

BUYER-SELLER RELATIONSHIPS IN INTERNATIONAL TRADE: DO YOUR NEIGHBORS MATTER?¹

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ABSTRACT We investigate if the presence of exporters, in the neighborhood of a firm, that previously transacted with a particular foreign buyer facilitates a match between the firm and this buyer. Using confidential U.S. customs data on trade transactions between U.S. importers and Bangladeshi exporters between 2002 and 2009, and information on the geographic location of Bangladeshi exporters, we show that the presence of neighboring exporters that previously transacted with a U.S. importer increases the likelihood of matching with the same U.S. importer for the first time. This suggests a role for business networks among trading firms, and for potential knowledge and information gains realized through them. Our research design allows us to isolate export spillovers that are partner-specific, from overall export spillovers previously documented in the literature. Thus, we further extend our understanding of network effects and spillovers at the micro level where international trade occurs.

JEL Classification: F1, R12, L25

Keywords: trade relationships, business networks, partner-specific spillovers

1. Introduction

An international trade transaction is the result of a successful match between a buyer and a seller across national borders. Between 2002 and 2009, 21,281 unique trading pairs (matches) were responsible for all textile and apparel shipments between the U.S. and Bangladesh.³ Despite the importance of matching between individual exporters and importers in international trade, our understanding of the factors that facilitate international buyer-seller matches is limited. In this paper, we study a particular factor - the role of neighboring exporters that have previously transacted with a particular importer in facilitating first-time matches between a potential individual seller and that importer.

We build on a nascent body of work exploring the formation of buyer-seller matches in international trade using confidential U.S. customs data. Eaton, Eslava, Jinkins, Krizan, and Tybout (2013) present a continuous-time model of heterogeneous sellers searching for buyers in a market and calibrate the model parameters using data on trade relationships between Colombian exporters and U.S. importers. Their study highlights the costs involved in matching internationally with a potential buyer. Initial matching costs are substantial, however, maintaining a trade relationship over time is also costly. The authors find that the initial cost of searching for and locating a buyer is more than thirteen times higher than the per shipment cost of maintaining the relationship.

Monarch (2013) and Dragusanu (2014) examine the U.S. importer's supplier choice. Monarch examines the frictions U.S. importers face in their decision to switch their Chinese trading partners using a dynamic discrete choice model. He models and estimates switching costs that are specific to partners (price and quality) and geography (Chinese cities). Dragusanu develops a model of sequential production where importers engage in costly search for suppliers

at all stages of production. She finds empirical support for the model's main prediction that there is positive assortative matching between U.S. buyers and Indian suppliers.

In this paper, we move beyond characterizing buyer-seller relationships to examine a particular determinant of these relationships - the presence of other exporters selling to a particular importer in the neighborhood of a firm. We broadly draw on the networks literature in international trade, namely, Rauch's (1999) "network/search" view of international trade, the idea that the search process in matching international buyers and sellers is "strongly conditioned by proximity and preexisting 'ties' and results in trading networks [...]" (p.8). Although we do not measure trading networks in the Rauch sense (Rauch, 1996 and 2001; Combes, Lafourcade, and Mayer, 2005)⁴, our measure of neighboring exporters represents a particular type of trading network - firms that are in the same geographic location selling to the same buyer in the previous period. Moreover, we are able to estimate the role of neighbors on individual international buyer and seller matches as opposed to trade flows at the national level, as has been the case in existing studies.

A large literature that examines the determinants of exporter status (Bernard and Jensen, 2004) has highlighted the role of neighboring exporters that improve the likelihood of firms exporting to foreign destinations (Koenig, 2009; Koenig, Mayneris, and Poncet, 2010). These studies find that greater presence of exporters selling to a specific foreign destination close to a firm can increase the likelihood that the firm exports to the same destination.⁵ The focus is on the role of information sharing enabled by having neighbors in close proximity exporting to a destination country. When firms do not internalize such information flows, it results in a positive externality, also known as export spillovers.

The idea is that the presence of exporters nearby exporting to the same destination can lower fixed costs of exporting to a particular country. This can happen if neighboring exporters facilitate knowledge transfer on destination-specific business norms and culture, of setting up foreign exchange accounts or service centers abroad, or of retaining customs agents, in addition to providing information on potential buyers, and easing search, and developing a buyer-supplier relationship. Koenig (2009) and Koenig et al (2010) use data on French exporters to find that greater presence of exporters nearby affects the decision to start exporting to a particular country, but not the volume of exports. Hence, the authors infer that the role of neighbors operates through lowering the fixed costs associated with exporting to a particular destination, but not the variable cost of exporting. Fernandes and Tang (2012) find that for Chinese exporters, new exporters' first-year sales and probability of survival are higher in cities where there are existing exporters selling to the same export destination within an industry.

Our paper differs from these studies in a crucial way. It looks at how the presence of neighboring exporters that have previously matched to a particular foreign buyer impacts the likelihood that a firm will match with the same foreign buyer for the first time. Hence, our focus is on the match between the importing and exporting firm, the micro units at which international trade occurs. In our analysis, since we examine the role of neighboring exporters on the likelihood of matching with a particular importer, we are able to separately identify export spillovers that are specific to the trade partner. To the best of our knowledge, there is no existing study that isolates the role of neighbors selling to a particular buyer in a given destination on the probability of matching with the same buyer. We believe that it is important to fill this gap in the literature. First, it is important to identify determinants of buyer-seller matches across international borders. Second, ascertaining if spillovers are specific to a trading partner at the

firm level and not just at the country level is a step further in the direction of isolating the nature of export spillovers and the channels through which they operate. This can be important for designing trade promotion measures.

Here, we note that either the importer or the exporter (either directly or through a buying house) might initiate the buyer-seller match.⁶ In our empirical analysis, we only observe the match, and not who initiated it or how it was initiated. However, we argue that the presence of neighboring exporters matter in both instances - where the importer or the exporter initiates the match. Neighboring exporters may enhance individual matches through various channels. The presence of exporting firms in the neighborhood selling to the same buyer can facilitate information sharing about exporting to that particular buyer. This might include knowledge of any needs of the importer that require customization such as the buyer's product specifications, custom packaging requirements, and its clientele's tastes and preferences. Additionally, there may be information sharing on locating a buyer, investing in activities that promote an exporter's product to a potential buyer such as advertising or participating in trade shows. The ability to obtain tacit knowledge is likely to lower the fixed and/or variable costs of exporting to a particular buyer. On the importer end, buyers may be more likely to learn about new suppliers when they are located in close proximity to existing suppliers. Buyers might also find it easier to verify product quality, or the likelihood that goods will be supplied on time and as per requirements when the potential exporter is geographically close, and part of the same business network as the exporter they already transact with.

To reiterate, by looking at the match between a buyer and a seller, we highlight the role of neighbors in information sharing on partner-specific transaction costs in addition to country-specific transaction costs. Thus, we relate the presence of exporters neighboring exporter i and

selling to an importer j on the first match status, that is the first time exporter i matches with importer j . We use confidential transaction level data on U.S. imports in textile and apparel products, henceforth referred to as textile products, from Bangladeshi exporters between 2002 and 2009, sourced from the U.S. Census Bureau. We select textile products because for textile shipments, we observe the manufacturer exporting the product, as opposed to trading agents in the transaction. Further, focusing on trade transactions between the U.S. and Bangladesh is motivated by the need to construct a sensible dataset while focusing on an important bilateral trade relationship.⁷ Bangladesh is the fourth largest apparel exporter to the U.S.⁸ Over three quarters of Bangladeshi exports are in textile and apparel products, with the U.S. being the second largest export destination (Tables 4 and 5, Trade Policy Review, 2012). Exporters in our sample are Bangladeshi textile manufacturing firms, while importers are U.S. firms operating in the manufacturing, wholesale, retail and other sectors of the economy.

We estimate a linear probability model of the first match status between each Bangladeshi exporter and each U.S. importer over the time period, as a function of the number of firms in the neighborhood that matched with that importer in the previous time period. A match occurs when the importer and exporter transact at least once for the first time in that time period. We relate the likelihood of a first match to a measure of exporter presence (or the size of the exporter network) in the neighborhood. Controlling for unobservable time-varying exporter and importer shocks, results from our preferred specification indicate that a one percent increase in the number of exporters, that previously matched to a particular U.S. importer, in the neighborhood of a firm results in a 0.15% increase in the likelihood of the firm matching with the same importer for the first time.

We also provide evidence on the nature of these partner-specific spillover effects. We find that the effects differ by both exporter and importer characteristics. Spillovers are concentrated among small exporters (those that have smaller average export sales). This suggests that smaller exporters may not have the internal resources of larger exporters that facilitate buyer-seller relationships, and experience higher likelihoods of matching with U.S. buyers that transact with neighboring exporters. We further find that spillovers are stronger when the importer is small relative to when the importer is large. This suggests that U.S. importers vary in their behavior of procuring and maintaining supplier relationships.

The rest of the paper is organized as follows. Section 2 presents our empirical model and identification strategy. Section 3 describes the data and measurement of key variables. Section 4 discusses the empirical findings and the final section concludes.

2. Empirical model and strategy

In order to motivate our empirical strategy, we assume that exporter i matches with importer j at time t if

$$\sum_{t=0}^{+\infty} \frac{\pi_{ijt}^m}{(1+r)^t} - f_{ijt} > 0 \quad , \quad (2.1)$$

where $\frac{\sum_{t=0}^{+\infty} \pi_{ijt}^m}{(1+r)^t}$ is the present discounted value of future profits from the match, r is a discount rate and f_{ijt} is the sunk fixed cost of matching that is specific to the match pair ij . Assuming that there is no uncertainty over future profits, we can rewrite (2.1) as an exporter i matches with importer j if

$$\frac{\pi_{ijt}^m}{r} - f_{ijt} > 0. \quad (2.2)$$

Profit, π_{ijt}^m , is a function of exporter and importer characteristics, like productivity, destination and origin market-specific factors like aggregate prices of inputs and the final good, and demand in the destination market. We treat each ij match as an independent match decision, which means that the alternative to exporter i not matching with importer j is that the match does not occur.

Within our framework, network effects or spillovers operate through lowering the sunk fixed cost of matching, which can be considerable. Using U.S.-Colombian trade transactions data, Eaton et al. (2013) estimate that the initial search cost of locating one buyer per year is about \$20,642. The cost drops to \$1,522 per shipment to maintain each client relationship once the initial match has been established. Thus, the initial cost of matching is a significant portion of total matching fixed costs. These estimates provide a sense of the magnitude of the costs involved in forming exporter-importer relationships, and in subsequently maintaining them, and underline our rationale for explicitly introducing partner-specific fixed costs of trading.

We decompose the initial fixed cost of matching (or the sunk cost) into three components as,

$$f_{ijt} = f_{ijt}^P + f_{it}^D + f_{jt}^D. \quad (2.3)$$

Superscript P denotes partner-specific fixed costs of matching that are specific to each ij pair and superscript D denotes country-specific fixed costs of matching. Country-specific initial period fixed costs include costs of navigating business norms and culture, search costs for a customs or shipping agent, setting up foreign sales or service offices and foreign currency accounts. We allow for the possibility that destination-specific fixed costs may vary by exporter or importer characteristics over time. Partner-specific initial period fixed costs include costs of searching and

advertising, learning about or communicating importers' tastes, clientele, customization or packaging requirements, or exporter capabilities.

To implement empirically we formulate,

$$f_{ijt} = g(z_{cjt,t-1}) + X_{it}^1 + X_{jt}^2 + \varepsilon_{ijt}, \quad (2.4)$$

where $z_{cjt,t-1}$ captures the number of exporters selling to importer j in city c at time $t - 1$, X_{it}^1 (X_{jt}^2) encompasses exporter-year (importer-year) shocks, and ε_{ijt} is an idiosyncratic error term.

The key idea is that greater presence in the neighborhood of exporters transacting with a particular U.S. buyer lowers the fixed costs involved for a potential exporter in matching with the same buyer. Evidence from surveys and case studies supports this idea. Egan and Mody (1992) document the search process from an importer's point of view. The authors identify primary ways U.S. buyers of bicycle and footwear gather information on potential suppliers in developing countries based on interviews with 28 U.S. importers. They find that U.S. buyers seek information on potential suppliers from within a network of product-specific buyers and suppliers of both final and intermediate goods. They also find information about suppliers at trade fairs and conferences. Finally, a more direct method of identifying suppliers is visits to the suppliers' factories to assess their logistical and human resource capabilities. We argue that this is likely easier if the potential exporter is in the neighborhood of an exporter they already transact with.

Cadot, Iacovone, Pierola, and Rauch (2011) and Eaton et al (2013) provide evidence on the search process from an exporter's point of view. Cadot et al (2011) present findings from survey responses from 395 firms across four African countries. 'Competitor's networks', a measure close to our empirical formulation of neighbors, feature in the top three ways in which first time exporters find buyers. Eaton et al (2013) provide references to results from interviews

with Colombian exporters that rank activities firms pursued in order to meet potential buyers abroad. These activities include building up an online profile, attending trade fairs, sending sales representatives to visit foreign clients, and maintaining a foreign sales office. Undertaking these activities are likely less costly if firms are able to learn through their business networks.

The probability that exporter i matches with importer j at time t can be written as:

$$Pr(\text{Match}_{ijt}) = Pr\left(\frac{\pi_{ijt}^m}{r} - f_{ijt} > 0\right). \quad (2.5)$$

Substituting (2.4) into (2.5) above, we have,

$$Pr(\text{Match}_{ijt}) = Pr\left[\varepsilon_{ijt} < f\left(g(z_{cjt-1}), X_{it}^1, X_{jt}^2, \frac{\pi_{ijt}^m}{r}\right)\right]. \quad (2.6)$$

We estimate a simple linear probability model of the first match, S_{ijt} , between exporter i and importer j at time t as follows,

$$S_{ijt} = \beta_1 z_{cjt-1} + \beta_2 Y_{it}^1 + \beta_3 Y_{jt}^2 + \varepsilon_{ijt}. \quad (2.7)$$

Here, Y_{it}^1 and Y_{jt}^2 are exporter-time and importer-time fixed effects or control variables.

We define a first match as the first time we observe a trade transaction in any textile products between an importer and exporter in a given year. Since we are interested in the first match decision, we drop all observations at the importer-exporter level after the year of the first match.

We employ a linear probability model similar to Bernard and Jensen (2004) and Fernandes and Tang (2012) to estimate (2.7).⁹ In our preferred specification, we include exporter-year and importer-year fixed effects to account for time varying exporter and importer shocks.

The time-varying exporter-time specific variables that enter the profit function, like exporter productivity, are absorbed by the exporter-time specific effect and any other unobserved time-varying exporter-specific shocks that determine match status.¹⁰ The exporter-

time fixed effects also capture destination-specific fixed costs that are common across all U.S. buyers, but vary across Bangladeshi exporters.

In our preferred specification we include importer-time fixed effects to operationalize the Y_{jt}^2 term. These effects control for time-invariant importer characteristics like firm ownership or state level programs aimed at increasing activity of local firms by providing matching services with foreign suppliers, and also for time varying shocks to productivity or subsequent profitability that may influence a trade relationship. In addition, they capture destination-specific fixed costs that are common across all Bangladeshi sellers, but vary across U.S. importers. We also report results for a less demanding specification that includes importer fixed effects and importer controls, specifically, firm age and employment that are well known to be correlated with firm characteristics such as productivity (Foster, Haltiwanger, and Krizan, 2001) and subsequently profitability (Helpman, Melitz, and Yeaple, 2004) instead of the importer-year effects.

The variable z_{cjt-1} captures network effects or spillovers from the presence of exporters to the same buyer j in exporter i 's area c in a previous period. We posit that network effects or spillovers operate primarily by lowering the sunk costs of matching between importer and exporter, after accounting for country-specific sunk costs. ε_{ijt} is an idiosyncratic error term. After controlling for exporter-year and importer-year fixed effects, we still leave out the determinants of match behavior that vary across city-importer and time. For instance, if there are efforts by local governments or trade associations to promote textile exports to particular U.S. importers within a city, or if particular U.S. importers have preferences to trade with exporters in particular Bangladeshi cities due to reasons that cannot be observed, then the coefficient on our own-city spillover variable may not be consistently estimated. To a certain extent, this

endogeneity problem is mitigated by using a lagged measure of nearby exporter presence, thus circumventing spurious correlation with any contemporaneous city-importer-specific unobserved factors. Standard errors in all our specifications are clustered at the importer-city level.

3. Data

3.1. Source

The data for this study are drawn from the Linked/Longitudinal Foreign Trade Transactions Database (LFTTD). The LFTTD is a confidential transaction-firm linked database linking individual trade transactions, both exports and imports, to the U.S. firms that make them.¹¹ The dataset contains information on the value, quantity, and date of transaction of a ten-digit Harmonized Commodity Description and Coding system (commonly called Harmonized System) products. The Harmonized System is an internationally standardized system of names and numbers for classifying traded products. The LFTTD also contains information about the trading parties and in particular, U.S. Customs Border Protection (CBP) requires U.S. importers to collect information about its foreign trading partner.¹² We focus on the universe of all U.S. import transactions (LFTTD-IMP) that occurred between 2002 and 2009.¹³ Moreover, we consider all import transactions of textile products from Bangladesh aggregated at the exporter-importer and year level. We consider textile products to include both textile or apparel products as defined under Section 102.21, Title 19, Code of Federal Regulations (CFR).¹⁴ They are classified as any products in two-digit HS codes 50 through 63.¹⁵ In the analysis sample, product codes 61 and 62 account for 89% of all transactions..

We only consider U.S. textile imports to permit focus on goods producing exporters and not other trading agents, such as export brokers or freight forwarders, who may have no role in

the actual matching process. The identifier for the exporter in the U.S. import transactions database is the manufacturer in case of textile products (see details below), and we exploit this useful feature of the data to circumvent this issue. In addition, we selected Bangladesh for two main reasons. First, textile exports account for close to 80% of total Bangladeshi exports over the sample period and this allows us to capture a significant portion of economic activity of this U.S. trading partner. Second, we wanted to select a trading partner that is a major player within the textile sector but that would still allow us to construct our dataset with ease as explained in the following section.

3.2. Dataset Construction

We utilize two sets of firm identifiers in the LFTTD-IMP. The first identifies the U.S. firm (importer) and the second identifies the Bangladeshi textile manufacturer (exporter). The exporter is uniquely identified by the “Manufacturer ID” (MID), a required field on Form 7501, the form U.S. importers are required to fill out by the U.S. CBP.¹⁶ The MID identifies the manufacturer or shipper of the merchandise by an alpha-numeric code that is constructed using a pre-specified algorithm with a maximum length of 15 characters (see Appendix for stylized examples).¹⁷ For textile shipments, the MID represents the manufacturer only in accordance with Title 19 CFR.¹⁸ Therefore, our data captures Bangladeshi textile manufacturers rather than trading agents who may or may not engage in the matching decision. The last three characters in the MID designate the city where the manufacturer is located, such that each manufacturer is assigned a MID that uniquely identifies its location.

We perform several basic data checks. First, we exclude transactions between related parties.¹⁹ Over the sample period, only about 2% of the total value of trade in textile products between the U.S. and Bangladesh occurs between related parties. Since we are interested in

exploring the role of neighbors on the first match status of a unique trade pair, we exclude trade transactions between the headquarters and subsidiaries of multinational firms. Next, we exclude transactions where the importer or exporter identifiers are missing or where the MID does not conform to the algorithm outlined in the CBP Form 7501 Instructions such as a MID that begins or ends with numeric characters, a MID that is a series of numbers, and the like.

[Insert Table 1 here]

Once the basic data checks are complete, we construct unique trading pairs using the importer and exporter firm identifiers for each year in the sample. There are 2,329 and 8,104 unique number of importers and exporters, respectively, over the sample period that results in 18,874,216 possible trading pairs in any single year.²⁰ We can see from Table 1 that as a share of the number of all possible trading pairs in a year, on average, only about 0.022% of pairings actually occur. This echoes the broader stylized fact in the trade literature, that trading is a rare activity. The final analysis dataset contains observations at the importer-exporter pair and year level.

In subsequent analysis, we explore heterogeneity in neighbor effects by importer size. In particular, we differentiate between small (those that employ less than 250 workers) and large (those that employ 250 or more workers) importers. We obtain information on an importer's basic firm characteristics from the Longitudinal Business Database (LBD). The LBD consists of data on all private, non-farm U.S. establishments in existence that have at least one paid employee (Jarmin and Miranda, 2002). There are 2,329 U.S. importers in our sample and we link 2,306 of these to the LBD to obtain information on firm employment, age, sector, and multi or single-unit status. For multi-units or firms with multiple plants, age is calculated as the difference between the year of interest and the year of establishment of its oldest plant. Since multi-unit

firms may operate in several sectors of the economy, the firm is considered to be operating in the sector where the largest share of its employment is housed.²¹ Since the LBD is an establishment level dataset, employment is first aggregated up to the firm level by sector. The firm is then assigned its “predominant” sector and its employment is aggregated to the firm level.²²

3.3. Variables

Since we are interested in examining the role of neighbors in facilitating first time matches, our main independent variable of interest is S_{ijt} that is a dummy variable that takes on a value of 1 for the first year t that exporter i and importer j begin trading and 0 otherwise. For instance, if we observe a trade transaction between ABC Garments Company in Bangladesh and XYZ Corporation in the U.S. from 2003 through 2007, S_{ijt} takes on value of 1 in 2003 and all other observations in the subsequent years are dropped from the data. Our main dependent variable of interest, z_{cjt-1} , is the number of other exporters that matched with importer j located in the same area, c , as exporter i at time $t-1$ and will be referred to as “# exporters-importer j , same city” in the tables.

The geographic area we consider is the city that is reported in the Manufacturer ID. The last three characters of the MID designates the city the manufacturer operates in. We verified the list of cities in our analysis sample against a list of all cities in Bangladesh. Bangladesh is divided into seven administrative divisions that are further divided into 64 districts (*zila*) and within districts, into 1,009 sub-districts (*upazila*).²³ The city information extracted from the MID approximately conforms to sub-districts.²⁴ Sub-districts are analogous to counties in the U.S. and are the second lowest tier of regional administration. Bangladesh is a small country with an area of about 57,000 square miles, roughly the size of the state of Iowa, therefore average area of a sub-district is about 56 square miles.²⁵ There are 282 cities in our analysis sample.

[Insert Table 2 here]

3.4. Descriptive Statistics

Table 2 presents summary statistics on the exporters and importers in our analysis sample. The first column is based on the entire analysis sample and the second and third columns further divide the sample by small and large U.S. importers. In our analysis sample, the number of Bangladeshi exporters is more than three times that of the number of U.S. importers. The table shows that an average U.S. importer tends to transact with about six Bangladeshi exporters. There is heterogeneity across small and large importers. Large U.S. importers, on average, tend to transact with about 12 Bangladeshi exporters while small importers match with only four exporters. However, the average Bangladeshi textile exporter matches with about two U.S. importers, no matter the size of the importer.

This pattern persists at the city level. On average, there are about 24 exporters and 14 importers in a city with a little less than three times the number of small importers transacting in a city compared to large importers. Our main variable of interest, the number of exporters in a city selling to a particular U.S. importer, is 0.53 on average. Here too, we see differences across small and large importers. The average number of exporters in a city selling to a particular U.S. importer in the previous period is 0.37 in the sample of small importers and increases to 1.42 when the importer is large. We get a sense of networks at work when we look at the number of cities an average U.S. buyer sources from. We see that an average importer sources from just under two cities, hinting at spatial clustering in buyer-seller matches. Large importers are not very different from small importers. A small U.S. importer sources from about two Bangladeshi cities while a large U.S. importer sources from about three Bangladeshi cities.

[Insert Table 3 here]

4. Results

4.1 Identifying the role of neighbors in matching individual importers and exporters

Table 3 presents results from our baseline regression described in equation (2.7). We look at the impact of the presence of firms that previously matched with a U.S. buyer in the neighborhood of a Bangladeshi exporter, defined by a city, on the probability of a first-time match between the same importer and the exporter, successively adding exhaustive fixed effects in each column. Column (1) includes year fixed effects only; column (2) includes exporter-year and importer fixed effects; column (3) includes exporter-year and importer fixed effects as well as time-varying importer controls of age and employment and column (4) includes exporter-year and importer-year fixed effects. We focus on results from column (4) in our discussion below as it contains the most exhaustive set of fixed effects.

We find that, controlling for exporter–time and importer–time factors that might determine first match status, nearby exporter presence is positively associated with the likelihood of a first–time match. From column (4), we find that an additional exporter in the city that previously matched with the same importer is associated with an increase of 0.00006 (with a *t*-statistic of 9.89) in the likelihood of a first-time match between a Bangladeshi exporter and a U.S. importer.²⁶ In elasticity terms, our results in column (2) indicate that a one percent increase in the number of exporters in a city selling to a buyer results in a 0.51% increase in the likelihood of a match with the same buyer for the first time.²⁷ This figure drops to 0.19% after we account for buyer fixed effects and controls, and to 0.15% once we account for buyer-year effects.²⁸

In the context of the literature on export spillovers, we can interpret our results as export spillovers that are specific to the trade partner. Thus, following our discussion in Section 2, our results suggest that partner-specific spillovers are especially beneficial in lowering the sunk costs

associated with a particular match that includes search costs that can be more than thirteen times higher than per period fixed costs of maintaining a trade relationship as indicated by estimates in Eaton et al (2013).

In order to compare our results to that in the existing literature, and to ensure that our results remain qualitatively similar when we account for the binary nature of our match variable, we implement a conditional logit model as in Koenig et al (2010). We estimate equation (2.7) with exporter-year fixed effects and time-varying importer controls and report the results in Table A2. Koenig et al (2010) search for evidence of export spillovers on a French exporter's decision to start exporting to a particular destination. Implementing a conditional logit model with year and firm-product-country fixed effects, they find that an additional exporter in the neighborhood increases the likelihood of beginning to export to the same destination by 0.16 percentage points.²⁹ Our conditional logit estimation results imply that an additional exporter in the neighborhood increases the likelihood of exporting to the same buyer for the first time by 0.70 percentage points.³⁰ Hence, our evidence suggests that spillovers at the firm level are much stronger than destination-specific spillovers, highlighting the importance of isolating spillovers that are partner-specific, and that operate by lowering partner-specific fixed costs of trading.

[Insert Table 4 here]

4.2 Heterogeneous neighbor effects

In order to explore the nature of the network/spillover effects established in our baseline results, in Table 4, we estimate equation (2.7) separately for small, medium, and large exporters. Exporters are designated into three size categories based on their average export sales in each year – large exporters have sales in the first quantile, medium exporters have sales in the second quantile, and small exporters have sales in the third quantile. The average annual value of a

transaction between a trade pair in our sample is a little over half a million U.S. dollars. Figure 1 shows the distribution of export value, in thousands of current U.S. dollars, over our sample period. We can see that about three-quarters of annual Bangladeshi textile export transactions are valued at less than \$500,000.

[Insert Figure 1 here]

In addition to establishing the heterogeneity of the neighbor effects based on exporter characteristics, this exercise addresses and alleviates concerns about results predominantly being driven by the presence of multi-plant exporters. The concern about multi-plant firms is that although our independent variable correctly assigns manufacturers to the cities they are located in, it is possible that the headquarter, rather than the manufacturing location of a multi-plant firm, is the unit responsible for developing trade relationships. Since we do not have firm level information for the Bangladeshi manufacturers in our sample to identify multi-plant status of a firm, we offer two reasons why we believe our results are not disproportionately being driven by the presence of multi-plant firms.

First, the export-oriented Bangladeshi textile sector is characterized by a large number of small firms rather than a few large firms (Yamagata, 2007) and large firms are typically associated with multi-unit status. Second, we rerun our baseline regressions on three separate samples that are divided according to exporters' average sales. It is more likely that units of multi-plant firms will tend to be larger in terms of total export value and therefore if the presence of such exporters in our sample are disproportionately driving our results we would expect the spillovers to be more pronounced for large exporters. Our results suggest otherwise – partner-specific spillovers exist only for small exporters. In fact, for medium and large exporters, the evidence for spillovers is not robust to controlling for buyer-year specific shocks to match status

(see columns (4) and (6)). Intuitively, this makes sense because we would expect smaller exporters to benefit more from the presence of neighboring exporters selling to the same buyer since large exporters are more likely to have well-established, internal networks that facilitate fostering buyer-seller relationships.

[Insert Table 5 here]

In Table 5, we estimate equation (2.7) separately for small and large U.S. importers. This is motivated by evidence that there is substantial heterogeneity within U.S. trading firms in terms of size and this could mask interesting patterns in the neighbor effect. Bernard, Jensen, and Schott (2010) document that pure wholesalers and retailers (defined as importers with 100% of their employment in either of those two sectors) are smaller in terms of employment, trade value and domestic sales, operate fewer U.S. establishments and are present in fewer U.S. states. Meanwhile “mixed” firms (defined as firms with less than 100% employment in retailing and/or wholesaling) are substantially larger, trade more products, trade with more countries, and are more likely to engage in related-party trade. In our sample, more than half of U.S. importers are wholesalers while a third are manufacturing and retail firms.

[Insert Figures 2 and 3 here]

Figures 2 and 3 show that the average export value and number of exporters per importer differ vastly by importer size in each of the sample years. The average import value of small importers is less than half that of large importers. Large importers also transact with almost twice the number of Bangladeshi exporters compared to small importers, on average. Large firms in the U.S. importing textile products from Bangladesh are likely to behave differently in procuring suppliers and so we expect spillover effects to differ across size categories. For instance, small U.S. importers might be more reliant on their existing suppliers for information on potential

future suppliers than large U.S. importers, who might have alternative means of search. Similarly, on the Bangladeshi side, exporters might find it more difficult to search and match with smaller U.S. buyers. Indeed, we do find support for the hypothesis that spillovers play a larger role in buyer-seller matches when the buyer is small.³¹ In Table 5, we divide the sample by importer size – small and large. Columns (1) and (2) presents results for the sample of small importers and columns (3) and (4) for the sample of large importers. We find that spillover effects for large firms are smaller than that for small firms, though both effects are positive and statistically significant.

[Insert Table 6 here]

4.3 Robustness checks

We carry out two additional checks of our baseline results presented in Table 6. Columns (1) and (2) test whether the impact of a higher number of neighbors that previously matched to the same U.S. importer remains significant for the top end of our sample in terms of number of neighbors, similar to Koenig et al (2010). The sample is restricted to observations for which the number of neighboring exporters exporting to the same importer is greater than 1.³² The purpose is to ensure that the partner-specific spillover effects are not only due to cases of textile exporters starting to export to a particular U.S. importer following an increase in the number of neighbors from zero to one. From our preferred specification in column (2), we find that, controlling for exporter–time and importer-time specific factors that might determine matches, an additional exporter in the city selling to the same importer is associated with an increase of 0.000059 (with a t-statistic of 16.02) in the likelihood of a first-time match between a Bangladeshi exporter and a U.S. importer. This is quantitatively and qualitatively similar to results from our preferred specification in Table 3, column 4. Our results confirm that the impact of spillovers remains

positive, significant, and almost identical in magnitude when considering cities with more than one neighboring exporter. Therefore, partner-specific export spillovers persist for exporters surrounded by one or more neighbors.

Columns 3 and 4 test whether the impact of a higher number of neighbors that previously matched to the same U.S. importer remains significant when we only consider cities where multiple products are produced. This addresses a particular concern that if there are cities that specialize in a product, and there are only certain U.S. importers who import those products, then these importers would have to trade with exporters in particular cities. Subsequently, all exporters in the neighborhood would be solely transacting with particular U.S. importers who demand particular products and our results would be an artifact of this specific scenario. Two-digit HS products 61 and 62 represent about 93% of all transaction value in our analysis sample. Therefore, we restrict our sample to cities where both product categories are manufactured. We find from column 4 that, controlling for exporter-time and importer-time specific factors that might determine matches, an additional exporter in the city that previously transacted with a U.S. importer is associated with an increase of 0.00006 (with a t-statistic of 17.81) in the likelihood of a first-time match between a Bangladeshi exporter and the same U.S. importer. This is quantitatively and qualitatively similar to results from our preferred specification in column 4, Table 3.

In summary, our results suggest that a one percent increase in the number of exporters in a city that previously matched with a U.S. importer results in a 0.15% increase in the likelihood of a match between an exporter in that city and the same buyer for the first time. Comparison with existing evidence suggests that this effect is economically significant. We also find

evidence of positive partner-specific export spillovers that vary with both exporter and importer characteristics. In particular, spillovers are stronger for small exporters and small importers.

5. Conclusion

This paper finds a statistically positive and economically significant role for other exporters in the neighborhood of a firm, that have previously matched to a particular importer, in improving the likelihood of that firm matching with the same importer for the first time. Thus, we further build on the existing empirical body of evidence that documents network effects in trade and positive export spillovers specific to destinations and products. Our study also contributes to the nascent investigations in the international trade literature on matches between buyers and sellers and their determinants.

Our results establish the importance of isolating the buyer-specific component of export spillovers and recognizing that there may be further variation in spillovers depending on exporter and importer characteristics. Earlier studies have underscored the role of trade promotion measures that bring about learning and information exchange among potential exporters about destination markets, including prevailing consumer tastes, demand conditions and customs procedures. We find that information externalities at the firm level are significant, and disseminating information on identifying individual buyers and sellers in the foreign country and their requirements and capabilities can help spur trade relationships. Finally, our study underscores the importance of linking firm-trade transactions data between country pairs to shed further light on the determinants of the relationship between buyers and sellers transacting across borders.

Acknowledgments

We thank Emin Dinlersoz, Meredith Crowley, Giovanni Peri and participants at the 2013 Center for Economic Studies seminar series, European Trade Study Group (Birmingham), University of Pretoria (South Africa) seminar series, Annual Research Data Center Conference, Comparative Analysis of Enterprise Data Conference, Midwest International Trade Meetings, Annual Meetings of the Society of Government Economists, North American Regional Science Conference, and the 2014 U.S. International Trade Commission seminar series for helpful comments. Any errors or omissions remain our own.

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TABLE 1.-UNIQUE MATCHES, BY YEAR

Year	Matches
2002	3,586
2003	3,327
2004	3,407
2005	4,012
2006	4,763
2007	4,785
2008	5,492
2009	4,924
2002 - 2009	21,281

Notes: The statistics are based on all U.S.-Bangladesh trade transactions in textile products only; "Matches" refers to unique importer-exporter combinations that have transacted in the given year in at least one textile product.

TABLE 2.-SUMMARY STATISTICS

Variable	All Importers		Small Importers		Large Importers	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Number of Exporters/Importer	5.64	14.15	4.10	7.55	12.27	27.37
Number of Importers/Exporter	1.82	1.64	1.84	1.64	1.77	1.63
Number of Exporters-Importer <i>j</i> , Same City	0.53	3.20	0.37	1.81	1.42	6.85
Number of Cities/Importer	1.87	1.76	1.67	1.16	2.81	3.05
Number of Importers/City	14.45	64.62	15.54	60.68	6.35	17.99
Number of Exporters/City	23.72	129.84	-	-	-	-

Notes: The statistics are based on our analysis sample, all possible U.S.-Bangladesh trade transactions in textile products only between 2002 and 2009; “Small” refers to importers that employ 1-249 workers and “Large” refers to importers that employ 250+ workers.

TABLE 3.-FIRST MATCH STATUS, ROLE OF NEIGHBORS

	(1)	(2)	(3)	(4)
# exporters-importer j, same city	0.00013 (51.83)	0.00013 (49.07)	0.000069 (11.21)	0.000062 (9.89)
Observations	131,965,095	99,454,323	99,454,323	131,965,095
Year Fixed Effect	Y	-	-	-
Importer Fixed Effect	-	-	Y	-
Importer Controls	-	Y	Y	-
Importer x Year Fixed Effect	-	-	-	Y
Exporter x Year Fixed Effect	-	Y	Y	Y

Notes: T-statistics reported in parentheses based on standard errors clustered at the importer-city level. Significance at *10%, **5%, ***1% level. The dependent variable, "First Match Status", takes on the value 1 in the first year a transaction is observed between a unique importer-exporter pair and is 0 otherwise. The independent variable is lagged one year. Importer controls include firm age and employment.

TABLE 4.-FIRST MATCH STATUS, ROLE OF NEIGHBORS BY EXPORTER SIZE.

	Small		Medium		Large	
	(1)	(2)	(3)	(4)	(5)	(6)
# exporters-importer j, same city	0.00012 (9.12)	0.00012 (6.66)	0.00004 (1.76)	0.00004 (1.21)	0.00005 (1.70)	0.00004 (1.50)
Observations	31,927,890	42,369,329	31,985,128	42,438,424	32,004,507	42,464,555
Importer Controls	Y	-	Y	-	Y	-
Importer Fixed Effect	Y	-	Y	-	Y	-
Importer x Year Fixed Effect	-	Y	-	Y	-	Y
Exporter x Year Fixed Effect	Y	Y	Y	Y	Y	Y

Notes: T-statistics reported in parentheses based on standard errors clustered at the importer-city level. Significance at *10%, **5%, ***1% level. The dependent variable, "First Match Status", takes on the value 1 in the first year a transaction is observed between a unique importer-exporter pair and is 0 otherwise. The independent variable is lagged one year. Importer controls include firm age and employment. Exporters are designated as small, medium, large based on three size quantiles using average value of export sales each year in the sample period.

TABLE 5.-FIRST MATCH STATUS, ROLE OF NEIGHBORS BY IMPORTER SIZE.

	Small		Large	
	(1)	(2)	(3)	(4)
# exporters-importer j, same city	0.000091 (8.80)	0.000088 (8.42)	0.000061 (7.29)	0.00005 (6.93)
Observations	81,514,392	109,897,375	17,939,931	20,763,398
Importer Controls	Y	-	Y	-
Importer Fixed Effect	Y	-	Y	-
Importer x Year Fixed Effect	-	Y	-	Y
Exporter x Year Fixed Effect	Y	Y	Y	Y

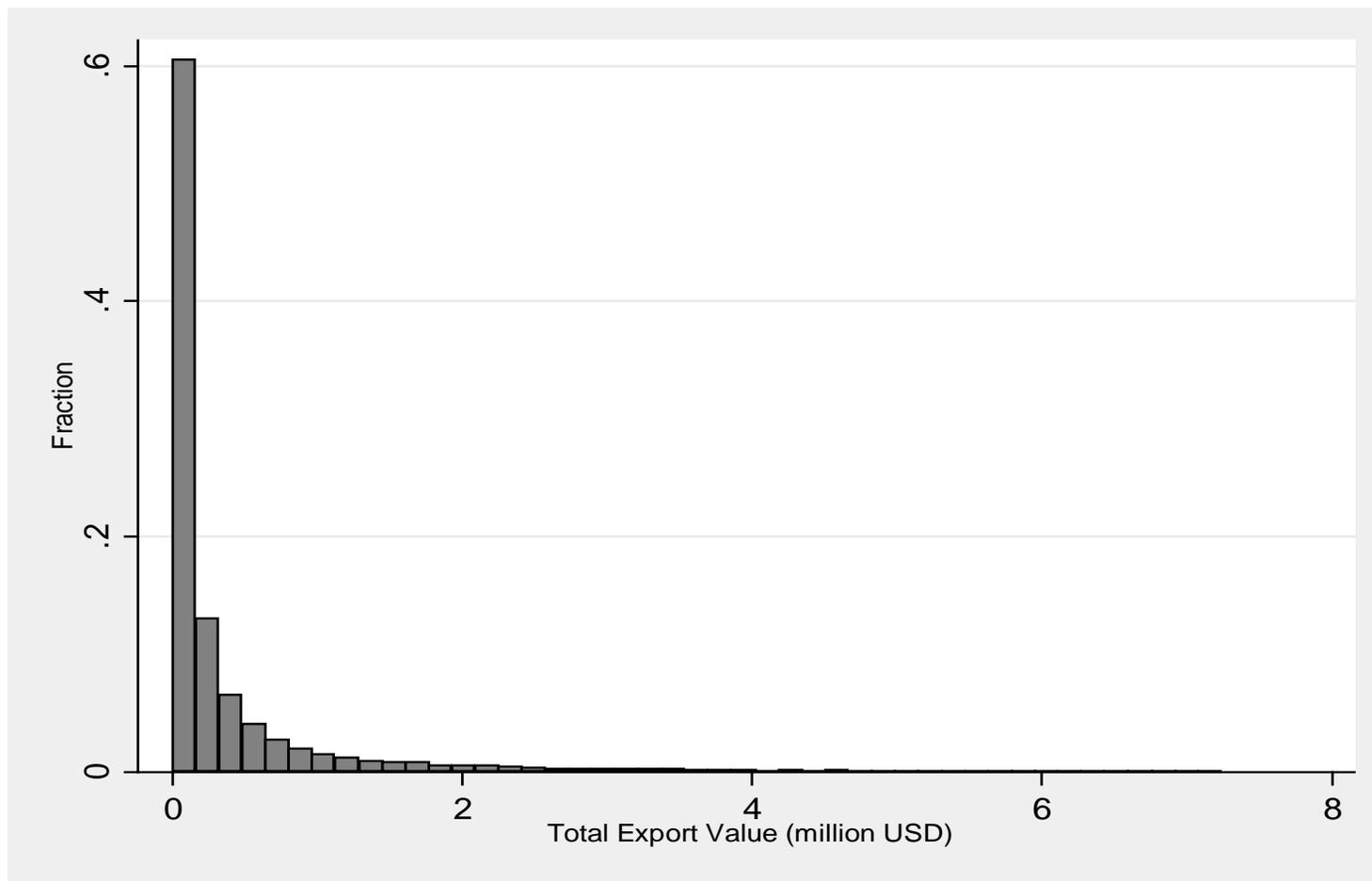
Notes: T-statistics reported in parentheses based on standard errors clustered at the importer-city level. Significance at *10%, **5%, ***1% level. The dependent variable, “First Match Status”, takes on the value 1 in the first year a transaction is observed between a unique importer-exporter pair and is 0 otherwise. The independent variable is lagged one year. Importer controls include firm age and employment. Importers are categorized into two size bins using average number of employees over the sample period. “Small” refers to 1-249 employees and “Large” refers to 250+ employees.

TABLE 6.-FIRST MATCH STATUS, ADDITIONAL TESTS.

	Test 1		Test 2	
	(1)	(2)	(3)	(4)
# exporters-importer j, same city	0.000067 (19.78)	0.000059 (16.02)	0.00007 (21.25)	0.000063 (17.81)
Observations	93,183,914	123,622,485	96,678,819	128,282,482
Importer Controls	Y	-	Y	-
Importer Fixed Effect	Y	-	Y	-
Importer x Year Fixed Effect	-	Y	-	Y
Exporter x Year Fixed Effect	Y	Y	Y	Y

Notes: T-statistics reported in parentheses based on standard errors clustered at the importer-city level. Significance at *10%, **5%, ***1% level. The dependent variable, "First Match Status", takes on the value 1 in the first year a transaction is observed between a unique importer-exporter pair and is 0 otherwise. The independent variable is lagged one year. Importer controls include firm age and employment. In columns 1 and 2 (3 and 4), the sample is restricted to observations for which the number of exporters selling to importer *j* in a city is greater than 1 (the sample is restricted to cities where multiple products are produced).

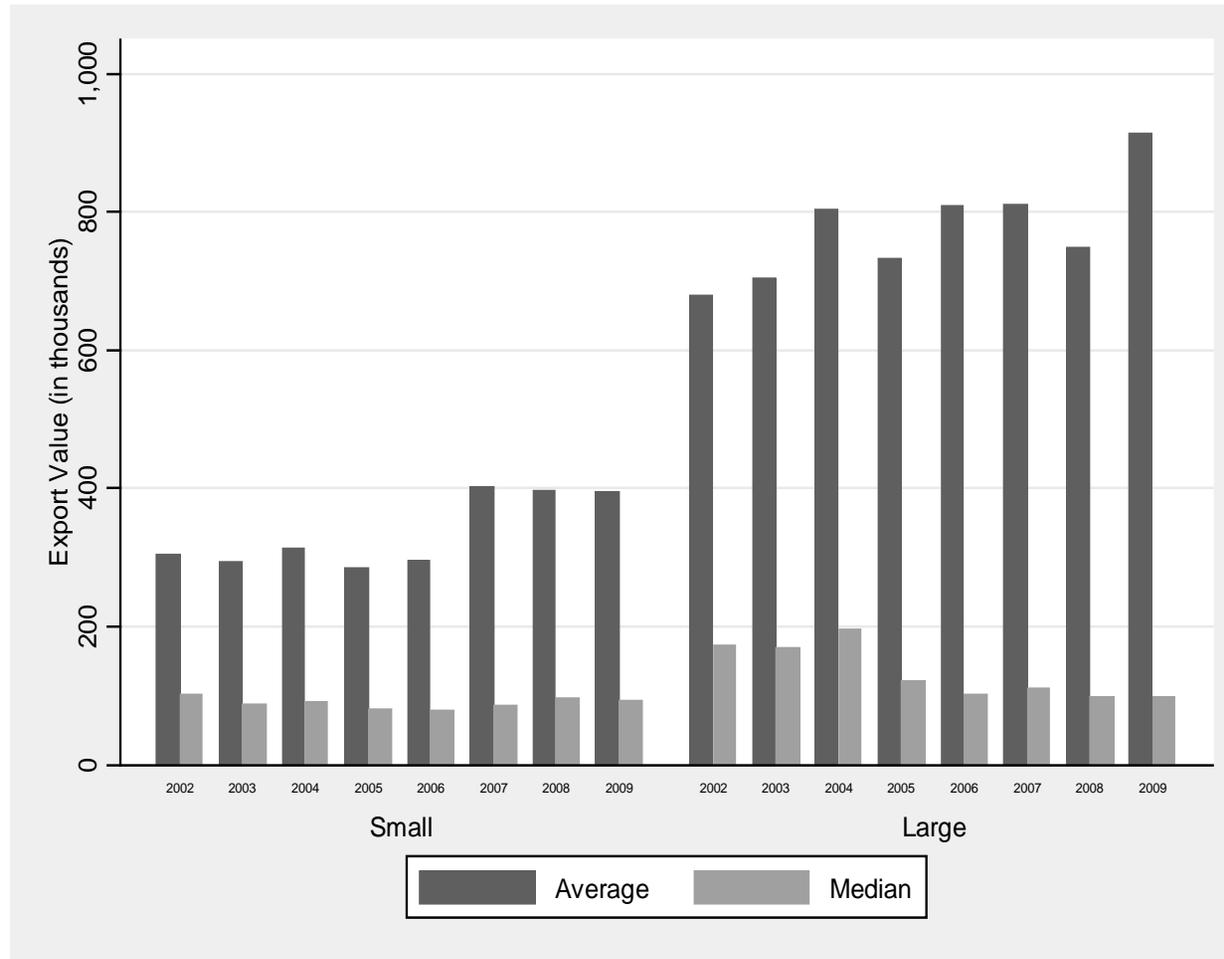
FIGURE 1.-DISTRIBUTION OF TOTAL EXPORT VALUE, 2002 – 2009.



Source: Authors' calculations.

Notes: Values are in current U.S. dollars.

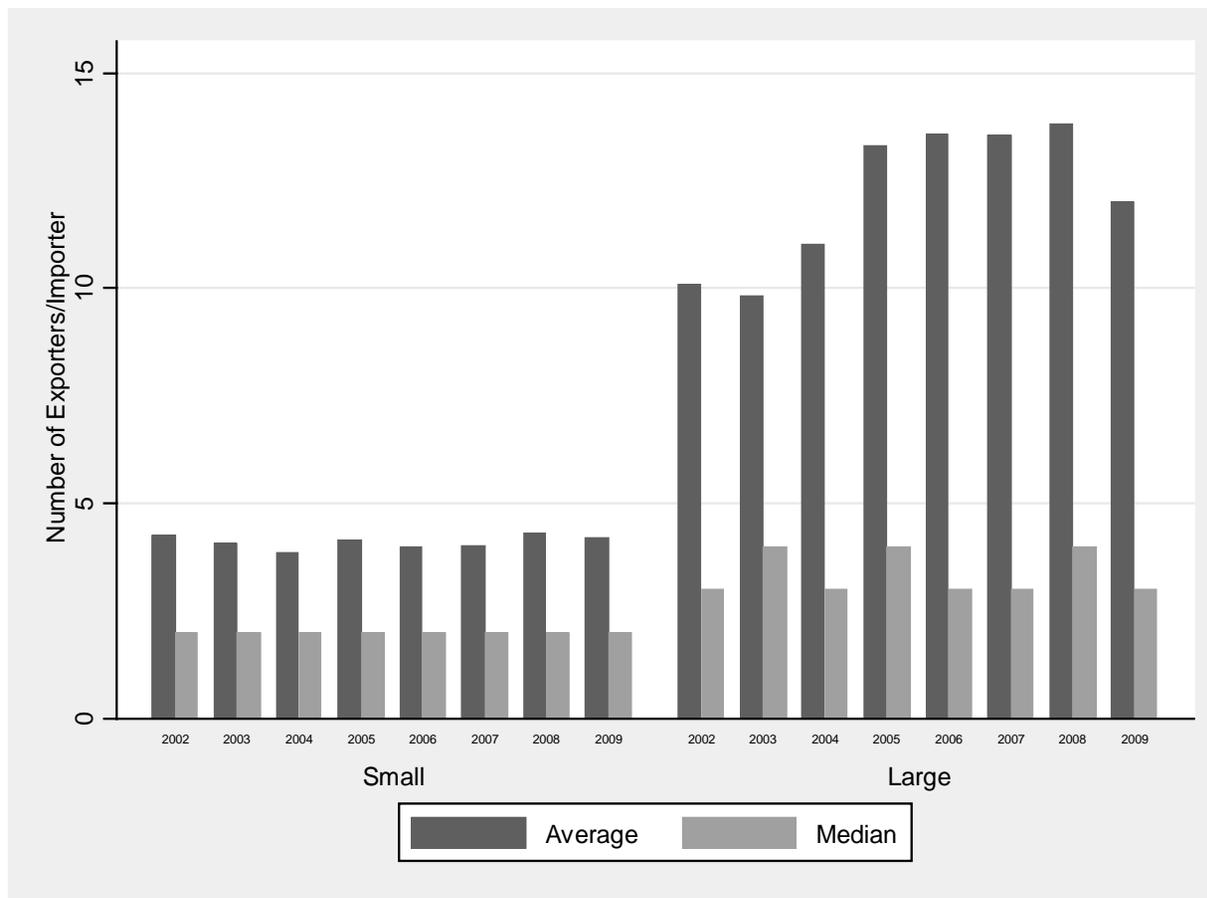
FIGURE 2.-EXPORT VALUE BY IMPORTER SIZE, 2002 – 2009.



Source: Authors' calculations.

Notes: Importers are categorized into two size bins using average number of employees over the sample period. "Small" refers to importers that employ 1-249 workers and "Large" refers to importers that employ 250+ workers; Values are in current U.S. dollars.

FIGURE 3.-NUMBER OF EXPORTERS PER IMPORTER, 2002 – 2009.



Source: Author's calculation.

Notes: Importers are categorized into two size bins using average number of employees over the sample period. "Small" refers to importers that employ 1-249 workers and "Large" refers to importers that employ 250+ workers.

APPENDIX A

TABLE A1.-MANUFACTURER ID EXAMPLE

Country	Exporter Name	Address	City	MANUFID
Bangladesh	Red Fabrics	1234 Tiger Road	Dhaka	BDREDFAB1234DHA
Bangladesh	Green Fabrics	1111 Lion Road	Dhaka	BDGREFAB1111DHA
Bangladesh	Blue Fabrics	88 Zebra Road	Chittagong	BDBLUFAB88CHI

Note: The above examples are based on fictitious names and addresses and are meant for illustrative purposes only.

TABLE A2.- FIRST MATCH STATUS, CONDITIONAL LOGIT.

	(1)
# exporters-importer j, same city	0.03179*** (0.000)
Observations	20,695,095
Exporter x Year Fixed Effect	Y
Importer Controls	Y

Notes: Robust standard errors in parentheses. Significance at *10%, **5%, ***1% level. The dependent variable, "First Match Status", takes on the value 1 in the first year a transaction is observed between a unique importer-exporter pair and is 0 otherwise. The independent variable is lagged one year. Importer controls include firm age and employment.

APPENDIX B: Uniqueness of City Information in MID

We extract the Bangladeshi textile manufacturer's location information from the manufacturer identifier (MID) as represented by the last three letters (refer to Table A1 for examples). It is possible that a three-letter city code could represent multiple cities. For instance, "TAN" could refer to either Tangail or Tanore that are located in Dhaka and Rajshahi divisions, respectively. We ensure that the city codes do not refer to multiple possible cities where textile manufacturers may be located. To this end, we first create a list of all unique three-letter city codes and then match it against the 2013 geographic administrative codes compiled by the Bangladesh Bureau of Statistics.³³ Close inspection of the three-letter city list indicate that cities conform to sub-districts (*upazilas*), the third lowest level of geographic administrative divisions. We compile a list of all possible sub-districts that correspond to each three-letter city code. We then identify the most likely sub-district using external information on textile manufacturers.

We utilize three external sources of firm information. We compile a list of all member firms belonging to the Bangladesh Garment Manufactures and Exporters Association (BGMEA), Bangladesh Knitwear Manufactures and Exporters Association (BKMEA), and the Bangladesh Textile Mills Association (BTMA) that all include a mailing and factory address for the firm.³⁴ BGMEA member factories account for 100% of total woven garments exports, over 95% of total sweater exports, and about 50% of total light knitwear exports from Bangladesh.³⁵ These three directories are the most reliable sources of information on Bangladeshi textile manufacturers. The BGMEA directory has been used as the sample frame for the country specific enterprise surveys conducted by the World Bank (Fernandes, 2008) as well as independent surveys (Klepper and Mostafa, 2009) examining issues specific to the Bangladesh garments industry. The World Bank enterprise survey for Bangladesh utilizes all three directories to form its sample frame.³⁶

We generate frequencies of the number of firms for all cities that appear in the directories. Then, we use this information to identify the most likely city represented by the three-letter code where it corresponds to more than one possible city from the list of geographic administrative codes. However, there are instances where a three-letter code corresponds to multiple cities of similar frequencies. For example, the three-letter code “MIR” may correspond to Mirzaganj in Barisal division, Mirsharai in Chittagong division, Mirpur (in Dhaka or Khulna divisions), or Mirzapur in Dhaka division. Both Mirpur and Mirzapur in Dhaka division are likely candidates. We identify three such codes that may correspond to multiple cities where textile manufacturers are located and that together account for about 6% of the total number of textile exporters in the sample. To confirm the robustness of our results to dropping these cities from our sample, we re-run our baseline specifications excluding firms located in these three cities. Our baseline results remain almost identical in both statistical significance and magnitude and are available upon request.

Footnotes

¹ Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed.

² Corresponding author.

³ See Table 1 for an annual distribution of unique U.S.-Bangladesh trading pairs in textile and apparel products.

⁴ These studies consider two types of networks – social and business. Social networks are typically measured as the stock of bilateral migrants and business networks are typically measured as links between plants/firms belonging to the same business group.

⁵ Bernard and Jensen (2004) consider the role of both geographic and sectoral spillovers in the export decision of a U.S. plant. Koenig (2009) and Koenig, Mayneris, and Poncet (2010) further consider the role of export spillovers on the decision of French firms to export to a particular country. Compared to Bernard and Jensen, the spillovers considered are destination specific and geography is at the much more disaggregated French employment area level rather than a U.S. state.

⁶ Buying houses are intermediaries that facilitate matches in numerous ways, for instance, by helping with search or by providing quality certification to buyers. Buying houses could represent one potential channel through which observed networks effects, or spillovers, operate. For instance, exporters might learn about one or more of these buying houses from their neighbors. Similarly, a firm located close to other exporters, that matched in the earlier period with an importer via a buying house, might be more visible to the buying house. Our conceptual

framework allows for the alternative interpretation that buying houses act on behalf of, or substitute for, U.S. importers.

⁷ Our research design requires us to analyze all possible trading pair matches and therefore we select a bilateral trade relationship where the number of buyers and sellers is relatively small but at the same time captures a significant portion of the economic activity of the trading partner. See Section 3 for further detail on data construction.

⁸ See <http://www.bdembassyusa.org/uploads/US%20-%20BD%20trade.pdf>.

⁹ See Fernandes and Tang (2012) for a discussion of the choice of a linear probability model over other binary-choice models.

¹⁰ Since we are using U.S. import transaction records, we only observe the product and value associated with the exporter's transaction with a U.S. importer. We do not observe exporter characteristics that may influence the decision to export to a U.S. importer such as total factor productivity, total wages, total employment, etc. Therefore, exporter-year fixed effects control for all time varying exporter characteristics that may influence export behavior.

¹¹ See <http://www.census.gov/ces/dataproducts/datasets/lfttd.html> for more information.

¹² A U.S. exporter is not required to assign and report a unique identifier for the foreign trading entity it transacts with.

¹³ Although, the LFTTD-IMP is available from 1992, we have chosen to focus on the most recent eight-year period for ease of constructing the analysis dataset. At the time we began the study, 2009 was the latest available year.

¹⁴ See <http://www.gpo.gov/fdsys/pkg/CFR-2011-title19-vol1/pdf/CFR-2011-title19-vol1-sec102-21.pdf>.

¹⁵ See <http://hts.usitc.gov/> for details on each HS chapter.

¹⁶ See form http://forms.cbp.gov/pdf/cbp_form_7501.pdf.

¹⁷ See Block 13 (pg. 7) for description of MID and Appendix 2 (pg. 30) for instructions on constructing MID at http://forms.cbp.gov/pdf/7501_instructions.pdf.

¹⁸ See <http://www.gpo.gov/fdsys/pkg/CFR-2011-title19-vol1/pdf/CFR-2011-title19-vol1-sec102-23.pdf>.

¹⁹ “Related party” trade refers to trade between U.S. companies and their foreign subsidiaries as well as trade between U.S. subsidiaries of foreign companies and their foreign affiliates. For imports, firms are related if either owns, controls, or holds voting power equivalent to 6 percent of the outstanding voting stock or shares of the other organization (see Section 402[e] of the Tariff Act of 1930).

²⁰ This illustrates why we focus on a single sector and trading partner. The need to construct all possible trading pairs precludes considering the universe of U.S. import transactions.

²¹ If instead payroll information is used to assign sectors, the categorization remains qualitatively unchanged.

²² Sales data are not readily available for all firms in the sample. Therefore, employment is used to assign a sector.

²³ See list of geo codes at <http://www.bbs.gov.bd/WebTestApplication/userfiles/Image/geocodeweb.pdf>.

²⁴ See Appendix A and B for further details.

²⁵ The spillover measures in Koenig (2009) and Koenig et al (2010) are measured at the level of the French employment area that is on average 937 square miles. For a map of the sub-districts of Bangladesh see

http://www.fao.org/fileadmin/templates/faobd/img/Administrative_Unit_Map.jpg.

²⁶ We report magnitudes for the ‘typical’ Bangladeshi exporter and U.S. importer. In other words, effects are calculated with all fixed effects set to zero.

²⁷ Elasticities are calculated using the “margins” command in STATA.

²⁸ Koenig (2009) finds that a 1% increase in the share of firms exporting to a country increases the probability of exporting to that country by 0.26%. This effect ranges from 0.15% to 0.33% when countries are grouped by a measure of market accessibility.

²⁹ This result is obtained using an average probability to start exporting in the sample of 30%.

See Koenig et al (2010, p.631) for details.

³⁰ Marginal effects are calculated using the “margins” command in STATA.

³¹ This, partly, also address the concern that the network effects we observe exist because large U.S. importers buying from small Bangladeshi exporters realize that the exporter cannot fulfill their order, and hence are forced to break their order up and allocate them to nearby exporters. Finding stronger positive network effects for small importers alleviates this concern to a certain extent.

³² The results remain unchanged if we consider a cutoff of 3.

³³ See <http://www.bbs.gov.bd>.

³⁴ Accessed at <http://www.bgmea.com.bd/member/memberlist#.UnEBEKyAqSo>,

<http://www.bkmea.com/member/index.php>, <http://www.btmadhaka.com/Mill%20List.html>

respectively.

³⁵ See <http://www.bgmea.com.bd/home/pages/AboutBGMEAT#.UnEBd6yAqSo>.

³⁶ See <http://siteresources.worldbank.org/INTPSD/Resources/336195-1092412588749/00--Bangladesh--1-78.pdf> for detailed discussion.