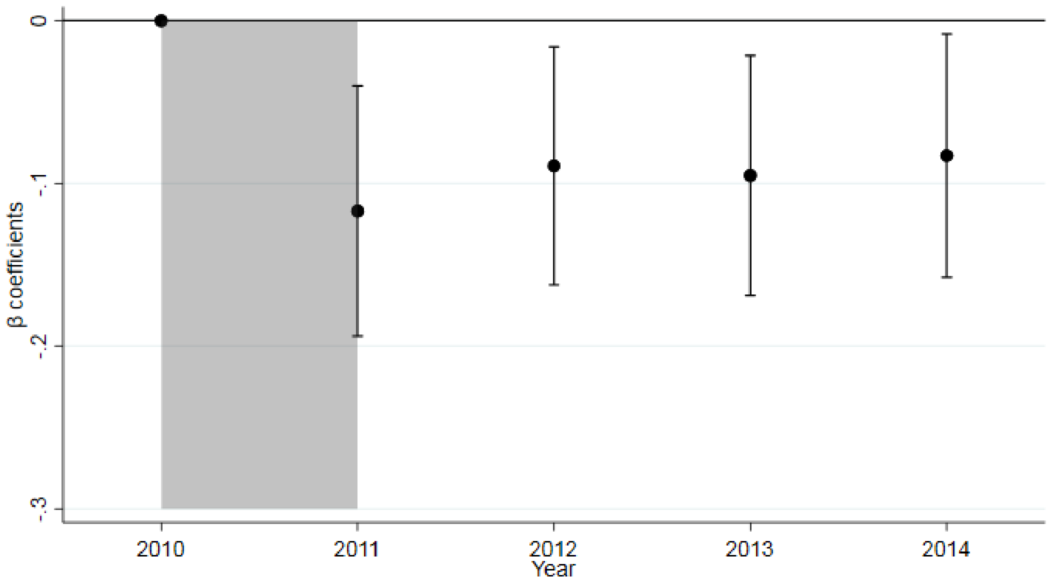
where $DomesticSuppliers_{it}$ is the log of the number of domestic suppliers supplying firm i at time t, $FirstImportIn2011_i$ is a dummy variable indicating whether firm i first imported in 2011, α_i is a set of buyer fixed effects, and δ_t is a set of year dummies.

I plot the β coefficients in Figure 5, and present the results in regression format in Table 10 in Appendix. I also show in Appendix Table 12 that this descriptive statistic is robust to using the value of domestic inputs as opposed to the number of suppliers. Relative to the control group,[32] new importers reduced their number of domestic suppliers

[31] There is also an increase in exporting, although this happens slightly later, this is discussed in detail in Spray (2017)

[32] In this case the control group is all other firms.

Figure 5: β coefficients from specification 12



Notes: The figure plots the β point estimates from specification 12 and the 95% confidence interval. The red vertical line shows the period of reduced trade costs. The outcome variable is the log of the number of domestic suppliers.

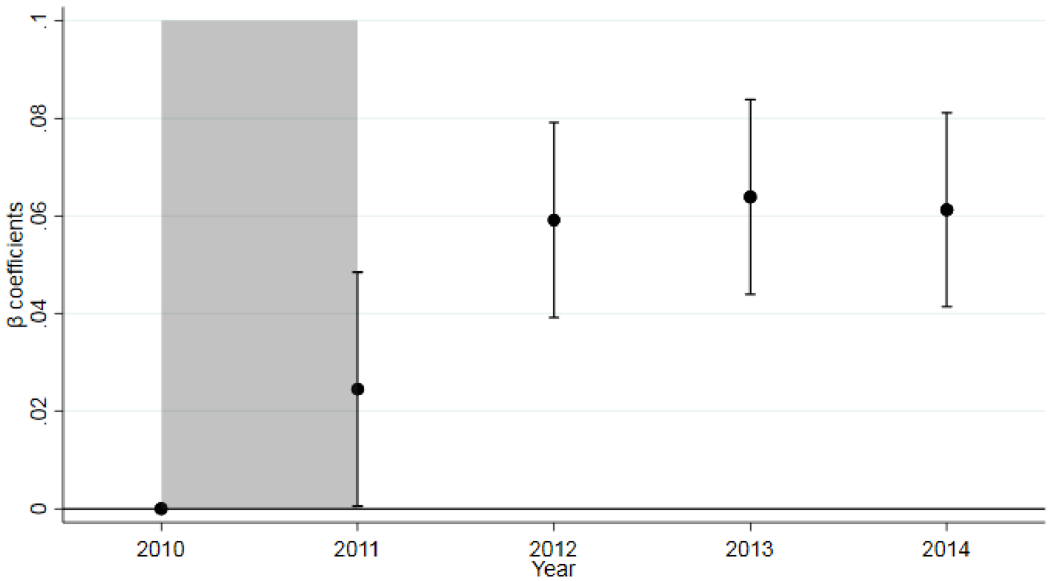
by 10% in the year of the international trade cost reduction. The effect declines over time, but is still significant at the 5% level two years later. This result is non-trivial, as we might expect new-importers to be generally expanding and hence adding both domestic and international suppliers. The fact that this is not the case suggests that firms choose either domestic or international sourcing strategies.

(iii) Suppliers which were dropped by new-importers rematched with non-importing firms

As I observe which specific suppliers were dropped by first-time importers in 2011, I now consider whether these dropped suppliers managed to replace their lost buyers with buyers who were importers, or buyers who only sourced goods domestically in Uganda. In order to show this, I estimate equation 13.

$$PropNonImportingBuyers_{ft} = \sum_t \beta_t(\delta_t \times Dropped_f) + \delta_t + \alpha_f + u_{ft} \tag{13}$$

Figure 6: β coefficients from specification 13



Notes: The figure plots the β point estimates from specification 13 and the 95% confidence interval. The red vertical line shows the period of reduced trade costs. The outcome variable is the log of the number of domestic suppliers.

where $Dropped_f$ is a dummy variable for whether supplier f was dropped by a buyer who first imported in 2011 and $PropNonImportingBuyers_{ft}$ is the proportion of buyers for supplier f at time t which do not import, excluding any buyers which were 2011 first-time importers to avoid a spurious correlation.

As shown in Figure 6 and Table 11, suppliers which lost a buyer to a 2011 first-time importer rematched with buyers who were not importers. This effect is significantly different to zero even four years after the event. I also show in Table 13 that it is robust to using the value of inputs as opposed to the number of suppliers.

We must treat these three descriptive statistics with caution as they show correlations as opposed to causal relationships. However, together, the results are consistent with the mechanism laid out in the simple model. When trade costs fell, importing became more attractive which led to a rebalancing of search in favour of international markets. This movement out of domestic search created space in the domestic market, allowing non-importing firms to match with the dropped suppliers.

4. Reduced-Form Evidence of Search Externalities

In this section, I look for evidence consistent with search externalities in both markets in reduced-form, and also present evidence on the relative size of these externalities between markets.

4.1. Motivating evidence

Figure 7 shows the percentage of supplier matches which have at least one buyer in the same neighborhood. The first bar shows that 21% of suppliers' new matches with domestic or import suppliers are in the same building as an existing customer.

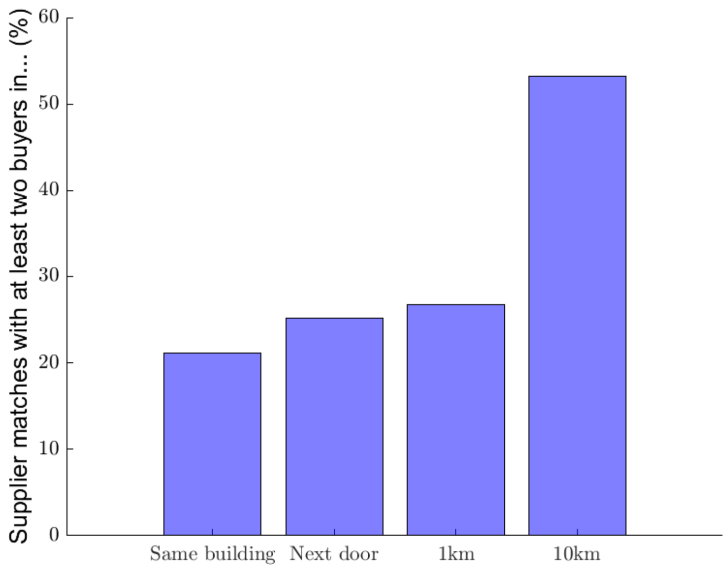
This tight proximity between suppliers' customers is consistent with the fact that it is easier to sell to customers in similar locations. One explanation for this is that information about potential suppliers may diffuse more easily among closely located buyers. This could be because closely located buyers have stronger relationships or because suppliers may bump into potential buyers operating close to their existing customers. This narrative is supported by comparing the percentage of matches with a buyer in the same building (21%) to the percentage of matches in the same or next-door buildings (25%), an increase of just 4% from adding next-door buildings. Firms in the same building are unlikely to be substantially different to their next-door neighbors, except in the ease with which information can diffuse. However, even when moving from one building to the next, the diffusion of knowledge appears to reduce substantially.

While these results are consistent with a positive information spillover, they do not exploit the richness of the data, and have nothing to say on the possible negative externality. In the next section, I move into a more formal characterization of this effect.

4.2. Empirical strategy

In order to explain the empirical strategy, consider the following example. Two firms in Kampala, {A,B}, are looking for a new supplier. Each firm can look for this supplier

Figure 7: Percentage of suppliers' matches which have an existing buyer in location



Notes: On the y-axis is the percentage of supplier matches with at least two buyer in the same location. On the x-axis, the location progressively gets wider away, such that *Next door* refers to the proportion of supplier matches with an existing buyer either in the same building or in the next-door building.

either locally or abroad. As discussed in Section 3.2.2, there are two ways A's search might influence $B's$ probability of matching; either B may pass information to A (a positive externality) or B may crowd-out A's chance of matching (a negative externality).

If information is easier to diffuse among firms located close to one another, then the spatial diffusion of firms can be used to identify different externalities. In order to test for a positive search externality, I consider whether one firm making a match increases the probability of geographically close firms making the same supplier match. To test for a negative externality, I consider whether one firm making a match decreases the probability of geographically distant firms making the same supplier match.

4.3. Dataset

I begin by generating a dataset of every buyer-supplier-year triplet separately for domestic and international suppliers. Given that I observe over 13,000 domestic buyers and 86,000 domestic suppliers over 6 years, this generates a dataset with 6.8 billion observations.

However, many matches are unlikely to ever be formed. For instance, you would not expect an iron ore mine to supply a tea factory. Instead, I trim this dataset to obtain a sample of likely matches. First, I drop suppliers which have never sold to the buyer's ISIC 4-digit industry. Second, I drop any buyer or supplier which does not make at least three matches over the entire sample period. Third, I drop any observations from the sample following the first observed match. This restricts the sample to only consider the first-time matches between firms which are active and which are in sectors which are likely to trade.

4.4. MAIN SPECIFICATION

The main specification is given by the linear probability model shown in equation 14

$$Y_{ift} = \mu X_{if,t-1}^{neighborhood} + \gamma X_{if,t-1}^{other-city} + \alpha_i + \alpha_t + u_{ift} \tag{14}$$

where Y_{ift} is a dummy $= 1$ if buyer i adds supplier f for the first-time in period t. $X_{if,t-1}^{neighborhood}$ is a count of number of firms who matched with supplier f in i's neighborhood in period $t-1$.[33] $X_{i,t-1}^{other-city}$ is a count of number of firms who added supplier f in $t-1$ but are not in i's city.

If information diffuses among firms about suppliers, we would expect these effects to occur more strongly among geographically closer firms. Therefore, $\mu > 0$ would be consistent with a positive externality.

If suppliers have a limited capacity to add multiple buyers at once, then firms making matches elsewhere in the country should decrease the probability of buyers in other locations making a match. Therefore, $\gamma < 0$ would be consistent with a negative congestion externality.

I consider four different definitions of neighborhood. The first two definitions of neigh-

[33] I run a robustness on this specification in Tables 17 and 18 where I test alternative functional forms showing results are robust to including a continuous measure of the number of new buyers in a neighborhood.

borhood consider any firm located in 10 km and 1 km radii, respectively. While these measures include a wide array of firms which could cause an information spillover, however, they suffer from the possibility that location-specific shocks hit geographically close firms. This motivates the use of two additional measures of neighborhood that consider firms located in the same building and firms located in next-door buildings. The second specification, shown in equation 15, compares the latter two definitions of neighborhood simultaneously, given that one might expect firms in the same building to be structurally very similar to those located in next-door buildings in all respects except that information is harder to diffuse across buildings than within buildings. Results would be consistent with a positive spillover if $\mu_1 > \mu_2 > 0$.

$$Y_{ift} = \mu_1 X^{same}_{if,t-1} + \mu_2 X^{nextdoor}_{if,t-1} + \gamma X^{other-city}_{if,t-1} + \alpha_i + \alpha_t + u_{ift} \tag{15}$$

In both specifications, I include buyer and time fixed effects (α_i and α_t) which control for unobserved buyer characteristics and time trends.

I consider domestic and international suppliers in separate regressions, and test whether the respective coefficients are different.

4.5. Results

As can be seen in column 1 of Table 2, each additional importer of supplier f within a 10 km radius increases the probability of buyer i matching with supplier f by 0.086%. This is a significant magnitude given that the baseline probability of a match is very low: 0.00393 for imports and 0.00398 for domestic samples. Column 3 demonstrate that this effect is larger when just looking at firms in the same building, which is consistent with information diffusion having a larger effect at shorter distances. Column 4 shows that a firm in the same building adding a new supplier has a much larger marginal effect, when compared to a firm in a next-door building adding a new supplier (0.09% vs. 0.001%, respectively). This is consistent with a local information spillover among firms in the same building, but that this becomes more difficult across buildings. Taken together,

TABLE 2: Import Suppliers

	(1)	(2)	(3)	(4)
	Y_{ift}	Y_{ift}	Y_{ift}	Y_{ift}
$X^{10km}_{if,t-1}$	0.0864***			
	(0.00693)			
$X^{1km}_{if,t-1}$		0.0819***		
		(0.00658)		
$X^{same}_{if,t-1}$			0.0910***	0.0907***
			(0.00624)	(0.00651)
$X^{nextdoor}_{if,t-1}$				0.00128
				(0.00994)
$X^{other-city}_{if,t-1}$	-0.00347*	-0.00242	-0.00240	-0.00234
	(0.00179)	(0.00172)	(0.00171)	(0.00177)
Observations	4834635	4834635	4834635	4834635
Year and Firm FE	YES	YES	YES	YES

Notes: Unit of observation is buyer i, supplier f and year t. Dependent variable Y_{ift} indicates a first match took place between buyer and supplier. X^k_{ift} is a count of buyers in region k which added supplier f in $t-1$. Coefficients are multiplied by 100 to read as percentage point marginal effects. Standard errors in parentheses are clustered at the buyer level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

these results are consistent with qualitative evidence that firms share information on import suppliers presented in Section 3.2.2.

Evidence on negative spillovers is also consistent across specifications. Where an additional buyer being added in a different city to buyer i in the previous year reduces the probability of i matching by between 0.0023% and 0.0035%. This effect is small and not statistically significant.

In Table 3, I show results for the same specification run on the sample of domestic suppliers. As in the import case, having an additional buyer in the same neighborhood increases the probability of buyer i matching with supplier f for all definitions of neighborhood. Unlike the import case, this effect is not significantly different from zero. Additionally, the magnitude of this positive coefficient is in all cases smaller than in the import case.

Unlike on the import side, evidence in Table 3 is consistent with congestion effects

Table 3: Domestic Suppliers

	(1)	(2)	(3)	(4)
	Y_{ift}	Y_{ift}	Y_{ift}	Y_{ift}
$X^{10km}_{if,t-1}$	0.00513			
	(0.00606)			
$X^{1km}_{if,t-1}$		0.00502		
		(0.00612)		
$X^{same}_{if,t-1}$			0.00509	0.00465
			(0.00613)	(0.00631)
$X^{nextdoor}_{if,t-1}$				0.000616
				(0.000322)
$X^{other-city}_{if,t-1}$	-0.00515***	-0.00515***	-0.00515***	-0.00516***
	(0.000962)	(0.000967)	(0.000972)	(0.000938)
Observations	27975967	27975967	27975967	27975967
Year and Firm FE	YES	YES	YES	YES

Notes: Unit of observation is buyer i, supplier f and year t. Y_{ift} indicates a first match took place between buyer and supplier. X^k_{ift} is a count of buyers in region k which added supplier f in $t-1$. Coefficients are multiplied by 100 to read as percentage point marginal effects. Standard errors in parentheses are clustered at the buyer level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

among domestic suppliers. In all specifications, an additional buyer in a different city in the previous year decreases the probability of the firm matching by 0.0052%. This is statistically significant at the 1% level.

Taking the results from Tables 2 and 3 together provides evidence consistent with a positive externality to search in international markets and a negative externality to search in the domestic market. As shown in the simple model, this should lead to higher welfare gains following a reduction in international trade costs.

4.6. Mechanisms and Alternative Explanations

I now consider two main possible alternative explanations for these results; either that very local shocks are driving results or that spillovers do exist, but that they are not search related. The full detail is provided in Appendix C.2.[34]

If firms in the same building were systematically different to firms in next-door buildings, then this might raise a concern that local shocks to specific industries drive results. To address this concern, in Appendix Table 14 I compare the proportion of firms in the same ISIC 4-digit sector in the same building to those in the next-door building. While there is a small difference, it is not statistically significant. However, when I look at firms further away, I do see this difference increasing. I therefore conclude that there is some firm agglomeration, but that it is happening at a block level and not at a building level. Moreover, the fact that the agglomeration decreases over space, but that the impact of an additional buyer in the neighborhood does not dramatically decrease between columns 1 and 3 of Table 2 suggests this is not a major concern.

A second alternative explanation is that a spillover is taking place, but that it is not search related. To allay these concerns, I test if the marginal effect is smaller among firms where one would expect search frictions to be less prevalent. In Appendix Table 15, I interact the independent variables with whether the import supplier exported from the East African Community (EAC). This is because one would expect search frictions to be smaller in local neighbors such as Kenya when compared to more distant locations.

Another prediction consistent with search frictions, is that suppliers which are not supply-constrained will be able to match with multiple buyers, and so we should not observe a negative congestion effect. As discussed in Section 3.2.2, this is the reason why we did not expect to find a strong congestion externality on foreign imports, given international suppliers are characterized by being large firms with cheap access to credit and multiple customers. Results in Appendix Table 16 show that domestic suppliers which are exporters, and hence less supply constrained, have a smaller negative effect from making a match elsewhere in the country. This is again consistent with the search narrative.

[34]A key point to keep in mind is that the main role of this section is to demonstrate a difference in imports and domestic suppliers externalities. As long as these concerns do not differ systematically across domestic and international suppliers, then we should be less concerned.

5. A Quantitative Model of Buyer-Supplier Search in Two Markets

Having shown reduced-form evidence consistent with greater positive search externalities in international markets compared to domestic markets, I now present a full dynamic quantitative model of optimal search among heterogeneous buyers and suppliers. This is done for three reasons. First, the structurally estimated parameters substantiate the reduced-form findings using a different yet complementary methodology.[35] Second, the structural model elucidates key mechanisms in how firms in Uganda respond to the international trade cost reduction. Third, it provides a quantitative estimate of the role of search externalities in welfare relative to a counterfactual experiment where I shut down this channel.

The simple model presented in Section 2 highlights the key mechanism, but misses a number of salient features in the data. The full model builds on the dynamic empirical model developed by Eaton, Jinkins, Tybout and Xu (2016) (EJTX (2016)). The main departure is that I add international and domestic suppliers, different search costs and matching functions, and a greater degree of firm heterogeneity.

The most important extension from the simple model is to incorporate firm heterogeneity. As shown in Table 1, only a subset of firms in Uganda import and these firms are on average significantly larger. In order to incorporate this feature, I allow firms to draw a marginal cost and then pay a fixed cost for searching internationally, therefore in equilibrium this means that only the lowest marginal cost firms import.

A second source of buyer heterogeneity comes in the number of matches made by firms. I observe in the data that a large mass of firms have a small number of suppliers, however, I also observe many firms with over 30 suppliers. I therefore allow buyers and

[35]The reduced-form methodology has the advantage of being clearer where the estimated coefficients come from. However, in this paper the reduced-form structure is restrictive and one might expect that there are multiple channels for search externalities to pass which are not picked up by the reduced-form. I therefore turn to a structural model which allows a more clearly model-driven pass through of externalities and has the large advantage of allowing the consideration of policy counterfactuals.

suppliers to make multiple matches by making the model dynamic, adding an additional search intensity decision, and exogenous link death probability. In addition to matching buyer size distributions, I also match supplier size distributions by allowing suppliers to make an optimal search decision.

5.1. Buyers and Suppliers

There is a measure B continuum of buyers, measure S_D continuum of domestic suppliers and measure S_I continuum of international suppliers.

Suppliers produce differentiated products (x) which they sell to buyers (b) once they match. Let $B(s_I)$ denote the set of buyers who match with international suppliers. Similarly, let $B(s_D)$ denote the set of buyers who match with domestic suppliers. Suppliers choose search intensity $\sigma_j^S(n)$. There is an exogenously given probability δ of an existing match being severed.

There are Γ buyer types indexed $i \in \{1, 2, ..., \Gamma\}$ with marginal cost c_i drawn from a known distribution, and match with $\mathbf{s} = \{s_I, s_D\}$ suppliers. This now warrants a change of subscripts from buyer b to buyer type i. Buyers choose their search intensity $\sigma_i^B(\mathbf{s})$ and choose the proportion of search they exert domestically, a such that $a \in [0, 1]$, and internationally, $1 - a$.

Buyers pay an iceberg trade cost τ_I on each unit of international goods and iceberg trade cost τ_D on each unit of domestic goods, where I normalize $\tau_D = 1$.

5.2. Consumers

Consumers have a nested CES utility function which shows their taste-for-variety over buyers (b) and products (x), such that

$$C = \left[\int_{b \in B} C_b^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} \tag{16}$$

$$C_b = \left[\sum_{x \in J(s_I)_b} (\psi_I C_b^x)^{\frac{\alpha-1}{\alpha}} + \sum_{x \in J(s_D)_b} (C_b^x)^{\frac{\alpha-1}{\alpha}} \right]^{\frac{\alpha}{\alpha-1}}, \tag{17}$$

where $J(s_I)_b$ is the set of international products x offered by buyer b and $J(s_D)_b$ is the set of domestic products x offered by buyer b, C_b^x is consumption of product x from buyer b, and C_b is consumption of the set of products offered by b. η and α are the elasticities of substitution among products and buyers, respectively. I assume all international products have the same demand shifter, ψ_I, and all domestic products have the same demand shifter, ψ_D, which I normalize to 1. If imports are higher quality products, we might expect $\psi_I > 1$ for imported goods, although I do not impose this.

5.3. Pricing and Division of Profits

As buyers now match with multiple suppliers, they sell multiple goods. They, therefore, internalize the price set on one good on the demand of their other goods. This yields a first order condition on prices given by

$$q_{xb} + \sum_{x' \in J_b} \frac{\partial q_{x'b}}{\partial p_{xb}} (p_{x'b} - c_{x'b}) = 0 \qquad \forall x \in J_b, \tag{18}$$

where $c_{x'b}$ is the marginal cost of supplying product x' to consumers through buyer b. The intuition behind Equation 18 is that buyers internalize that their pricing on one good alters demand on other goods.

The instantaneous profit flow created by buyer b and its set of suppliers is now given by a summation over the profit provided by each product x in buyer b's bundle (J_b), such that

$$\pi_b(\mathbf{s}) = \frac{E}{\eta P^{1-\eta}} \left[\sum_{x \in J_b} \left(\frac{\eta}{\eta - 1} \right)^{1-\alpha} \tau_L \tilde{c}_b^{1-\alpha} \right]^{\frac{1-\eta}{1-\alpha}}, \tag{19}$$

for $L \in \{D, I\}$ and where $\tilde{c}_b = c_b/\psi_L$ is the quality-adjusted marginal cost, $\mathbf{s} = \{s_I, s_D\}$ is a vector of the number of international and domestic suppliers, P is the standard CES aggregate price index and E is household expenditure. As long as $\alpha > \eta > 1$, then the profit function is increasing in the aggregate price index and decreasing in marginal cost.

This condition also ensures that there are diminishing returns to the number of suppliers, given that adding a new supplier appears in the summation $x \in J_b$ which leads to an increase in profit but at a decreasing rate, as long as the exponent $\frac{1-\eta}{1-\alpha} < 1$.[36] If the buyer matches with a domestic supplier then $\tau_D = \psi_D = 1$. For higher international trade costs (τ_I) or smaller international demand shifter (ψ_I) profits from matching with an international supplier are smaller.

As buyers now have multiple suppliers, division of profits becomes more complex. I assume Stole and Zwiebel (1996) bargaining which gives each seller a profit flow z_{ji} equal to their bargaining share multiplied by their marginal contribution to profit which depends on whether the good is domestic or international $L \in \{D, L\}$.[37]

$$\begin{aligned} z_{ji}(\mathbf{s}) &= \Lambda \frac{\partial \pi_i^T(\mathbf{s})}{\partial s_L} \\ &= \frac{\Lambda}{\alpha - 1}\left(\frac{\eta}{\eta - 1}\right)^{-\eta} \frac{E}{P^{1-\eta}} \left[\sum_{j \in J_b} \tau_L \tilde{c}_i^{1-\alpha}\right]^{\frac{\alpha-\eta}{1-\alpha}} \tau_L \tilde{c}_i^{1-\alpha} \end{aligned} \tag{20}$$

Equation 20 is very close to being a structural equation which would be estimatable in the data, therefore allowing the recovery of key parameters. However, the seller's profit z_{ji} is not observable in the data. Instead, the data shows a firm-to-firm transaction which includes both profit and compensation for marginal costs in production of each good. If a constant fraction λ of the variable costs is attributable to the seller,[38] then the revenue transfer can be expressed between firms r_{ji} in terms of fixed effects and observables

$$r_{ji}(\mathbf{s}) = (h_{j|i})^{\frac{\alpha-\eta}{\alpha-1}} \frac{E}{P^{1-\eta}} \left(\frac{\eta}{\eta - 1}\right)^{-\eta} \left(\tau_L \tilde{c}_{ji}\right)^{1-\eta} \left[\frac{B}{\alpha - 1} + \lambda\right], \tag{21}$$

[36] In this way profit depends on the number of suppliers, however, this is not to be confused with diminishing returns to scale in the matching function discussed in Section 5.4.

[37] Stole and Zwiebel (1996) is a generalization of Rubinstein bargaining to multiple firms based on Shapley value which gives firms a constant fraction of revenue

[38] This assumption only influences the estimation of the structural equation for the purpose of extracting the elasticity of substitution parameters. In all other aspects I consider the buyer and supplier to be jointly maximising profits.

where r_{ji} is the revenue for seller j from buyer i, $h_{j|i} = \frac{\tau_L \tilde{c}_j^{1-\alpha}}{\sum_{l=1}^{J} s_l \tau_L \tilde{c}_i^{1-\alpha}}$ is the within buyer-i revenue share of a type-j seller, λ is the seller's fraction of marginal cost. Equation 21 is a structural equation which I follow EJTX (2016) in estimating from the data in order to obtain elasticity of substitution parameters η.

5.4. Search and Matching

Relative to the simple model, modelling search-and-matching is made more complex by the addition of a search intensity choice for buyers and suppliers (σ^B, σ^S respectively) and given that buyers have a choice on the proportion of search done domestically (a).[39]

Following EJTX (2016), I define a new variable, visibility (H) of a type-i buyer in domestic and international markets, respectively, as

$$\begin{aligned} H_{i,D}^B(\mathbf{s}) &= a_i(\mathbf{s})\sigma_i^B(\mathbf{s})M_i^B(\mathbf{s}) \\ H_{i,I}^B(\mathbf{s}) &= (1 - a_i(\mathbf{s}))\sigma_i^B(\mathbf{s})M_i^B(\mathbf{s}), \end{aligned} \tag{22}$$

where $M_i^B(s_D, s_I)$ is a measure of type-i buyers with $\mathbf{s}$ sellers. Intuitively, buyers of type-i are more visible if they are searching more ($a_i\sigma_i, (1 - a_i)\sigma_i$) and if there is a larger mass of them (M_i^B).

The overall visibility of buyers in the domestic and international market is a summation over all buyer types and for any number of existing matches.

$$H_L^B = \sum_{i=1}^{I} \sum_{s_L=0}^{s_{L_{max}}} H_{i,L}^B(\mathbf{s}) \text{ for } L \in \{D, I\} \tag{23}$$

Domestic and international sellers' visibility (H_D^S, H_I^S) are defined symmetrically to buyers

$$\begin{aligned} H_D^S(n) &= \sigma_D^S(n)M_D^S(n) \\ H_I^S(n) &= \sigma_I^S(n)M_I^S(n). \end{aligned} \tag{24}$$

[39]Where as in the simple model $a \in [0, 1]$ and the amount of search internationally is $1 - a$.

The matching function is similar to the simple model, but is now increasing in buyer and seller visibility

$$X_D(H_D^S, H_D^B) = \left(H_D^B\right)^{\gamma_B}\left(H_D^S\right)^{\gamma_S} \tag{25}$$

$$X_I(H_I^S, H_I^B) = \left(H_I^B\right)^{\beta_B}\left(H_I^S\right)^{\beta_S}. \tag{26}$$

As in the simple model discussed in Section 2.3, the matching function exponents are key objects in the model. A positive externality to search would be indicated by high γ_S, γ_B and β_S, β_B. This is because, at the margin, an increase in buyers or sellers visibility will lead to a large increase in the number of matches. There are increasing returns to scale in domestic matching if $\gamma_S + \gamma_B > 1$. By contrast, a congestion externality to search would be indicated by low γ_S, γ_B and β_S, β_B, as more firms entering leads to very few new matches. There are decreasing returns to scale in domestic matching if $\gamma_S + \gamma_B < 1$. A low γ_S would indicate that congestion is largely on the domestic supplier-side. Whereas, a low γ_B would indicate that there is high congestion among domestic buyers. In Section 6, I structurally estimate the exponents using simulated method of moments.

The match flow per unit of buyer visibility θ is a measure of market tightness and is defined separately in the domestic and international markets, given by

$$\theta_D = \frac{X_D(H_D^S, H_D^B)}{H_D^B} \qquad \theta_I = \frac{X_I(H_I^S, H_I^B)}{H_D^B}. \tag{27}$$

A higher value of θ simply indicates that the hazard-rate of finding a match is higher.[40]

5.5. Search Cost

In order to make sure that buyers do not enter a sorting equilibrium of only searching domestically or internationally, I assume positive and convex search costs[41] with a fixed cost of search F_S and an additional fixed cost of international search F_I only paid if the

[40] θ_{S_L} is defined symmetrically for $L \in \{D, I\}$ type suppliers.

[41] See Section 2.4 for further justification of this assumption.

firm chooses to search internationally.

$$k^B = \left(\left(a\sigma^B\right)^v + \left((1-a)\sigma^B\right)^v\right)^v + F_S + F_I, \quad v > 1 \tag{28}$$

Fixed costs are common in the trade literature following Melitz (2003) as they ensure that high marginal cost firms only sourcing domestically. They represent the up-front costs firms pay in entering international trade (see for instance Antras et al. (2017). I structurally estimate F_S, F_I in Section 6.

Sellers have a parallel set of search costs which are convex in the seller search intensity

$$k_L^S = \left(\sigma^S\right)^v, \quad \text{for } L \in \{D, I\} \text{ and } v > 1, \tag{29}$$

which for simplicity are assumed to be the same for domestic and international suppliers.

5.6. Optimal Search

Buyers solve the following maximization problem by picking their optimal search intensity σ and the proportion of that search intensity in the domestic market a

$$V_i^B(\mathbf{s}) = \max_{a,\sigma^B}\left\{\frac{\pi_i^B(\mathbf{s}) - k^B(a_i,\sigma_i^B) + s_D\delta V_i^B(s_D-1) + a\sigma^B\theta_D^B V_i^B(s_D+1) + s_I\delta V_i^B(s_I-1) + (1-a)\sigma^B\theta_I^B V_i^B(s_I+1)}{\rho + s_D\delta + s_I\delta + a\sigma^B\theta_D^B + (1-a)\sigma^B\theta_I^B}\right\}, \tag{30}$$

where $V_i^B(\mathbf{s})$ is the present value of a type$-i$ buyer that is matches with vector $\mathbf{s} \in \{s_I, s_D\}$ sellers, ρ time preferences, δ is an exogenously given link death parameter.

Buyers receive profit equal to gross profit minus search costs, $(\pi_i^B(\mathbf{s}) - k^B(a_i, \sigma_i^B))$, until one of four events occurs with an endogenously given hazard: either (i) a buyer drops a domestic supplier $\left(V_i^B(s_D-1)\right)$, (ii) adds a domestic supplier $\left(V_i^B(s_D+1)\right)$, (iii) drops an international supplier $\left(V_i^B(s_I-1)\right)$, or (iv) adds an international supplier $\left(V_i^B(s_D+1)\right)$.

This yields policy functions for optimal search and the proportion of search in the domestic market where the change in cost of search is equal to the change in the value function from adding an additional domestic or international supplier multiplied by the hazard of these events occurring

$$\frac{\partial k^B(\sigma^B, a)}{\partial \sigma^B} \leq a\theta_D^B \Delta_{s_D} V_i^B + (1-a)\theta_I^B \Delta_{s_I} V_i^B \tag{31}$$

$$\frac{\partial k^B(\sigma^B, a)}{\partial a} \leq \sigma^B \theta_D^B \Delta_{s_D} V_i^B - \sigma^B \theta_I^B \Delta_{s_I} V_i^B \tag{32}$$

where $\Delta_{s_L} V_i^B = V_i^B(s_L+1) - V_i^B(s_L)$ for $L \in \{D, I\}$. Equation 31 and 32 hold with equality when a firm searches both internationally and domestically ($a < 1$).

Suppliers solve a parallel problem, where the value V to any seller matching with a type-i buyer who has $\mathbf{s}$ suppliers depends on their type L and is given by

$$\begin{aligned} V_{D,i,s}^S &= \frac{r_i(\mathbf{s}) + (s_D - 1)\delta V_{D,i,s_D-1}^S(s_D-1) + a_i\sigma_i^B\theta_D^B V_{D,i,s_D+1}^S}{\rho + s_D\delta + a_i\sigma_i^B(\mathbf{s})\theta_D^B} \\ V_{I,i,s}^S &= \frac{r_i(\mathbf{s}) + (s_I - 1)\delta V_{I,i,s_I-1}^S(s_I-1) + (1-a_i)\sigma_i^B\theta_I^B V_{I,i,s_I+1}^S}{\rho + s_I\delta + (1-a_i)\sigma_i^B(\mathbf{s})\theta_I^B} \end{aligned} \tag{33}$$

Intuitively, the supplier gets revenue $r_i(\mathbf{s})$ as defined in equation 21, until they either lose a match with probability $(s_L - 1)\delta$ or gain a match with probability depending on whether the supplier is domestic or international $a_i\sigma^B\theta_D^B, (1-a_i)\sigma_i^B\theta_I^B$. Taking expected value of a match is a summation over buyer types:

$$V_L^S = \sum_i \sum_{s=0}^{\infty} V_{L,i,s+1}^S P_i^B(\mathbf{s}), \qquad \text{for Ł} \in \{D, I\} \tag{34}$$

where $P_i^B(\mathbf{s}) = H_i^B(\mathbf{s})/H^B$ is the share of matches involving buyers of type$-i$ with $\mathbf{s}$ sellers.

Optimal seller search is then given by a parallel set of policy functions

$$\frac{\partial k_D^S(\sigma_D^S, s_D)}{\partial \sigma_D^S} = \theta_D^S V_D^S \tag{35}$$

$$\frac{\partial k_I^S(\sigma_I^S, s_I)}{\partial \sigma_I^S} = \theta_I^S V_I^S. \tag{36}$$

The optimal level of seller search is, therefore, the expected value of a new relationship multiplied by the probability of a match.

5.6.1. Equilibrium

The model is completed via an equation of motion, where the change in the mass of buyers with **s** sellers is given by,

$$\begin{aligned}\dot{M}_i^B(s) = \Big[&\underbrace{a_i\sigma_i^B\theta_D^B M_i^B(s_D-1,s_I)}_{i} + \underbrace{\delta(s_D+1)M_i^B(s_D+1,s_I)}_{ii} + \underbrace{(1-a_i)\sigma_i^B\theta_I^B M_i^B(s_D,s_I-1)}_{iii} \\ &+ \underbrace{\delta(s_I+1)M_i^B(s_I+1,s_D)}_{iv}\Big] - \Big[\underbrace{a_i\sigma_i^B\theta_D^B}_{v} + \underbrace{\delta s_D}_{vi} + \underbrace{(1-a_i)\sigma_i^B\theta_I^B}_{vii} + \underbrace{\delta s_I}_{viii}\Big] M_i^B(s_D,s_I).\end{aligned} \tag{37}$$

Equation 37 shows the change in mass of type$-i$ buyers with **s** sellers is equal to flows in (i+ii+iii+iv) minus flows out (v+vi+vii+$viii$). Flows in is made up of the mass of type$-i$ buyers who have: (i) $s_D - 1$ suppliers multiplied by the probability of adding a domestic supplier; (ii) $s_D + 1$ suppliers multiplied by the probability of losing a domestic supplier; (iii) $s_I - 1$ suppliers multiplied by the probability of adding a international supplier; (iv) $s_I + 1$ suppliers multiplied by the probability of losing a international supplier. Flows out is made up of the mass of type$-i$ buyers who have **s** suppliers multiplied by the probability of: (v) adding a domestic supplier; (vi) losing a domestic supplier; (vii) adding a international supplier; ($viii$) losing a international supplier. Finally, the measure of buyers of type$-i$ with $s_L = 0$ is given by

$$\begin{aligned}\dot{M}_i^B(0,s_I) = &\Big[\delta M_i^B(1,s_I) + (1-a_i)\sigma_i^B\theta_I^B M_i^B(0,s_I-1) + \delta(s_I+1)M_i^B(0,s_I)\Big] \\ &-\Big[a_i\sigma_i^B\theta_D^B + (1-a_i)\sigma_i^B\theta_I^B + \delta s_I\Big] M_i^B(0,s_I).\end{aligned} \tag{38}$$

$$\dot{M}_i^B(s_D,0) = \Big[\delta M_i^B(s_D,0) + a_i\sigma_i^B\theta_D^B M_i^B(s_D-1,0) + \delta(s_D+1)M_i^B(s_D,0)\Big] \\ -\Big[(1-a_i)\sigma_i^B\theta_I^B + a_i\sigma_i^B\theta_D^B + \delta s_D\Big]M_i^B(s_D,0). \tag{39}$$

A symmetric set of equations exists for suppliers.

As in EJTX (2016), I look for a stationary equilibrium at the steady state, I set $\dot{M}_i^B(s) = \dot{M}_j^S(n) = 0$ and solve the system of equations for all buyer types and suppliers given in equations 37, 38 and 39. I treat each buyer type as exogenously given.

6. Estimation

Model estimation takes place in three steps: 1) Estimating the transfer equation to obtain elasticity of substitution parameters; 2) Externally calibrating parameters using the literature, and; 3) Structurally estimating the model using simulated method of moments.

6.1. Estimating transfer equation

I follow EJTX (2016)'s methodology in estimating a transfer equation between buyers and suppliers in order to identify the elasticities of substitution between buyers. I estimate the structural equation 21 via Ordinary Least Squares (OLS). Equation 21 relates the revenue passed between buyers and suppliers (r_{ji}) to the within buyer$-i$ revenue share of seller j. When taking logs and adding time dummies (d_t) and a stochastic noise parameter (ϵ), I can recover the coefficient on $\ln h_{j|i}$ which incorporates the elasticity of substitution between products (α) and elasticity of substitution across buyers (η)

$$\ln r_{ji}(\mathbf{s}) = \frac{\alpha-\eta}{\alpha-1}\ln h_{j|i} + 1 - \eta \ln \tilde{c}_{ji} + d_t + \epsilon_{jit} \tag{40}$$

where r_{ji} is the revenue passed from buyer i to supplier j and $h_{j|i}$ is the within buyer-i revenue share of seller j.

In order to address the term $\ln \tilde{c}_{ji}$, I include different fixed effects options. As in EJTX (2016), I address the concern that there is comovement in $\ln h_{j|i}$ and $\ln r_{ji}$, not driven by

TABLE 4: Estimating the transfer equation

	(1) OLS-FE	(2) IV-FE	(3) OLS-FE
$\ln h_{j\|i,t}$	0.869***	0.957***	
	(0.00373)	(0.00391)	
$\ln n_{it}$			-0.300***
			(0.0130)
Match FE	yes	yes	no
Buyer FE	no	no	yes
Importer FE	no	no	yes
Year FE	yes	yes	yes
N	686170	686170	686170

Notes: Unit of observation is buyer i supplier j and year t. Standard errors in parentheses clustered at the buyer level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

the components of the model, by using an instrument for $\ln h_{j|i}$ which is equal to a share-weighted average of the number of buyers of the *other* sellers at buyer j. The instrument should be correlated with h through common shocks for similar products but should not influence revenue through any other channel.

I also run a separate model where I assume that all suppliers are identical except in allowing fixed effects to differ between import and domestic suppliers. In this case, I include just the log of the number of suppliers as the explanatory variable.

The first result from Table 4 is that the coefficient $\frac{\alpha-\eta}{\alpha-1} < 1$. Therefore, I conclude, as in EJTX (2016), that the elasticity of substitution across varieties (α) exceeds the elasticity of substitution across buyers (η). Therefore, as shown in equation 19, there are decreasing returns to adding new suppliers.[42] Note that this is not to be confused with returns to scale in the matching function, which I estimate within the model. In column 2 of Table 4, I adopt the IV strategy and observe that the estimate increases but remains below 1.

Finally in column 3, I estimate the transfer equation where I assume all suppliers have

[42]As discussed after equation 19, this condition ensures that there are diminishing returns to the number of suppliers, given that adding a new supplier appears in the summation $x \in J_b$ which leads to an increase in profit but at a decreasing rate, as long as the exponent $\frac{1-\eta}{1-\alpha} < 1$.

the same marginal costs. Intuitively, for a given buyer adding another supplier lowers the revenue transferred to all other suppliers. As shown in Appendix equation B.11, the coefficient on $\ln n$ is equal to $-\frac{\alpha-\eta}{\alpha-1}$. Intuitively, for a given buyer adding another supplier lowers the revenue transferred to other suppliers.

This gives a smaller coefficient than that in columns 1 and 2, but the result is still below 1 $\left(\frac{\alpha-\eta}{\alpha-1} = 0.3\right)$. Given the model's assumption that all suppliers have the same marginal cost, I use column 3 as my preferred specification.

6.2. Externally calibrated parameters

There are 8 parameters that are externally calibrated. The elasticity of substitution with respect to products α is set to 4.35 as in EJTX (2016). Using $\alpha = 4.35$, I can infer from column 3 of Table 4 that $\eta = 3.35$. This is coincidentally identical to the value estimated in EJTX (2016).[43] Firms' productivities are assumed to be Pareto distributed with shape parameter $\kappa = 4.25$ following Melitz and Redding (2015). The remaining parameters are adopted from the literature and are displayed in Table 5.

6.3. Internally calibrated parameters

I structurally estimate 7 key parameters of the model ($\xi = \{F_D, F_I, \psi_I, \gamma^S, \gamma^B, \beta^S, \beta^B\}$) using Simulated Method of Moments (SMM). This method selects the model parameters to minimize the difference between the simulated model generated moments and the moments in the data, by minimizing the following objective function

$$\hat{\zeta} = \text{argmin}_{\zeta}\mathscr{L}(\zeta) = \text{argmin}_{\zeta}\frac{1}{N}[M_m(\zeta) - M_d]'W_N\frac{1}{N}[M_m(\zeta) - M_d] \tag{41}$$

where ζ is a vector of moments to be targeted internally, $\mathscr{L}(\zeta)$ quadratic loss function to be minimized, $M_m(\zeta)$ vector of model moments, M_d vector of corresponding data counterparts of the moments of interest, $M_m(\zeta) - M_d$ is the orthogonality condition and

[43]EJTX (2016) use Colombian data finding a coefficient of -0.382 for rubber products and -0.289 for textiles. They take a middle point of these estimates to obtain -0.3 which works out as an $eta = 3.35$

Table 5: Model Parameters

	Externally Calibrated Parameter	Value		Data source
α	Elasticity of sub. products	4.35		Eaton et al. (2016)
η	Elasticity of sub. buyers	3.35		Estimated in transfer equation
Λ	Bargaining coefficient	0.5		Eaton et al. (2016)
υ	Convexity of search cost	2		Eaton et al. (2016)
δ	Death parameter	0.4		Calculated in data
τ	Iceberg trade cost	1.45		Atkeson and Burstein (2008)
κ	Pareto shape parameter	1.45		Melitz and Redding (2015)
ρ	Time preference	0.05		Eaton et al. (2016)
	Internally Calibrated Parameter	**Value**		**Most important moment**
ψ_I	Import premium	1.92	(0.0211)	Ratio of imports to domestic among importers
F_D	International fixed cost	0.24	(0.0061)	Prop of firms import
F_I	Domestic fixed costs	0.001	(0.0001)	Number of active firms
γ_B	D buyer matching CD share	0.45	(0.0093)	Prob. of a new match for dom. buyer
γ_S	D supplier matching CD share	0.50	(0.0087)	Prob. of a new match for dom. supplier
β_B	I buyer matching CD share	0.60	(0.0112)	Prob. of a new match for imp. buyer
β_S	I supplier matching CD share	0.66	(0.0106)	Prob. of a new match for imp. supplier

Notes: Standard errors in parentheses based on 25 bootstrapped samples drawn with replacement.

W_N is a positive semi-definite weighting matrix which for simplicity is the identity matrix.

As shown in Table 6, I obtain 10 moments from the data using periods prior to the trade cost reduction. Intuitively, the proportion of buyers which are importers and the ratio of imports to domestic inputs among importers ties down the import premium and the import fixed cost. The mass of active firms ties down the domestic fixed cost. Each of the matching parameters are tied down by the combination of the probability of a new match for their type (domestic, international, buyer, supplier) and also the mass of active buyers and suppliers of their type in the population.

The results are given in Table 5. Importantly, I find that imports have a 1.92 times quality premium over domestic goods which is consistent with imported goods being of a higher standard. However, fixed costs of searching for imports are 240 times higher than the fixed cost of searching for domestic goods.

The most important parameters are the matching coefficients γ and β. Consistent with the reduced form evidence, I find that there are decreasing returns to search in the domestic market ($\gamma^S + \gamma^B < 1$). By contrast, there are increasing returns to search in the international market ($\beta^S + \beta^B > 1$). In Section 7, I show numerically that this results in higher consumer welfare following a fall in transport costs.

TABLE 6: Model fit

Moment	**Model Value**	**Data Value**
Ratio of imports to domestic among importers	0.58	0.59
Proportion of firms which import	0.24	0.20
Prob. of a new match for international suppliers	0.20	0.28
Prob. of a new match for domestic suppliers	0.30	0.31
Prob. of a new match for international buyer	0.32	0.35
Prob. of a new match for domestic buyer	0.18	0.24
Number of active international suppliers	11,100	8,400
Number of active domestic suppliers	14,400	13,600
Number of active international buyer	5,700	4,800
Number of active domestic buyer	18,300	19,200

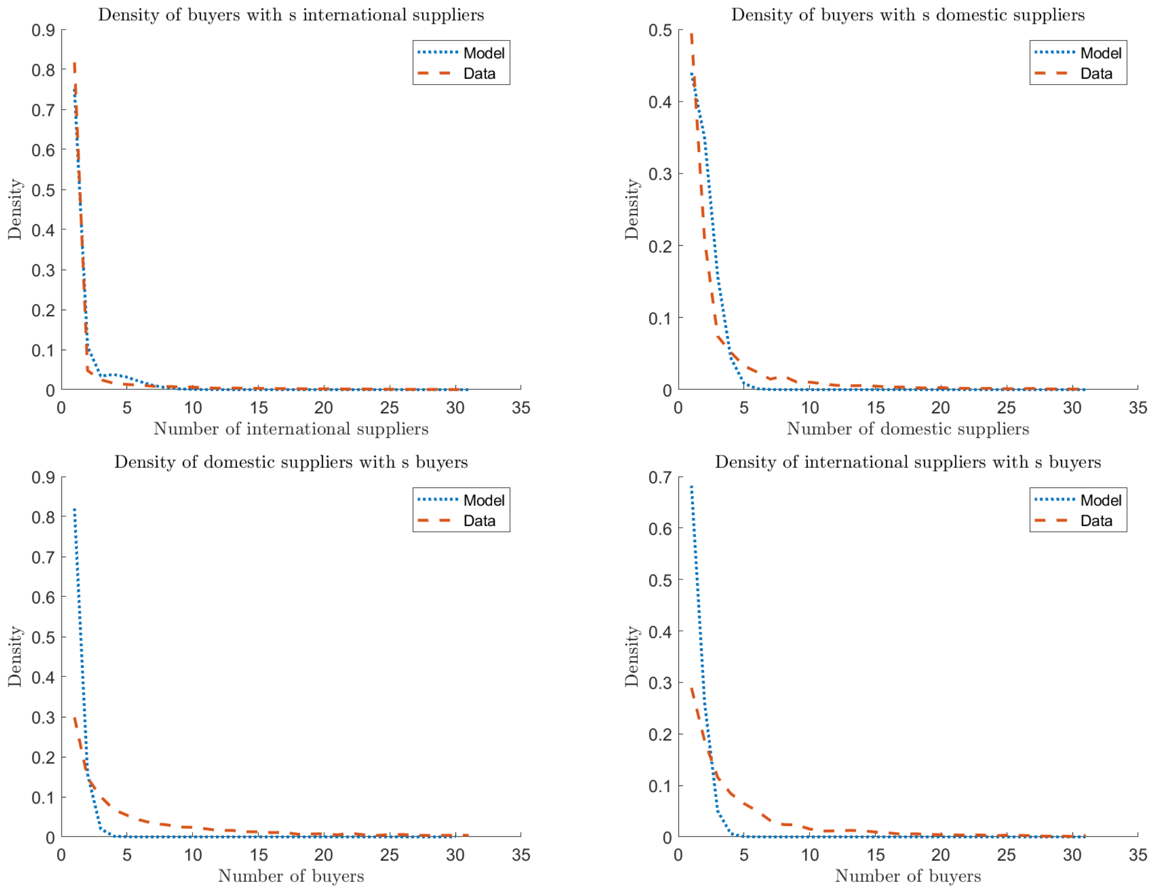
Notes: Table shows model generated moments and corresponding data moments. The ratio of imports to domestic among importers is calculated by dividing the total import value by the total value of inputs (imports + domestic goods). The proportion of firms which import is simply the proportion of buyers which imported in 2010 divided by the total number of buyers. The probability of a new match for an each type of buyer and supplier is calculated by seeing the proportion of firms which add a new match. The number of active firms is calculated as the number of firms in the dataset with positive sales in 2010.

6.4. MODEL FIT

Table 6 compares the simulated model moments with their data counterparts, highlighting a close fit. The model also does well in matching untargeted moments. For example, as shown in the top two charts of Figure 8, the model's generated mass distribution of buyers with different numbers of domestic and international suppliers closely matches its data counterpart.

However, as shown in the bottom two charts of Figure 8, the model does less well in matching the distribution of supplier with different numbers of buyers. Although the shape of the distribution is similar, the model overestimates the density of suppliers with a small number of buyers. This is because the model has less flexibility on the supplier side relative to the buyer side given I assume all buyers have the same marginal costs. It is also consistent with fit of the quantitative model in Lim (2017) which also underpredicts the extent of connections of the most connected firms.

Figure 8: Model fit: buyer and supplier out-degree



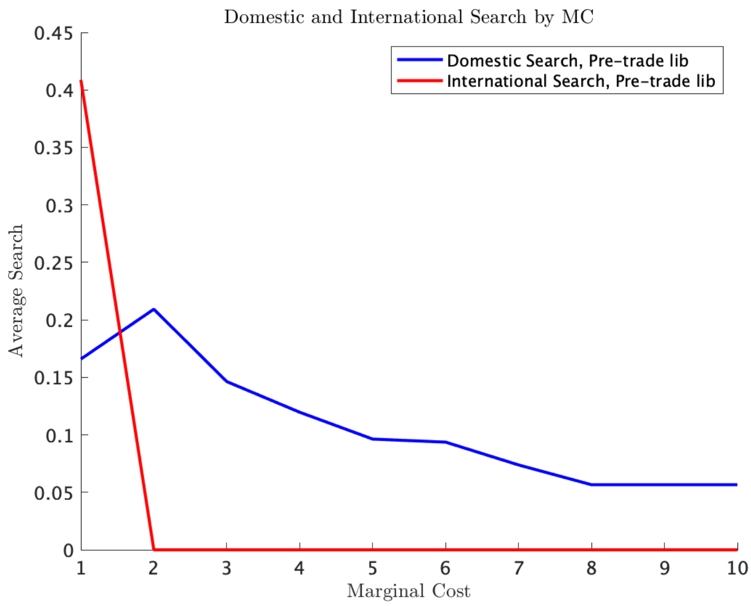
Notes: The top two figures shows the density of buyers with different numbers of international and domestic suppliers, respectively. the bottom two figures shows density of international and domestic suppliers with different numbers buyers. The blue lines show the model predicted density and the orange lines show the true value observed in the data.

6.5. Heterogeneity

In addition to the model's aggregate predictions, it also demonstrates that firms behave differently depending on their marginal cost. In Figure 9, I group firms into marginal cost bins from 1 to 10 on the x-axis, and show the average level of search for each firm in each bin in international (red) and domestic markets (blue) on the y-axis. Due to the large fixed cost of importing, only the lowest marginal cost firms choose to search internationally. These firms also search domestically due to the convex costs to searching in each market.

Firms just below the threshold of paying the import fixed cost end up spending more

Figure 9: Search by marginal cost



Notes: The x-axis breaks buyers into 10 different marginal cost bins, where 1 indicates the lowest marginal costs and 10 equals the highest marginal costs. The y-axis shows the average search undertaken by buyers in each of these groups. The solid red and blue lines show the amount of domestic and international search, respectively, before the trade cost reduction.

on searching in the domestic market than the lower marginal cost firm, causing the peak in domestic search for firms in the second marginal cost bin. This is because, the lower marginal cost firms (in marginal cost group 1) have higher convex search costs given that they search both domestically and internationally. Following this peak, as marginal costs increase, firms spend progressively less on search given the diminishing marginal returns to adding new suppliers is more binding to firms with higher marginal cost.

7. Counterfactual Simulations

I now test the external validity of the model by simulating a reduction in transport costs to match the observed reduction in East African trade costs shown in Section 3.2.3. I then demonstrate the role of search externalities through two counterfactual experiments.

7.1. Experiment 1: Transport cost reduction under structurally estimated parameters

As discussed in detail in Section 3.2.3, between 2010 and 2011, the cost to import a shipping container into Uganda fell rapidly by 25% driven by policy at the East African Community level.

Results from simulating this reduction in the model are shown in Table 7. The proportion of firms that import increases from 20% to 23%, as it becomes profitable for more firms to pay the fixed cost of importing. The average import search intensity increases by 21% and domestic search intensity decreases by 3%. The large increase in import search translates into a 20% increase in the average number of import suppliers.

The aggregate figures hide important heterogeneity which demonstrates the influence of search externalities. It also maps to the descriptive statistics shown in Section 3.2.3 and the comparative statics shown in 2.5. As shown in Figure 10, firms in the second marginal cost group become importers and existing importers increase their search leading to the average number of import suppliers increasing from 2.05 to 2.47. This directly maps to descriptive statistic (i): *as transport costs fall, imports increase.* As they do this, they are pushed up their convex search cost constraint and so reduce the amount they search domestically (domestic search for marginal cost bin 2 firms decreases from 0.21 to 0.14). This maps to descriptive statistic (ii): *new importers drop domestic suppliers.* This then increases market tightness in the international market and reduces market tightness in the domestic market. Consequently, higher marginal cost firms, which do not import, increase their domestic search as the probability of finding a domestic match increases (average search for firms in marginal cost bin 3 increases from 0.15 to 0.18). This maps to descriptive statistic (iii) *dropped domestic suppliers re-match with non-importing buyers.*

Table 7 also reports the observed changes in firm outcomes as seen in the Government of Uganda tax data. The observed change is the same direction and of a similar magnitude to that seen in the simulation. The main disparity is in domestic suppliers, where the reduction is overestimated by the model. This is because there was growth in the domestic

Table 7: Outcomes from 25% transport cost reduction

Outcome	High τ	Low τ	Change	Data
Percentage of Importers	20.01	23.05	15.2%	16%
Av. Import Suppliers	2.05	2.47	20.1%	19%
Av. Domestic Suppliers	2.70	2.52	-6.5%	-1.6%
Domestic Search ($a\sigma$)	0.119	0.115	-3.14%	
Import Search ($(1-a)\sigma$)	0.704	0.851	20.88%	
Consumer Welfare			5.2%	

Notes: Table shows the model generated outcome variables under the high and low trade cost equilibriums and the percentage change. This is compared to the observed percentage change in the real data. Average refers to the average number of suppliers over all firms.

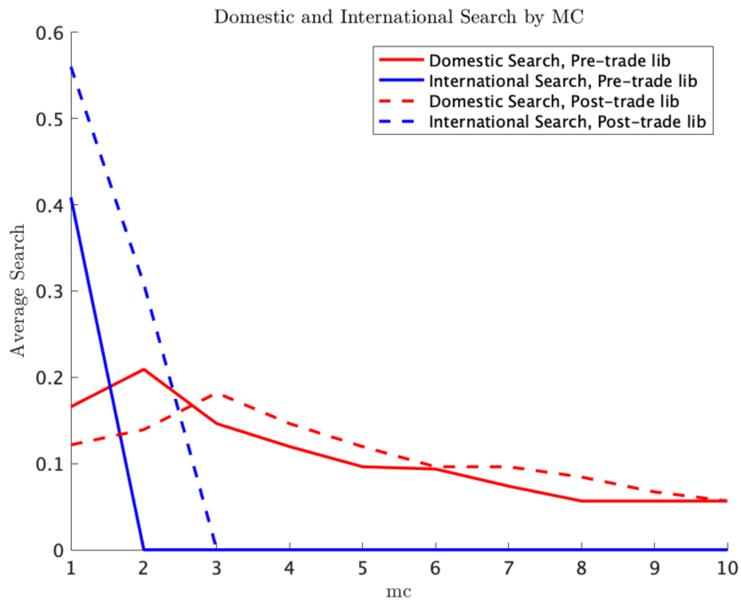
economy outside of the influence of the trade cost reduction. As the results from the trade cost reduction were not used in the parametrization of the model, the fit to the observed shift provides external validity to the model.

Figures 11 and 12 provide more detail on the change in the distribution of firm size. The trade cost reduction lead to an increase in the number of international suppliers for firms of all sizes. The biggest shift, however, comes at the tails of the distribution where the number of firms with greater than 15 suppliers increases by 1.7%. There is also a shift in the number of medium-sized importers as the proportion of firms which import increases by 16%.

Finally, the model shows that a 25% transport cost reduction led to a 5.2% increase in consumer welfare. As shown in Section 2.5, this is due to: i) the lower marginal cost of importing having an income effect, and ii) the increase in matching efficiency from moving to the increasing returns to scale international market.[44]

[44] An extension would consider the short and long-run effects from the intervention. In the short-run, the model predicts that the reallocation of search towards the international market frees up space in the domestic market given domestic suppliers can now re-match. However, in the long-run these firms may no longer be profitable causing firm exit and reversing the gains from a reduction in domestic market tightness. This could be incorporated into the model with a fixed-cost on suppliers.

FIGURE 10: Search by marginal cost



Notes: The x-axis breaks buyers into 10 different marginal cost bins, where 1 indicates the lowest marginal costs and 10 equals the highest marginal costs. The y-axis shows the average search undertaken by buyers in each of these groups. The solid red and blue lines show the amount of domestic and international search, respectively, before the trade cost reduction. The red and blue dashed lines show the amount of domestic and international search, respectively, after the trade cost reduction.

FIGURE 11: Mass of firms with S_I international suppliers

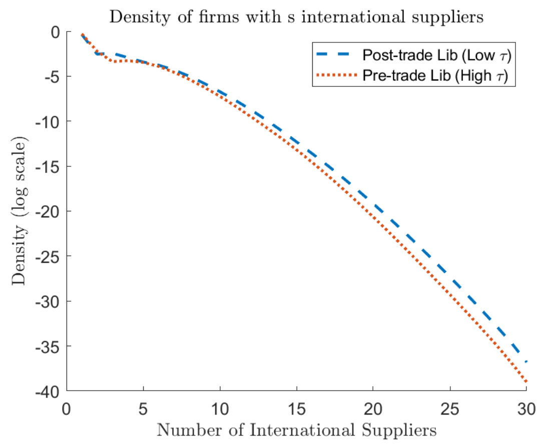
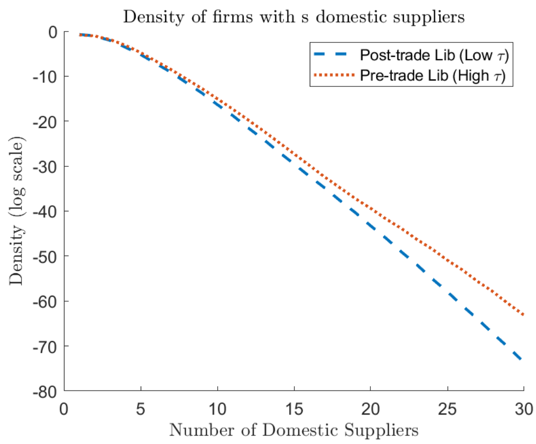


FIGURE 12: Mass of firms with S_D domestic suppliers



Notes: Figures show model predictions on the density of buyers with different number of suppliers before and after the trade cost fall. the left hand panel shows the density of buyers with s_I international suppliers and the right hand panel shows the density of buyers with s_D domestic suppliers. The orange line shows the density prior to the trade cost fall and the blue line shows the density after the trade cost fall.

7.2. Experiment 2: Transport cost reduction under constant returns to scale matching function

The second counterfactual experiment tests how much search externalities influence consumer welfare. I shut down the difference in search externalities between markets by assuming that both markets have the same constant returns to scale matching function.

Table 8 compares the results of the second experiment to those with structurally estimated matching parameters. When both matching functions are constant returns to scale, the most obvious difference between the two experiments is the smaller magnitude by which the average number of import suppliers increases (11.1% vs. 20.1%). This is due to the import market becoming tighter, making it relatively harder for firms to match for each unit of search.

Domestic search also decreases in the CRS experiment. This leads to a larger reduction in the average number of domestic suppliers suppliers (-9.8% vs. -6.5%). This is because the reduction in search domestically does not have the mitigating effect of reducing congestion in the domestic search market.

Figure 13 shows the average number of suppliers for buyers on the y-axis, and different trade cost reductions on the x-axis. This is plotted for both the case of different search externalities (IRS) and where both matching functions are constant returns to scale (CRS). Figure 13 shows that for larger trade cost reductions, the difference in the predicted number of suppliers diverges. For a 10% reduction in search costs the average number of international suppliers increases by 2.4% in the increasing returns to scale simulation and 1.7% in the constant returns to scale model. Whereas for a 25% reduction in search costs the average number of international suppliers increases by 20% in the increasing returns to scale simulation and 11% in the constant returns to scale model, a larger difference. This non-linearity in the model is due to the non-linearity in the two matching function - as more firms switch into the increasing returns to scale sector from the decreasing returns to scale sector there is an increasingly large impact on matching efficiency.

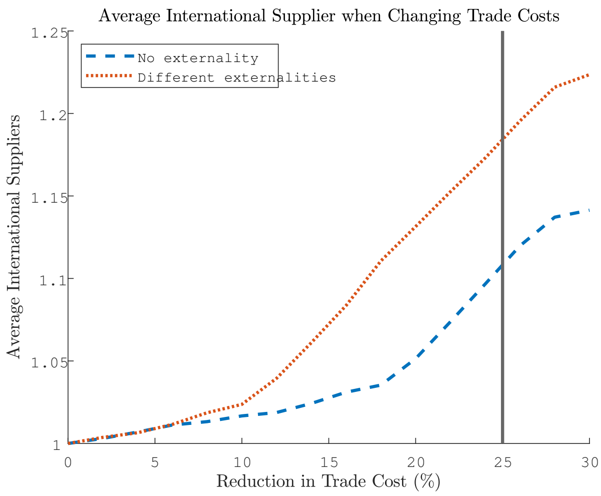
This non-linearity is also shown in Figure 14, where consumer welfare is increasing as

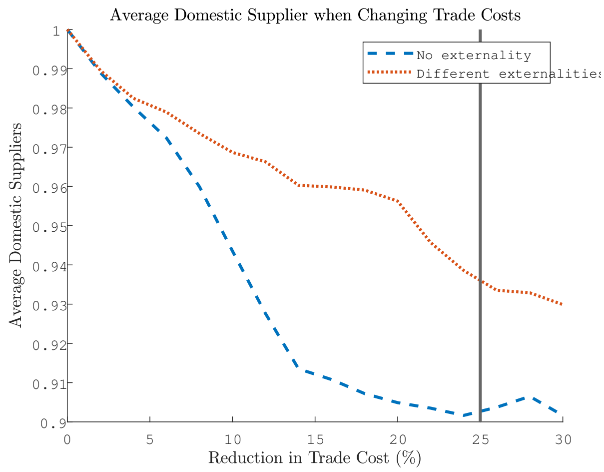
Table 8: Outcomes from 25% transport cost reduction under different matching functions

Outcome	Change IRS	Change CRS	Real Change
Percentage of Importers	15.20%	12.77%	16%
Av. Import Suppliers	20.1%	11.10%	19%
Av. Domestic Suppliers	-6.5%	-9.77%	-1.6%
Domestic Search ($a\sigma$)	-3.14%	-5.82%	
Import Search ($(1-a)\sigma$)	20.88%	17.65%	
Consumer Welfare	5.2%	4.4%	

Notes: Table shows the change in the model generated outcome variables under the model estimated parameters on the matching function which allow different externalities between both markets (IRS), under the case where the matching function is assumed to be constant returns to scale for both markets (CRS), and the observed change in the data. Average refers to the average number of suppliers over all firms.

Figure 13: Average number of international and domestic suppliers for different reductions in trade costs when search externalities are shut down (CRS) compared to structurally estimated parameters (IRS)

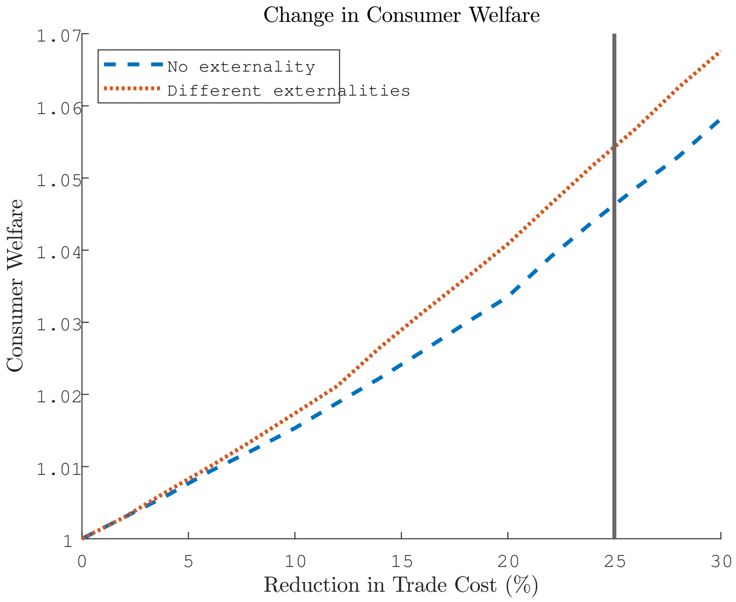




Notes: The y-axis shows the change in the average number of suppliers where the baseline is normalized to 1. The x-axis shows the reduction in trade costs from 0 to 30%. The orange line (IRS) shows the change in the average number of suppliers when the model is estimated using the structurally estimated parameters which allows for increasing returns to scale in matching internationally and decreasing returns to scale in matching domestically. The blue line (CRS) shows the change in the average number of suppliers when the model is estimated shutting down differences in the returns to scale in matching between domestic and international markets.

trade costs fall, and is increasing more rapidly in the simulation which allows for different externalities. A 25% reduction in trade costs results in a 15% larger increase in consumer welfare in the simulation with different search externalities, compared to the simulation with the same externalities in both markets.

Figure 14: Consumer welfare gains from trade when search externalities are shut down (CRS) compared to structurally estimated parameters (IRS)



Notes: The y-axis shows the change in consumer welfare where the baseline is normalized to 1. The x-axis shows the reduction in trade costs from 0 to 30%. The orange line (IRS) shows the change in the average number of suppliers when the model is estimated using the structurally estimated parameters which allows for increasing returns to scale in matching internationally and decreasing returns to scale in matching domestically. The blue line (CRS) shows the change in the average number of suppliers when the model is estimated shutting down differences in the returns to scale in matching between domestic and international markets.

7.3. Experiment 3: Search cost reduction

Table 9: Outcomes from 25% search cost reduction

Outcome	Change following 25% decrease in domestic search costs	Change following 25% decrease in import search costs
Percentage of Importers	-0.48%	10.16%
Av. Import Suppliers	-0.74%	35.1%
Av. Domestic Suppliers	10.02%	-4.54%
Domestic Search ($a\sigma$)	9.93%	-1.62%
Import Search ($(1-a)\sigma$)	-0.97%	40.57%
Consumer Welfare	3.4%	4.3%

Notes: Table shows the change in the model generated outcome variables under a 25% decrease in domestic search costs and a 25% decrease in international search costs. Average refers to the average number of suppliers over all firms.

In experiment 3, I simulate the Ugandan government's stated target for 2019 to reduce search costs for suppliers by 25% (Government of Uganda, 2019). The specific sub

Figure 15: Search by marginal cost if reduce domestic search costs by 25%

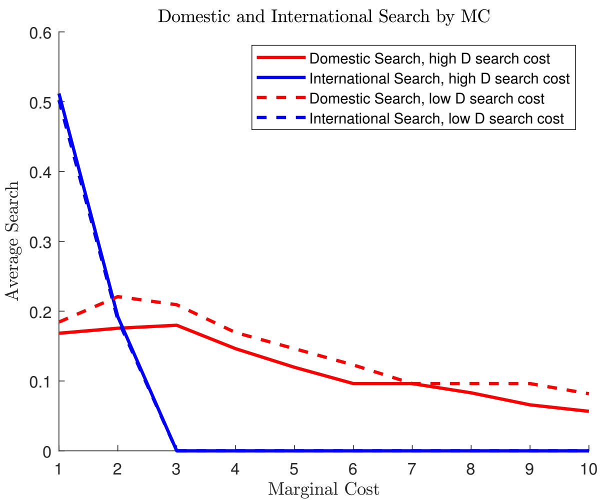
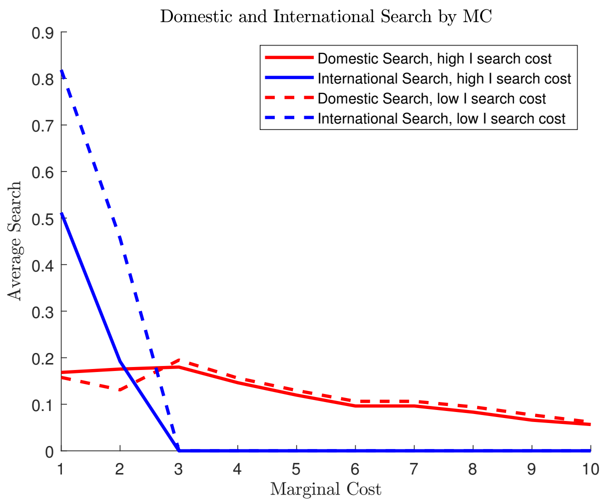


Figure 16: Search by marginal cost if reduce international search costs by 25%



Notes: The x-axis breaks buyers into 10 different marginal cost bins, where 1 indicates the lowest marginal costs and 10 equals the highest marginal costs. The y-axis shows the average search undertaken by buyers in each of these groups. The solid blue and red lines show the amount of domestic and international search, respectively, before the reduction in search costs. The blue and red dashed lines show the amount of domestic and international search, respectively, after the search cost reduction. The left graph shows the impact for reducing domestic search costs. The right graph shows the impact from reducing international search costs.

targets are i) establishing a internet platform support programme (e.g. organize quarterly trainings on the use of Ali Baba), ii) encourage firms peer-to-peer learning (e.g. organize quarterly peer groups with Uganda business groups), iii) target key firms in supplier development programmes (e.g. establish anchor firm support unit and annual public-supplier meetings). Intervention (ii) mimics the work done by the Chinese government and documented by Cai and Szeidl (2017), where firms which meet regularly for business meetings have been shown to increase the number of clients by 12% and the number of suppliers by 9%.

The idea behind this experiment is to consider whether the government's stated target would improve firm outcomes and where the search cost reduction would be best targeted. In order to consider this question, I run two separate counterfactual experiments - first lowering the domestic search costs and then the import search costs.

The outcomes from the experiment are given in Table 9 and Figure 15. When reducing domestic search costs, there is a sharp increase in buyers' domestic search and consequently the average number of domestic suppliers increases by 10%. This is of a similar magnitude to the 9% increase in suppliers found in Cai and Szeidl (2017) following the business-meeting intervention. As can be observed in Figure 15, this increase in domestic search is observed across all levels of buyer marginal cost. However, the increase in the number of domestic matches is relatively modest (10%), as the increase in domestic search leads to an increase in domestic market congestion. There is also a small decline in international search (-1%), as firms make a substitution decision away from international markets.

As shown in Table 9 and Figure 16, when reducing international search, there is a large increase in import search (40.6%) leading to a 35% increase in import suppliers. As can be observed in Figure 16, this is concentrated among the low marginal cost firms, as for all other firms they still do not choose to pay the import fixed cost. These firms, reduce the amount they search domestically, given they are still subject to a convex cost of searching in both markets. This then frees up space in the domestic market, captured by higher marginal cost firms. Therefore, the second experiment acts in a similar way to the trade cost reduction in leading to welfare gains through both the lower marginal costs and the benefit of moving from the decreasing returns to scale market to the increasing returns to scale market. As a consequence, reducing international search costs increases consumer welfare by 4.3%.

By contrast, when domestic search costs fall, firms increase domestic search, however, this leads to a large increase in domestic market tightness due to the domestic congestion. Therefore, the impact of the reform is muted.

These results provide support for the government of Uganda's policy of lowering search costs as the impact on welfare is of a similar magnitude to lowering international trade costs by 25%. The results show that the impact of the reforms will be greater if the government focusses on lowering international search costs. Therefore, the government may focus on their planned interventions to train firms on using platforms such as Ali Baba and Amazon and by having firms meet with firms who have experience of importing in a similar vein to Cai and Szeidl (2017).

8. Concluding Remarks

Using novel data on both domestic and international firm-to-firm transactions from Uganda, I show that the presence of search frictions between buyers and suppliers, in a low-income country, can have a significant impact on how firms respond to a trade liberalization.

I show in a model of firm-to-firm search and matching in two markets that the relative size of search externalities determines the extent of sourcing reallocation, as well as changes to consumer welfare. Given the importance of the search externality parameters, I then show through both reduced-form evidence and structural model estimation that there are stronger positive externalities in international markets compared to domestic markets. I then demonstrate through model simulations that the impact of this channel on consumer welfare is quantitatively significant.

While, the estimates in this paper are specific to the Ugandan context, however, the mechanisms are general to any setting which has search frictions between buyers and suppliers. There is reason to believe that the relative size of the effects maybe larger in a low-income country setting where search frictions are substantial, although, this is speculative without obtaining similar data in a different setting. This does suggest a channel for future work.

The results in this paper provide support for policy intervention to address search frictions. As is the case with all search frictions, the first-best outcome would be to remove the search friction entirely. In the context of the model presented in this paper, this would mean all firms finding and matching with suppliers costlessly. In practice this is not feasible, instead, governments can focus on reducing search costs. The Ugandan government's goal of providing training on platforms such as Ali Baba and Amazon to Ugandan businesses will have a large impact as these channels directly target lowering international search costs. Similarly, encouraging firms to learn from each other has been shown in other contexts to improve firm-to-firm matching (Cai and Szeidl, 2017).

Results from this paper suggest the Ugandan government should focus on interventions that target reducing the cost to international search as opposed to domestic search. This is because lowering the cost to domestic search may simply increase congestion leading to a small increase in matches. However, lowering international search costs will increase both international matches and reduce domestic congestion.

REFERENCES

Albornoz, Facundo, Héctor F Calvo Pardo, Gregory Corcos, and Emanuel Ornelas, "Sequential exporting," *Journal of International Economics*, 2012, *88* (1), 17–31.

Allen, Treb, "Information frictions in trade," *Econometrica*, 2014, *82* (6), 2041–2083.

Antras, Pol and Arnaud Costinot, "Intermediated trade," *The Quarterly Journal of Economics*, 2011, *126* (3), 1319–1374.

_ , Teresa C Fort, and Felix Tintelnot, "The margins of global sourcing: Theory and evidence from us firms," *American Economic Review*, 2017, *107* (9), 2514–64.

Arkolakis, Costas, Arnaud Costinot, and Andres Rodriguez-Clare, "New trade models, same old gains?," *American Economic Review*, 2012, *102* (1), 94–130.

Arnosti, Nick, Ramesh Johari, and Yash Kanoria, "Managing congestion in matching markets," *Available at SSRN 2427960*, 2018.

Atkeson, Andrew and Ariel Burstein, "Pricing-to-market, trade costs, and international relative prices," *American Economic Review*, 2008, *98* (5), 1998–2031.

Bernard, Andrew B and Andreas Moxnes, "Networks and trade," *Annual Review of Economics*, 2018, *10*, 65–85.

_ and J Bradford Jensen, "Exceptional exporter performance: cause, effect, or both?," *Journal of international economics*, 1999, *47* (1), 1–25.

_ and _ , "Why some firms export," *Review of Economics and Statistics*, 2004, *86* (2), 561–569.

_ and Swati Dhingra, "Contracting and the Division of the Gains from Trade," 2015.

_ , **Andreas Moxnes, and Karen Helene Ulltveit-Moe**, "Two-sided heterogeneity and trade," *Review of Economics and Statistics*, 2018, *100* (3), 424–439.

_ , _ , **and Yukiko Saito**, "Geography and firm performance in the Japanese production network," *NBER Working Paper No. 21082*, 2015.

_ , **Esther A Bøler, and Swati Dhingra**, "Firm-to-firm connections in Colombian imports," Technical Report, National Bureau of Economic Research 2018.

Bisztray, Márta, Miklós Koren, and Adam Szeidl, "Learning to import from your peers," *Journal of International Economics*, 2018, *115*, 242–258.

Bulzomi, Anna, Peter Danssaert, Sergio Finardi, and Ken Matthysen, "Supply Chains and Transport Corridors in East Africa," *International Peace Information Service and TransArms-Research*, 2014.

Cai, Jing and Adam Szeidl, "Interfirm relationships and business performance," *The Quarterly journal of economics*, 2017, *133* (3), 1229–1282.

Carvalho, Vasco M, "From micro to macro via production networks," *The Journal of Economic Perspectives*, 2014, *28* (4), 23–47.

Casaburi, Lorenzo and Rocco Macchiavello, "Loyalty, exit, and enforcement: Evidence from a Kenya dairy cooperative," *American Economic Review*, 2015, *105* (5), 286–90.

Chaney, Thomas, "The network structure of international trade," *American Economic Review*, 2014, *104* (11), 3600–3634.

Donaldson, Dave, Amanda Jinhage, and Eric Verhoogen, "Beyond borders: Making transport work for African trade," *IGC Growth Brief Series 009*, 2017.

Eaton, Jonathan, David Jinkins, James R Tybout, and Daniel Yi Xu, "Two-sided Search in International Markets," *Mimeo*, 2016.

_ , **Samuel Kortum, Francis Kramarz et al.**, "Firm-to-Firm Trade: Imports, exports, and the labor market," *Brown University, unpublished manuscript*, 2017.

Fafchamps, Marcel and Simon Quinn, "Networks and manufacturing firms in africa: Results from a randomized field experiment," *The World Bank Economic Review*, 2016, *32* (3), 656–675.

Fieler, Ana Cecília, Marcela Eslava, and Daniel Yi Xu, "Trade, quality upgrading, and input linkages: Theory and evidence from colombia," *American Economic Review*, 2018, *108* (1), 109–46.

Fradkin, Andrey, "Search frictions and the design of online marketplaces," 2015.

Government of Uganda, "Uganda Economic Growth Forum: Import Substitution and Export Promotion for Growth," 2019.

Horton, John J, "Online labor markets," in "International workshop on internet and network economics" Springer 2010, pp. 515–522.

Hosios, Arthur J, "On the efficiency of matching and related models of search and unemployment," *The Review of Economic Studies*, 1990, *57* (2), 279–298.

International Monetary Fund, "Article IV Consultation," *International Monetary Fund*, 2019.

Jensen, Robert, "The digital provide: Information (technology), market performance, and welfare in the South Indian fisheries sector," *The quarterly journal of economics*, 2007, *122* (3), 879–924.

Kamal, Fariha and Asha Sundaram, "Buyer–seller relationships in international trade: Do your neighbors matter?," *Journal of International Economics*, 2016, *102*, 128–140.

Kathage, Angus Morgan, "Understanding the informal economy in African cities: Recent evidence from Greater Kampala," *World Bank Blogs*, 2018.

Krolikowski, Pawel Michal and Andrew H McCallum, "Goods-market frictions and international trade," 2017.

Lim, Kevin, "Firm-to-firm Trade in Sticky Production Networks," Technical Report, Society for Economic Dynamics 2017.

Macchiavello, Rocco and Ameet Morjaria, "The value of relationships: evidence from a supply shock to Kenyan rose exports," *American Economic Review*, 2015, *105* (9), 2911–45.

_ **and** _ , "Competition and Relational Contracts in the Rwanda Coffee Chain," 2019.

Mangin, Sephorah and Benoît Julien, "Efficiency in search and matching models: A generalized hosios condition," *Becker Friedman Institute for Research in Economics Working Paper*, 2018, (2018-10).

Manova, Kalina, "Credit constraints, heterogeneous firms, and international trade," *Review of Economic Studies*, 2012, *80* (2), 711–744.

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

_ **and Stephen J Redding**, "New trade models, new welfare implications," *American Economic Review*, 2015, *105* (3), 1105–46.

Overseas Development Institute, "Productive employment and transformation in Uganda," Technical Report, ODI 2015.

Petrongolo, Barbara and Christopher A Pissarides, "Looking into the black box: A survey of the matching function," *Journal of Economic literature*, 2001, *39* (2), 390–431.

Rauch, James E, "Business and social networks in international trade," *Journal of economic literature*, 2001, *39* (4), 1177–1203.

_ **and Joel Watson**, "Starting small in an unfamiliar environment," *International Journal of industrial organization*, 2003, *21* (7), 1021–1042.

_ **and Vitor Trindade**, "Ethnic Chinese networks in international trade," *Review of Economics and Statistics*, 2002, *84* (1), 116–130.

Rogerson, Richard, Robert Shimer, and Randall Wright, "Search-theoretic models of the labor market: A survey," *Journal of economic literature*, 2005, *43* (4), 959–988.

Sen, Ritwika, "Enhancing local content in Uganda's oil and gas industry," Technical Report, WIDER Working Paper 2018.

Spray, John, "Reorganise, Replace or Expand? The role of the supply-chain in first-time exporting," *Cambridge INET Working Paper 1741*, 2017.

_ **and Sebastian Wolf**, "Industries without smokestacks in Uganda and Rwanda," *Mimeo*, 2016.

_ **and Victor Steenbergen**, "Made in Rwanda: Establishing a publicly available supplier database for Rwanda," *Policy Note. Technical report, International Growth Centre*, 2017.

Startz, Meredith, "The value of face-to-face: Search and contracting problems in Nigerian trade," *Available at SSRN 3096685*, 2016.

Steenbergen, Victor and John Sutton, "Establishing a Local Content Unit for Rwanda," *Policy Note. Technical report, International Growth Centre*, 2017.

Steinwender, Claudia, "Real effects of information frictions: When the states and the kingdom became united," *American Economic Review*, 2018, *108* (3), 657–96.

Stole, Lars A and Jeffrey Zwiebel, "Intra-firm bargaining under non-binding contracts," *The Review of Economic Studies*, 1996, *63* (3), 375–410.

Tintelnot, Felix, Ayumu Ken Kikkawa, Magne Mogstad, and Emmanuel Dhyne, "Trade and domestic production networks," Technical Report, National Bureau of Economic Research 2018.

World Bank, "Doing Business 2011," *World Bank Group*, 2011.

_ , "Doing Business 2016 : Trading Across borders," *World Bank Group*, 2016.

_ , "Uganda Economic Update, 13th Edition, May 2019 : Economic Development and Human Capital in Uganda - A Case for Investing More in Education," *World Bank Group*, 2019.

A. Context Appendix

A.1. Map of trade corridor

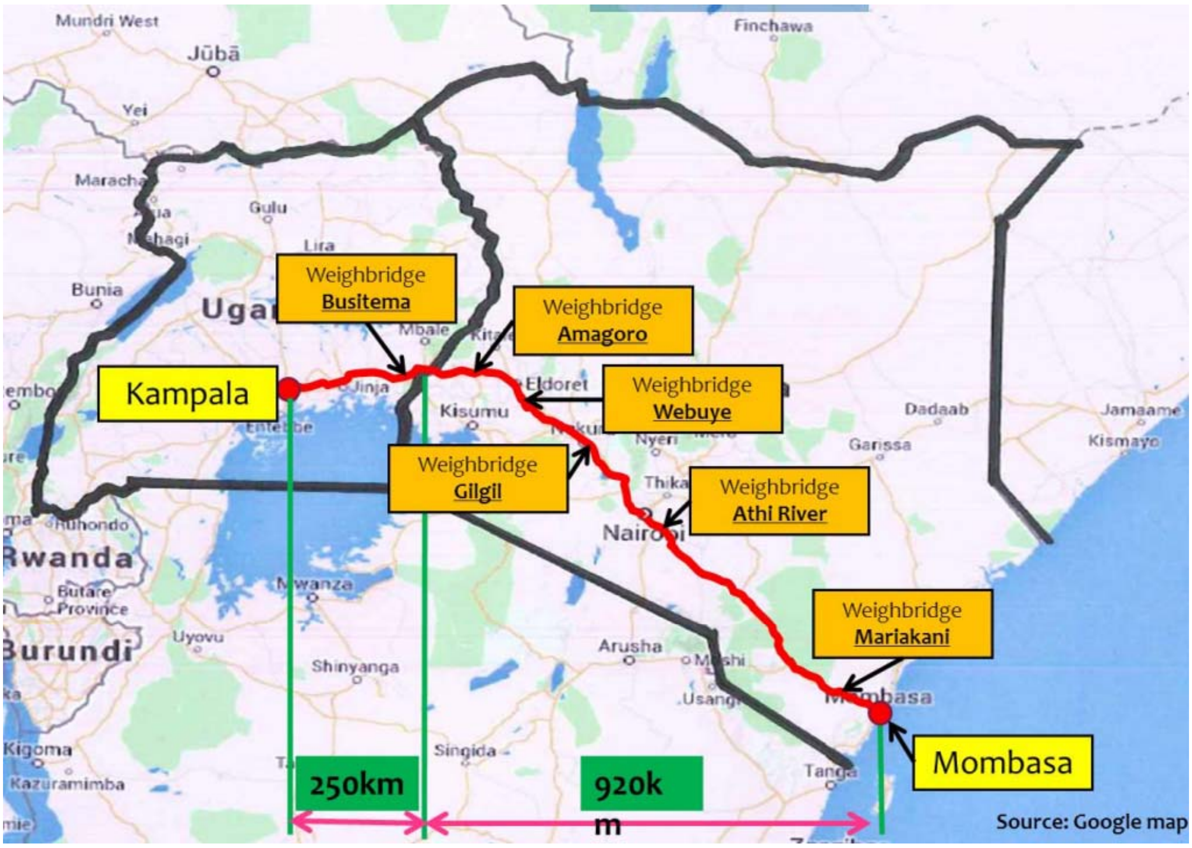


Figure 17: Map of trade corridor, Osawa, WCO

A.2. Data comparison

Given research using tax data remains rare, one potential concern might be that the data is of low quality. This section addresses this concern by comparing the tax data used in this study to other freely available data sources.

Figure 18 shows a comparison between the raw export trade data used in this study and trade data from the WTO. From the graph it appears as if the WTO data is understating the actual export volumes. However, for the purposes of this study, the important fact is how closely the two lines track one another showing that the data is strongly correlated

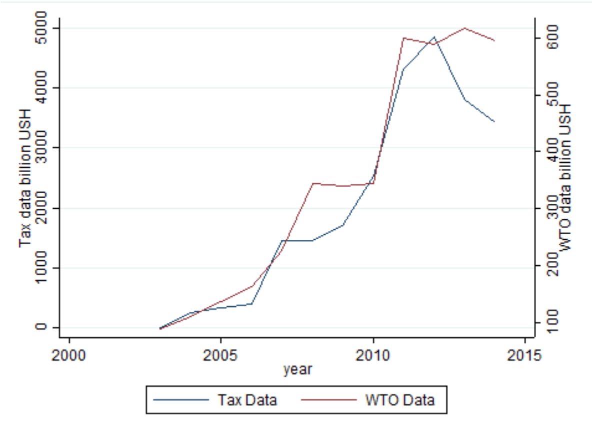


Figure 18: Exports data comparison

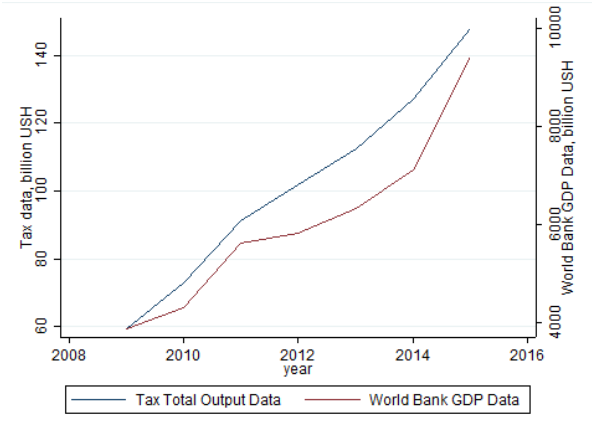


Figure 19: GDP and total output

Notes: The left-hand figure compares the Uganda Revenue Authority (URA) export data with data obtained from the World Trade Organization. The right-hand figure compares total output data from the URA's tax data with GDP data from the World Bank.

with the external source.

Figure 19 shows a comparison between the total output variable used in the tax data and GDP data from the World Bank. Unsurprisingly, the tax data is smaller than the GDP data given the tax data only observes formal sector firms. Importantly, like in 18, the correlation between the two lines is very strong again supporting the reliability of the tax data.

Finally, Spray and Wolf (2016) show the distribution of firms in each sector is consistent with those in the Uganda Business Census.

B. Mathematical Appendix

B.1. Comparative Statics in the two-period model

The buyer picks their optimal a in order to solve the following maximization problem

B.1.1. Reallocation

$$\pi_b = \frac{E}{\eta P^{1-\eta}} \left(\frac{\eta}{\eta - 1} \right)^{1-\alpha} \tau_I \tilde{c}_{xb}^{1-\alpha} \tag{B.1}$$

$$\max_a \left\{ a\sigma\theta_D \pi(s_D) + (1-a)\sigma\theta_I \pi(s_I) - k(a) \right\}. \tag{B.2}$$

This yields a first order condition

$$\sigma\theta_D \pi_{s_D} - \sigma\theta_I \pi_{s_I} - \frac{\partial k}{\partial a} = f(a, \tau_I) = 0. \tag{B.3}$$

Totally differentiating B.3 and rearranging yields the comparative static of how a changes as τ changes

$$\frac{\partial f}{\partial a}\frac{\partial a}{\partial \tau_I} + \frac{\partial f}{\partial \tau_I} \implies \frac{\partial a}{\partial \tau_I} = -\frac{\frac{\partial f}{\partial \tau_I}}{\frac{\partial f}{\partial a}}. \tag{B.4}$$

Solving for each of these terms separately gives an explicit solution,

$$\frac{\partial a}{\partial \tau_I} = \frac{-\sigma\theta_I \frac{\partial \pi_i^B(s_I)}{\partial \tau_I}}{\frac{\partial^2 k}{\partial a^2} - \sigma\frac{\partial \theta_D}{\partial a}\pi_i^B(s_D) + \sigma\frac{\partial \theta_I}{\partial a}\pi_i^B(s_I)} \tag{B.5}$$

$$\frac{\partial a}{\partial \tau_I} = \frac{-\sigma\theta_I \frac{\partial \pi_i^B(s_I)}{\partial \tau_I}}{\frac{\partial^2 k}{\partial a^2} - \sigma^2(\gamma^B - 1)\theta_D B_D \pi(s_D) - \sigma^2(\beta^B - 1)\theta_I B_I \pi(s_I)} \tag{B.6}$$

B.1.2. MATCHING EFFICIENCY

Consumer Welfare is broken into matching efficiency A and consumption C.

$$\begin{aligned} W(a) &= \left[\int_{b\in B(s_I)} \psi_I C_b^{\frac{\eta-1}{\eta}} + \int_{b\in B(s_D)} C_b^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}} \\ &= \underbrace{\left[a\sigma\theta_D + \psi_I(1-a)\sigma\theta_I\right]}_{A}\underbrace{\left[\int_{b\in B} C_b^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}}_{C}. \end{aligned} \tag{B.7}$$

Rewriting the matching efficiency A by expanding the market tightness yields the following equation,

$$A = a^{\gamma_B} S^{\gamma_S} B^{\gamma_B-1} + \psi_I(1-a)^{\beta_B} S^{\beta_S} B^{\beta_B-1}. \tag{B.8}$$

taking a partial derivative of A

$$\begin{aligned} \frac{\partial A}{\partial \tau_I} =& \gamma_B a^{\gamma_B-1} S^{\gamma_S} B^{\gamma_B-1}\frac{\partial a}{\partial \tau_I} - \beta_B\psi_I(1-a)^{\beta_B-1} S^{\beta_S} B^{\beta_B-1}\frac{\partial a}{\partial \tau_I} \\ & \frac{\partial a}{\partial \tau_I}\left[\gamma_B a^{\gamma_B-1} S^{\gamma_S} B^{\gamma_B-1} - \beta_B\psi_I(1-a)^{\beta_B-1} S^{\beta_S} B^{\beta_B-1}\right] \end{aligned} \tag{B.9}$$

The first term > 0 as shown in equation B.6, the second term determines the direction of the effect

$$\begin{aligned} \frac{\partial A}{\partial \tau_I} < 0 \iff & \gamma_B a^{\gamma_B-1} S^{\gamma_S} B^{\gamma_B-1} < \beta_B\psi_I(1-a)^{\beta_B-1} S^{\beta_S} B^{\beta_B-1} \\ & \gamma_B a^{\gamma_B-1} < \beta_B\psi_I(1-a)^{\beta_B-1} S^{\beta_S-\gamma_S} B^{\beta_B-\gamma_B} \end{aligned} \tag{B.10}$$

Therefore, the change in welfare due to matching efficiency following a fall in trade costs depends on a, ψ_I and the matching exponents $\gamma_B, \gamma_S, \beta_B, \beta_S$. The main takeaway from equation B.10 is that for a sufficiently large and $\psi \geq 1$, the change in welfare due to matching depends on the relative size of the matching exponents. If $\gamma_B < \beta_B$ and $\gamma_S < \beta_S$ i.e. returns to search are higher in the international market, then an increase in trade cost will lower welfare given firms move from matching in the increasing returns to scale international market to the decreasing returns to scale domestic market.

B.2. Transfer Equation

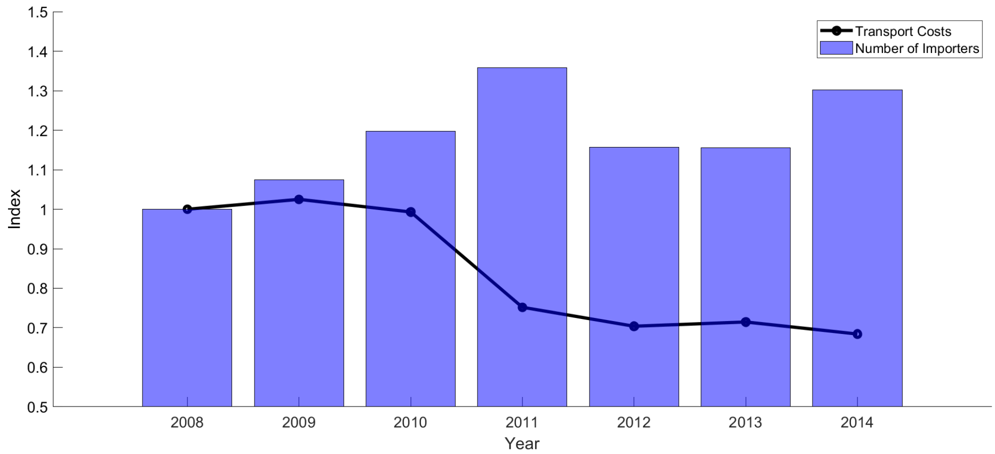
As shown in EJTX (2016), if cost per unit quality does not vary across products within buyers then the transfer equation collapses to the following

$$r_{ji}(\mathbf{s}) = \frac{E}{P^{1-\eta}}\left(\frac{\eta}{\eta-1}\right)^{-\eta} s^{\frac{\alpha-\eta}{1-\alpha}}\tilde{c}^{1-\eta}\left[\frac{\Lambda}{\alpha-1} + \lambda\left(\frac{\eta}{\eta-1}^{\eta-1}\right)\right]. \tag{B.11}$$

C. Empirical Appendix

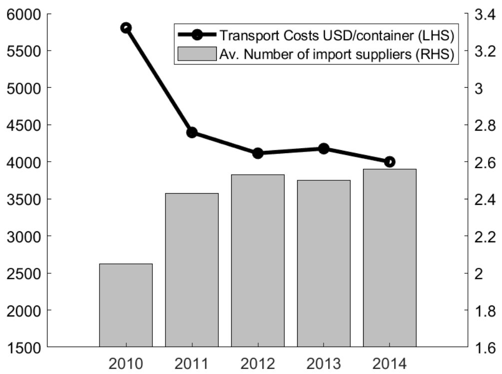
C.1. Descriptive Statistics

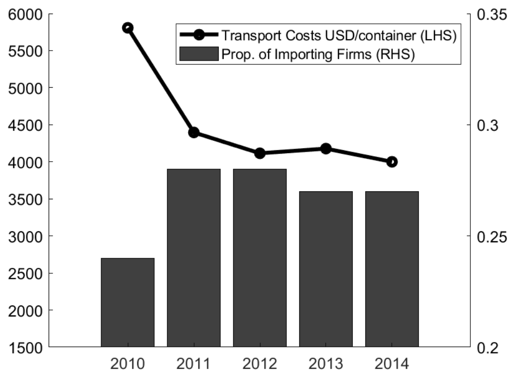
Figure 20: Transport Costs and Imports



Notes: The black line shows transport cost in USD per 20-foot container from the World Bank's Trading Across Border Index between 2007-2014, the bars contains data on the total number of importers. The data for comes from customs dataset. Reforms took place between 2010 and 2011.

Figure 21: Transport Costs and Imports





Notes: The black line shows transport cost in USD per 20-foot container from the World Bank's Trading Across Border Index, light grey bars on the left-hand graph show the average number of import suppliers for importers, and dark grey bars on the right-hand graph show the proportion of firms which import. The reason for the shorter time series is that I do not know the identity of import suppliers prior to 2010.

TABLE 10: Newly added domestic suppliers among new importers

	(1) Number of domestic suppliers	(2) Number of domestic suppliers
First Time Import in $2011_i \times 2011_t$	-0.167***	-0.104***
	(0.0243)	(0.0244)
First Time Import in 2011_i	0.712***	
	(0.00981)	
Observations	162190	162190
Year FE	YES	YES
Buyer FE	NO	YES

Notes: Unit of observation is buyer i and year t. Standard errors in parentheses clustered at the buyer level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE 11: Dropped suppliers' new matches

	(1) Proportion of buyers don't import	(2) Proportion of buyers don't import
Dropped by 2011 first time $\text{importer}_f \times 2011_t$	0.0370***	0.0404***
	(0.00821)	(0.00608)
Dropped by 2011 first time importer_f	0.0267***	
	(0.00329)	
Observations	96470	96470
Year FE	YES	YES
Buyer FE	NO	YES

Notes: Unit of observation is supplier f and year t. Standard errors in parentheses clustered at the buyer level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE 12: Value from domestic suppliers among new importers

	(1) Value of domestic suppliers	(2) Value of domestic suppliers
First Time Import in $2011_i \times 2011_t$	-0.354***	-0.304***
	(0.0572)	(0.0381)
First Time Import in 2011_i	1.658***	
	(0.0230)	
Observations	160138	108380
Year FE	YES	YES
Buyer FE	NO	YES

Notes: Unit of observation is buyer i and year t. Standard errors in parentheses clustered at the buyer level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE 13: Dropped suppliers' new matches - value

	(1) Proportion of value from buyers which don't import	(2) Proportion of value from buyers which don't import
Dropped by 2011 first time importer$_f$ × 2011$_t$	0.0292***	0.00631
	(0.00697)	(0.00486)
Dropped by 2011 first time importer$_f$	0.00292	
	(0.00360)	
Observations	96103	84908
Year FE	YES	YES
Buyer FE	NO	YES

Notes: Unit of observation is supplier f and year t. Standard errors in parentheses clustered at the buyer level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE 14: Same and next-door balance table

Distance	**Proportion of firms in same sector**	**Difference with same building**
Same building	0.097	
	(0.296)	
Next-door building	0.088	-0.009
	(0.284)	(0.014)
Next-door building $< distance < 0.1km$	0.060	-0.037***
	(0.237)	(0.012)
$0.1km < distance < 0.15km$	0.051	-0.046***
	(0.219)	(0.017)
$0.15km < distance < 0.2km$	0.044	-0.053**
	(0.204)	(0.021)
$0.2km < distance < 0.25km$	0.040	-0.057**
	(0.196)	(0.026)

C.2. Robustness Tests

C.2.1. Very local shocks drive results

To address the concern that shocks drive reduced form results, I look at the proportion of firms in the same building which are in the same ISIC 4-digit sector and compare that to the proportion of firms in the next-door building. Results are shown in Table 14. While there is a small difference, it is not statistically significant. However, when I look at firms further away, I do see this difference increasing. I therefore conclude that there is some firm agglomeration, but that it is happening at a block level and not at a building level.

C.2.2. Spillover exists but is not search related

A second alternative explanation is that a spillover is taking place, but that it is not search related. For instance, we might expect that transport costs could be driving the

TABLE 15: Imports Suppliers from East African Community

	(1)
	Y_{ift}
X_{t-1}^{same}	0.0931***
	(0.00665)
$X_{t-1}^{same} \times EAC_f$	-0.0346**
	(0.0151)
$X_{t-1}^{other-city}$	-0.00223
	(0.00176)
$X_{t-1}^{other-city} \times EAC_f$	-0.00486
	(0.00552)
Observations	4834635

Notes: Unit of observation is buyer i, supplier f and year t. Y_{ift} indicates a first match took place between buyer and supplier. X_{ift}^{k} is a count of buyers in region k which added supplier f in $t-1$. EAC_f indicates the supplier operates in the East African Community. Coefficients are multiplied by 100 to read as percentage point marginal effects. Standard errors in parentheses clustered at the buyer level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

results. To allay these concerns, I test if the marginal effect is smaller among firms where one would expect search frictions to be less prevalent. To test for this, I interact the independent variables with whether the import supplier exported from the East African Community (EAC). This is because one would expect search frictions to be smaller in local neighbors like Kenya or Tanzania when compared to more distant locations. We would therefore expect when estimating equation C.1 that the positive search externality for EAC suppliers is weaker ($\mu_2 < 0$).

$$Y_{ift} = \mu_1 X_{if,t-1}^{same} + \mu_2 X_{if,t-1}^{same} \times EAC_f + \gamma_1 X_{if,t-1}^{other-city} + \gamma_2 X_{if,t-1}^{other-city} \times EAC_f + \alpha_f + \alpha_i + \alpha_t + u_i \tag{C.1}$$

Results shown in Table 15 confirm that suppliers in the EAC have a smaller positive spillover. This is again consistent with a narrative in which search is driving results.

Another prediction consistent with search frictions, is that suppliers which are not supply-constrained will be able to match with multiple buyers, and so we should not

TABLE 16: Domestic Export Suppliers

	(1)
	Y_{ift}
X_{t-1}^{same}	0.00236
	(0.00358)
$X_{t-1}^{same} \times exporter_f$	0.00358
	(0.00802)
$X_{t-1}^{other-city}$	-0.00574***
	(0.000680)
$X_{t-1}^{other-city} \times exporter_f$	0.00268**
	(0.000609)
Observations	27975967

Notes: Unit of observation is buyer i, supplier f and year t. Y_{ift} indicates a first match took place between buyer and supplier. X_{ift}^k is a count of buyers in region k which added supplier f in $t-1$. $exporter_f$ indicates supplier f is an exporter. Coefficients are multiplied by 100 to read as percentage point marginal effects. Standard errors in parentheses clustered at the buyer level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

observe a negative congestion effect.

As discussed in Section 3.2.2, this is the reason why we did not expect to find a strong congestion externality on foreign imports, given international suppliers are characterized by being large firms with cheap access to credit and multiple customers. By contrast, domestic Ugandan firms are characterized by being small with limited access to credit. You might therefore expect that Ugandan firms cannot make multiple matches in a given period, thus making the domestic market more congested.

If this is indeed the case, I would expect domestic Ugandan suppliers which are also exporters to act in a similar way to foreign exporters, as they are less likely to be supply constrained. This is tested in equation C.2.

$$Y_{ift} = \mu_1 X_{if,t-1}^{same} + \mu_2 X_{if,t-1}^{same} \times Exporter_f + \gamma_1 X_{if,t-1}^{other-city} + \gamma_2 X_{if,t-1}^{other-city} \times Exporter_f + \alpha_i + \alpha_t + u_{ift} \tag{C.2}$$

Results in Table 16 show that domestic suppliers which are exporters, and hence less supply constrained, have a smaller negative effect from making a match elsewhere in the country. This is again consistent with the search narrative.

Table 17: Domestic Suppliers

	(1)	(2)	(3)	(4)
	Y_{ift}	Y_{ift}	Y_{ift}	Y_{ift}
$Z_{t-1}^{10km^2}$	0.00453			
	(0.00524)			
$Z_{t-1}^{1km^2}$		0.00743		
		(0.00538)		
Z_{t-1}^{same}			0.00920*	
			(0.00540)	
Z_{t-1}^{same}				0.00919*
				(0.00557)
$Z_{t-1}^{nextdoor}$				-0.0235
				(0.0169)
X_{t-1}^{other}	-0.00778***	-0.00771***	-0.00768***	-0.00795***
	(0.00188)	(0.00187)	(0.00187)	(0.00188)
Year and Buyer FE	Yes	Yes	Yes	Yes
Observations	27975967	27975967	27975967	27975967

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE 18: Import Suppliers

	(1)	(2)	(3)	(4)
	Y_{ift}	Y_{ift}	Y_{ift}	Y_{ift}
$Z_{t-1}^{10km^2}$	0.115***			
	(0.00140)			
$Z_{t-1}^{1km^2}$		0.136***		
		(0.00158)		
Z_{t-1}^{same}			0.133***	
			(0.00158)	
Z_{t-1}^{same}				0.134***
				(0.00158)
$Z_{t-1}^{nextdoor}$				0.0185***
				(0.000692)
X_{t-1}^{other}	-0.00178***	-0.00130***	-0.00173***	-0.00155***
	(0.000357)	(0.000357)	(0.000357)	(0.000357)
Year and Buyer FE	Yes	Yes	Yes	Yes
Observations	4834635	4834635	4834635	4834635

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$