Buyer–seller relationships in international trade: Do your neighbors matter?☆

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A B S T R A C T

Using confidential U.S. customs data on trade transactions between U.S. importers and Bangladeshi exporters between 2003 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 is associated with a greater likelihood of matching with the same U.S. importer for the first time. This suggests a role for neighbors in generating importer–exporter matches. Our research design permits us to isolate potential gains from neighborhood exporter presence that are partner-specific, from overall gains previously documented in the literature.

Published by Elsevier B.V.

1. Introduction

International trade involves forming and sustaining relationships between buyers and sellers across borders. A burgeoning literature, facilitated by access to micro data, explores buyer–seller matches in trade, and highlights the costs associated with locating a trade partner, maintaining a trade relationship (Benguria, 2015; Eaton et al., 2014; Bernard, Moxnes and Ulltveit-Moe, 2014a), and switching trade partners (Monarch, 2014). While this literature underscores the prominence of relationship-specific costs in cross-border buyer–seller matching, relatively little is known about the nature of these costs and their determinants. In this study, we propose that the presence of exporters selling to a particular foreign buyer in the neighborhood of a firm can lower the costs of matching, increasing the likelihood of a match between the firm and the same buyer.

We argue that neighbors can help in numerous ways. First, neighboring exporters can lower the costs of locating a trade partner. Such search costs are a pervasive feature of all cross-border trade transactions, and can be considerable. In addition, neighbors can provide a buyer with access to information on a seller's strengths, reliability and reputation, and a seller with access to information on a buyer's clientele and customization requirements, thus lowering costs of matching. This can be particularly important when one or both trading partners are located in a developing country, where information flows are imperfect and reliable information on key activities relating to generating and sustaining a match can be costly to obtain.

In this paper, we focus on the role of neighboring exporters in a Bangladeshi city that have previously transacted with a particular U.S. importer in facilitating a first-time match between a potential

individual Bangladeshi seller and that U.S. importer.[1] We relate the presence of exporters neighboring exporter x and selling to an importer m on first-match status, that is the first time exporter x matches with importer m. 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 2003 and 2009, sourced from the U.S. Census Bureau. Exporters in our sample are Bangladeshi textile manufacturing firms, while more than half of U.S. importers are wholesalers and the rest comprise mainly of manufacturing and retail firms.

We estimate a linear probability model of the first match between each Bangladeshi exporter and each U.S. importer. A match occurs when the importer and exporter transact for the first time in our sample period. Thus, for each importer–exporter pair that matched in some year in our sample period, our first-match status variable switches from a 'zero' in the years prior to the first match, to a 'one' in the year the match first occurred. All subsequent years that a pair trades in following the first match are excluded from the analysis sample. The match status variable remains 'zero' for all years in our sample for importer–exporter pairs that never matched. We then relate the likelihood of a first match between an importer–exporter pair to a measure of exporter presence (or the size of the exporter network) to that same importer in the neighborhood of the exporter. The level of detail in the data allows us to identify the effect of neighbors using variation over time in the number of neighboring exporters, after accounting for time-invariant unobserved shocks specific to the importer–exporter pair and for time-varying shocks to the importer and exporter individually.

Results from our preferred specification indicate that a 1% increase in the number of exporters that previously matched with a particular U.S. importer in the neighborhood of a firm is associated with a 0.15% increase in the likelihood of the firm matching with the same importer for the first time. Our results are robust to instrumental variables and propensity score matching estimation strategies, alternative measures of the neighbor variable, a stricter definition of first-time matches, and various cuts of the data. Although we are unable to observe learning and cost-sharing directly in the data, we provide evidence consistent with these gains being the channel via which neighbor effects operate.

We believe that our study makes several contributions. First, it exploits the richness of disaggregated two-sided trade transactions data, including information on the spatial location of exporters, to identify a determinant of buyer–seller matches across international borders. In doing so, we argue that neighbors can lower the costs of matching discussed and underscored in previous studies. Second, it adds to the rich literature that examines the determinants of exporter status (Bernard and Jensen, 2004) and the export spillover literature that highlights the role of neighboring exporters in improving the likelihood of firms exporting to foreign destinations (Koenig, 2009; Koenig et al., 2010). The studies seeking evidence for export spillovers find that greater presence of exporters close to a firm selling to a specific foreign destination can increase the likelihood that the firm exports to the same destination as well as improve survival in that destination (Fernandes and Tang, 2012, 2014; Cadot et al., 2013).

The idea is that the presence of exporters nearby exporting to the same destination can lower fixed costs of exporting to a particular country if, in the presence of imperfect information, neighboring exporters facilitate knowledge transfer and cost-sharing. Knowledge transfer and cost-sharing may include destination-specific dimensions, like sharing information on business norms and culture, setting up foreign exchange accounts or service centers abroad, retaining customs agents, and sharing monetary and transaction costs related to these activities.

Moreover, learning and cost-sharing may pertain to aspects specific to trade partners (importing and exporting firms). Neighbors might lower search costs and costs of identifying a trade partner by making a buyer or seller more 'visible' to the partner. In addition, sellers may learn of any needs of the buyer that require customization, such as the buyer's product specifications, custom packaging requirements, and its clienteles' tastes and preferences. On the importer end, buyers may learn about a seller's strengths, capacity and reputation when they are located in close proximity to existing suppliers. They might find it easier to verify product quality by organizing visits to the factory, or learn about 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.

In our analysis, since we examine the role of neighboring exporters in increasing the likelihood of matching with a particular importer, conditional on the exporter already exporting to the destination country (the U.S.), and the importer already importing from the source country (Bangladesh), we are able to isolate gains 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. By ascertaining if information gains specific to a trade partner at the firm level, and not just at the country level, are significant, we take a step further in the direction of isolating the nature of export spillovers and the channels through which they operate.

In the framework we employ in this study, we note that either the importer or the exporter (either directly or through a buying house) might initiate the buyer–seller match.[2] 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.

Finally, our paper also relates to the work on networks and international trade, which highlights the important role that immigrant networks (Rauch, 1996, 1999, 2001; Aleksysnka and Peri, 2014), social and business networks (Combes et al., 2005) and exporter networks (Chaney, 2014) play in generating trade.[3] Our measure of neighboring exporters can be seen to represent a particular type of trading network — firms that are in the same geographic location that sold to the same buyer in the previous period.

We also provide evidence on the nature of gains from neighbors, which we call neighbor effects. We find that neighbor effects are stronger when the exporter is large relative to when the exporter is small. This suggests that larger exporters potentially have the capacity to translate gains from neighbors into actual matches. We also present evidence that effects are weaker in cities with more competitive environments, and tend to weaken as the number of neighbors increases, consistent with the idea that potential information gains dissipate with more neighbors.

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

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[1] We focus on first-time matches because the literature documents the dominance of costs involved in locating trade partners and establishing a relationship, relative to recurrent costs incurred to maintain a trade relationship (Eaton et al., 2014).

[2] 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 neighbor effects 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.

[3] These studies focus on aggregate trade patterns and do not empirically analyze trade relationships at the level of individual buyers and sellers.

2. Conceptual framework and empirical strategy

2.1. Model

In order to motivate our empirical strategy, we adapt the framework proposed by Bernard et al. (2014a) to model buyer–seller matches in international trade. The basic set up is as follows.[4] Each economy has three sectors of production, a homogenous good sector characterized by perfect competition, and an intermediate and a final good sector, both characterized by monopolistic competition. Intermediates are traded, while the final good is non-traded. Each seller produces a variety of intermediates. Buyers assemble intermediate varieties into a final good. Each buyer produces one variety of the final good. Both sellers and buyers are heterogeneous in efficiency.

Workers are employed in the production of the homogenous good and intermediates, but not in the production of the final good. The homogenous good is freely traded and is produced using constant returns to scale, where one unit of labor produces ω_k units of the good, where k indexes country. The price of the homogenous good is normalized to one, so that the wage rate in the economy is given by ω_k. The production function of the final good is CES over intermediate varieties, with elasticity of substitution equal to $\sigma > 1$.

Consumers consume the homogenous good and a continuum of differentiated final goods. Upper level utility is Cobb–Douglas, with μ being the expenditure share on the differentiated final good. Utility from the differentiated final good is CES with the elasticity of substitution between varieties also given by σ. Intermediate goods incur a variable trade cost of $\tau_{ij} > 1$ to be shipped from country i to country j such that τ_{ij} of the good has to be shipped for one unit to arrive at the destination.

To highlight the role of neighbors in facilitating matches between individual exporters and importers, buyers and sellers in this model incur a relationship-specific fixed cost of matching, which is borne by the seller and expressed in labor units. We allow fixed costs to vary across buyer–seller (importer–exporter) pairs motivated by existing evidence. Eaton et al. (2014), using U.S.–Colombian trade transactions data, estimate that the initial search cost of locating one buyer per year is about $51,471. The cost drops to $2,855 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. The fixed cost is given by

$$f_{mx}^{ij} = f\left(n_{mx}^{ij}\right). \tag{2.1}$$

Here, f_{mx}^{ij} is the fixed cost of matching between buyer m (importer) located in country j and seller x (exporter) located in country i.[5] n_{mx}^{ij} is the total number of sellers in country i in the neighborhood of x selling to buyer m in country j. We assume that $f'\left(n_{mx}^{ij}\right) < 0$. In words, fixed costs are lower when the number of neighbors exporting to the same importer in the foreign country is larger. $f(n_{mx}^{ij})$ refers to fixed costs that are partner-specific, or, specific to pair mx, and depend on the number of sellers near x that sell to buyer m. These fixed costs might include search costs or costs of learning about the buyer's customization requirements, tastes of buyer m's clientele, seller x's strengths, capacity, reputation and reliability.

The key idea explored in our paper 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 as well as by directly visiting suppliers' factories to assess their capabilities. We argue that this is likely easier if the potential exporter is in the neighborhood of an exporter they already transact with.

Cadot et al. (2011) and Eaton et al. (2014) 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, features in the top three ways in which first time exporters find buyers. Eaton et al. (2014) 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 is likely less costly if firms are able to learn through their business networks, in our context, from neighboring exporters.

Given that sellers charge a constant mark-up over marginal cost, the seller's profit from a mx match is given by,

$$\pi_{x,mx}^{ij} = \left[\frac{p_x^{ij}}{q_m^j}\right]^{(1-\sigma)} Y_j - f_{mx}^{ij}$$
$$= \theta_x^{\sigma-1}\left(\gamma \tau^{ij} w_i\right)^{(1-\sigma)}\left(q_m^j\right)^{(\sigma-1)} - f_{mx}^{ij}. \tag{2.2}$$

Here, p_x^{ij} is seller x's price for its intermediate variety, q_m^j is the price index for intermediates of buyer m in country j, Y_j is income in destination country j, θ_x is efficiency of seller x and γ is the constant mark-up over marginal cost, given by $\frac{\sigma}{\sigma-1}$. The price index for intermediates of buyer m in country j is given by,

$$q_m^j = \left(\sum_i \sum_{x=1}^{n_m^{ij}} p_x^{ij(1-\sigma)}\right)^{\frac{1}{1-\sigma}}. \tag{2.3}$$

Given that the buyer also charges a constant mark-up over marginal cost, her profit is given by:

$$\pi_m^j = \left[\frac{P_m^j}{Q^j}\right]^{(1-\sigma)} \mu Y_j$$
$$= \varphi_m^{\sigma-1}\left(\gamma q_m^l\right)^{(\sigma-1)}\left(Q^j\right)^{(\sigma-1)} \mu Y_j, \tag{2.4}$$

where P_m^j is the price for buyer m's final good variety, Q^j is the price index for the final good in country j and φ_m is buyer efficiency. We define,

$$f_{mx}^{ij} = \alpha + b\left(n_{mx}^{ij}\right) + \varepsilon_{mx}^{ij} \tag{2.5}$$

where ε_{mx}^{ij} is an idiosyncratic error term, a is a constant and $b' < 0$. In equilibrium, since $\pi_m^j = 0$, q_m^j from Eq. (2.4) can be written as a function of $q_m^j(\varphi_m, \gamma, Q^j, \mu, Y_j)$. Substituting the expression for the fixed cost into the seller's profit function (2.2), the probability of a mx

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[4] For the sake of simplicity, we ignore time subscripts in our conceptual framework, which is static. In our empirical analysis, we exploit variation in matches and neighborhood exporter presence over time to identify the effect of neighbors on buyer–seller matches.

[5] Krautheim (2012) models the cost for a firm of exporting to a destination country similarly in his analysis of exporter networks and the effect of distance in international trade. Note, however, that his formulation of the fixed costs of exporting is destination-country specific, and not specific to an importer–exporter pair.

match $P(Y_{mx} = 1)$, conditional on exporter x exporting to country j, is given by the probability that $\pi_{x,mx}^{ij} \geq 0$, or the probability that

$$0 \leq \theta_x^{\sigma-1} \left(\gamma \tau^{ij} w_i\right)^{(1-\sigma)} \left(q_m^j\left(\varphi_m, \gamma, Q^j, \mu, Y_j\right)\right)^{(\sigma-1)} - \left(a + b\left(n_{mx}^{ij}\right) + \varepsilon_{mx}^{ij}\right). \tag{2.6}$$

After rearranging terms we have,

$$P(Y_{mx} = 1) = F\left(\theta_x, \sigma, \gamma, \tau^{ij} w_i, \varphi_m, Q^j, \mu, Y_j, n_{mx}^{ij}, \varepsilon_{mx}^{ij}\right) \tag{2.7}$$

While γ, σ, and μ are constants, the terms Q^j, Y_j, τ^{ij}, w_i vary either by exporting or importing country (i or j, respectively) or by the exporting country-importing country pair, ij. Since we study a particular bilateral relationship in our empirical analysis, these terms are captured by a constant term. We capture θ_x, φ_m by importer and exporter (buyer and seller) fixed effects, respectively, and n_{mx}^{ij}, the key variable of interest, by the number of exporters exporting to buyer (importer) m in exporter x's neighborhood. Hence, n_{mx}^{ij} represents the size of the network of neighbors.

The innovation in our study is that our empirical framework allows us to tease out the impact of n_{mx}^{ij} on the likelihood of the mx match, via its effect on f_{mx}^{ij}. Previous studies have focused on the impact of neighboring exporters on the likelihood that seller x exports to country j (in other words, the likelihood that seller x sells to any or several buyers in country j). Here, the idea is that an additional neighbor lowers the fixed cost of exporting to j, which, in our formulation, would be given by $f_x^j + \sum_{m=1}^{M_x} f_{mx}^{ij}$, where f_x^j is a destination (country) specific fixed cost of exporting and M_x is the total number of buyers in country j that seller x exports to. The destination-specific fixed cost of exporting, f_x^j, might include learning about business norms, culture, customs procedures, hiring and retaining shipping agents, establishing and maintaining foreign service offices or foreign-exchange accounts. Also, $f_x^j = f_x(N_x^{ij})$, $f'_x(N_x^{ij}) < 0$, where N_x^{ij} is the number of exporters neighboring x selling to country j.

Note that this design cannot establish if an additional neighbor facilitates exporting by lowering $f_x(N_x^{ij})$, or the relevant component of $f(n_{mx}^{ij})$, or both. For instance, consider an exporter x who would earn positive profits from matches $m_1 x, m_2 x$ and $m_3 x$, where m_1, m_2 and m_3 are importers in country j. This exporter will export to destination j if profits from these matches are at least equal to the destination-specific fixed cost of exporting, f_x^j. Assume that exporter x cannot cover the destination-specific fixed cost of exporting with these profits. If an additional neighbor, exporting to importer m_1, were to lower the partner-specific fixed cost of matching $f_{m_1 x}^{ij}$, the resultant increase in potential profits from a $m_1 x$ match (as denoted in Eq. (2.2)) might enable exporter x to cover f_x^j, and hence start exporting to country j. In this scenario, the neighbor effect operates by lowering the partner-specific fixed cost of matching. Alternatively, this neighbor might lower f_x^j, allowing x to start exporting to country j, in which case, the neighbor effect operates by lowering the destination-specific fixed cost of matching.

In our empirical framework, we study matches between sellers in country i and buyers in country j, conditional on the seller exporting to j, and indeed, the buyer importing from i. Given that the destination-specific fixed cost of exporting f_x^j, has already been incurred, the neighbor effect we observe works by lowering the partner-specific fixed cost of matching, f_{mx}^{ij}, increasing the likelihood that x sells to m. Hence, our framework allows us to establish the relevance of the partner-specific component of the neighbor effect, and shed further light on the channels via which network effects in international trade operate.

2.2. Pair-level estimation

We estimate Eq. (2.7) with a linear probability model as follows,

$$P(Y_{mxt} = 1) = \alpha + \beta_1 z_{cm,t-1} + \delta_{mx} + \theta_{mt} + \gamma_{xt} + \varepsilon_{mxt}. \tag{2.8}$$

First, we construct a set of all possible importer–exporter matches from the universe of all U.S. importers and Bangladeshi exporters in textiles in our sample period, 2003 through 2009. Next, in each year, we include only those importers (exporters) that are involved in a trade transaction with Bangladesh (the U.S.). Hence, if an exporter does not transact with any U.S. buyer in a given year, the exporter is excluded from the sample for that year. Similarly, if an importer does not transact with any Bangladeshi seller in a given year, the importer is excluded from the sample for that year. Restricting our analysis sample in this manner allows us to consider the probability of an importer–exporter match conditional on the importer (exporter) having traded with the source (destination) country. As discussed in Section 2.1, this set up enables us to isolate the effect of neighbors on facilitating matches by lowering partner-specific fixed costs of matching.

Y_{mxt} is a categorical variable that takes on a value of 1 the first time we observe a trade transaction between an importer m and exporter x in a given year t between 2003 and 2009. For the year 2003, we categorize a match as a first-time match if the match did not happen in 2002. 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. For all years prior to the first match, Y_{mxt} takes on a value of 0. For instance, if we observe trade transactions between ABC Garments Company in Bangladesh and XYZ Corporation in the U.S. from 2004 through 2007, Y_{mxt} takes on the value 0 in 2003 and 1 in 2004, after which any transactions between ABC and XYZ are dropped from the sample. Note that if the importer–exporter pair did not match at all in our sample period, Y_{mxt} takes on a value of zero for all years for the pair.

The variable $z_{cm,t-1}$ captures neighbor effects from the presence of exporters to the same buyer m in exporter x's area c in the previous period and will be referred to as "Neighbors $(t-1)$" in the tables. We posit that neighbor effects operate primarily by lowering the fixed costs of matching between an importer and an exporter, after accounting for time-invariant unobserved heterogeneity specific to each matched pair and annual shocks specific to each importer and exporter individually. Competition and congestion effects could potentially weaken any positive effects, therefore, we expect β_1 to be strictly positive as long as the positive effects of neighbors dominate.[6]

The importer–exporter (pair) fixed effect, δ_{mx}, captures unobserved time-invariant shocks specific to the importer–exporter pair, like partner-specific comparative advantage, that might affect the likelihood of a first match. The importer-year (θ_{mt}) and exporter-year (γ_{xt}) fixed effects control for time-varying shocks specific to each importer and exporter, respectively. These include importer and exporter specific heterogeneity and technology or productivity shocks that are firm-specific. Additionally, given that each exporter is associated with a unique city that does not change over the time period of this analysis, the exporter-year fixed effects also account for city-specific shocks associated with neighborhood exporter presence in the previous period that might result in greater likelihood of matching. This includes unobserved technology or infrastructure quality shocks at the city level, or shocks to product-specific expertise such as the supply of skilled labor that results in specialization in particular products at the city level. Thus, we associate changes in the size of a firm's network of neighbors exporting to each U.S. importer over time to the match between the firm and the U.S. importer, thereby exploiting within-pair variation over time to identify our neighbor effect. Finally, ε_{mxt} is an idiosyncratic error term.

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[6] We note here that it is beyond the scope of the paper to disentangle the two countervailing forces as in Bloom et al. (2013), for example.

3. Data

3.1. Source

The data for this study are drawn from the Longitudinal Firm 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.[7] The dataset contains detailed information on trade transactions of a ten-digit Harmonized Commodity Description and Coding system (commonly called Harmonized System or HS) product including the value, quantity, date of transaction, and information about the trading parties.

We focus solely on U.S. import transactions (LFTTD-IMP) that occurred between 2003 and 2009.[8] Moreover, we only consider all import transactions of textile products from Bangladesh. Textile products include both textile or apparel products as defined under Section 102.21, Title 19, Code of Federal Regulations (CFR),[9] classified as any product in two-digit HS codes 50 through 63.[10] Over our sample period, textile products on average account for 94% of total import value from Bangladesh.[11] Moreover, product codes 61 (knitted apparel) and 62 (non-knitted apparel) account for 96% of all textile transactions by value.

We only consider U.S. textile imports to permit focus on goods-producing exporters and not other selling 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 supposed to identify the manufacturer and this requirement is especially stringent in case of textile products (see details below), and we exploit this useful feature of the data to circumvent this issue. 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.[12] Bangladesh is the fourth largest apparel exporter to the U.S.[13] 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). This allows us to capture a significant portion of economic activity of this U.S. trading partner. To a large extent, the scale of activity in the textile sector in Bangladesh also alleviates the concern that exporter presence in the neighborhood in sectors other than textiles might be an omitted variable in our estimation, biasing our estimates.

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 that U.S. importers must file with the U.S. Customs and Border Protection (CBP).[14] The MID identifies the manufacturer or

Table 1
Matches by year.

Year	All Matches	First Time Matches
2003	3327	1828
2004	3407	1780
2005	4012	2399
2006	4763	2987
2007	4785	2866
2008	5492	3220
2009	4924	2615
2003–2009	30,710	17,695

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. "First Time" refers to matches that occur for the first time in the relevant year since 2002. For the year 2003, "First Time Matches" refer to matches that occurred in 2003, but did not occur in 2002.

shipper of the merchandise by an alphanumeric code that is constructed using the name and address of the exporter following a pre-specified algorithm with a maximum length of 15 characters (see Table A1 in Appendix A for stylized examples).[15] For textile shipments, the MID represents the manufacturer only in accordance with Title 19 CFR.[16] 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.[17] 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.

Once the basic data checks are complete, we identify unique trading pairs using the importer and exporter firm identifiers for each year in the sample. There are 2115 and 7360 unique number of importers and exporters, respectively, over the sample period. These include Bangladeshi sellers that exported to some U.S. firm and U.S. buyers that imported from some Bangladeshi firm in any year between 2003 and 2009. Table 1 shows the number of pairs in each year with column (2) showing total number of matches and column (3) showing the number of first-time pairings. We see that there are a total of 17,695 first-time pairings over the sample period. Note that a first-time match refers to the first time an importer and an exporter transact after the year 2002.

The number of first-time matches rises steadily, with a slight drop in the final year, 2009. We can see that about half of all matches are first-time matches. Our final analysis dataset contains observations on all possible importer–exporter pairs constructed from the unique number of importers and exporters in each year. Pairs that matched (traded) in any year between 2003 and 2009 appear in our sample for every year from 2003 until the year the first match occurred. Pairs where no match occurred are in our data from 2003 until 2009. To reiterate, U.S. importers who did not import from any Bangladeshi exporter in a

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[7] See http://www.census.gov/ces/dataproducts/datasets/lfttd.html for more information.

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

[9] See http://www.gpo.gov/fdsys/pkg/CFR-2011-title19-vol1/pdf/CFR-2011-title19-vol1-sec102-21.pdf.

[10] See http://hts.usitc.gov/ for details on each HS chapter.

[11] The remaining 6% of import value is distributed among a variety of two-digit HS product codes.

[12] We employ high-dimension fixed effects to control for unobserved heterogeneity in our empirical analysis. Due to computational constraints, this empirical design requires us to 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.

[13] See http://www.bdembassyusa.org/uploads/U.S.%20-%20BD%20trade.pdf.

[14] See form http://forms.cbp.gov/pdf/cbp_form_7501.pdf. See Kamal, Krizan, and Monarch (2015) for a detailed analysis of the MID variable.

[15] 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.

[16] See http://www.gpo.gov/fdsys/pkg/CFR-2011-title19-vol1/pdf/CFR-2011-title19-vol1-sec102-23.pdf.

[17] 19 U.S.C. §1401a(g) outlines seven different ways in which parties may be related in a U.S. import transaction. The ownership-based definition states firms are related if either owns, controls, or holds voting power equivalent to 5% of the outstanding voting stock or shares of the other organization.

Table 2
Summary statistics.

Variable	All importers		Small importers		Large importers	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Number of exporters/importer	11.90	32.39	8.17	13.29	24.94	62.32
Number of importers/exporter	1.62	1.37	1.72	1.55	1.51	1.15
Number of exporters/city	22.62	159.37	–	–	–	–
Number of importers/city	11.28	53.43	12.42	50.83	5.37	16.27
Number of cities/importer	3.11	3.61	2.60	1.90	4.88	6.47

Notes: Neighbors $(t-1)$ measures the number of exporters in city c selling to importer m at time $t-1$. 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.

given year as well as Bangladeshi exporters who did not export to any U.S. importer in a given year are excluded for that year from the analysis sample.

Traders in our sample might be first-time importers or exporters when we first observe them, or might have traded before 2002. In a robustness check, we perform our analysis after retaining solely those exporters who enter the universe of Bangladeshi textile exporters to the U.S. in or after 2002, to ensure that any first-time match we see represents a true first-time match, and not a previous match with a gap in the year 2002. We find that our results are robust to restricting our sample in this manner.

In a subsequent analysis, we explore heterogeneity in neighbor effects by importer size. We obtain information on an importer's basic firm characteristics from the Longitudinal Business Database (LBD) that consists of data on all private, non-farm U.S. establishments in existence that have at least one paid employee (Jarmin and Miranda, 2002). We link over 95% of the importers in our sample to the LBD to obtain information on firm employment, age including year of birth, and industry. For firms with multiple plants, age is calculated as the difference between the year of interest and the year of establishment of its oldest plant and the firm is considered to be operating in the sector where the largest share of its employment is housed.

The geographic area that we consider as a neighborhood to define our neighbor variable is the city reported in the Manufacturer ID. The last three characters of the MID designate 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 1009 sub-districts (*upazila*).[18] The city information extracted from the MID approximately conforms to sub-districts (see Appendix A for further details). 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 mile², roughly the size of the state of Iowa, and therefore, the average area of a sub-district is about 56 mile².[19] However, it is a denser country, with the density of population at 1149 people per square kilometer of land area, relative to 34 for the United States in 2009.[20]

3.3. Descriptive statistics

Table 2 presents the 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. "Small" ("large") importers are those that employ an average of 1–249 (250 or more) employees over the sample period. 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 twelve Bangladeshi exporters. There is heterogeneity across small and large importers. Large U.S. importers, on average, tend to transact with about twenty-five Bangladeshi exporters while small importers match with only about eight exporters. The average Bangladeshi textile exporter matches with under two U.S. importers and tends to match with a slightly higher number of small importers versus large importers.

This pattern persists at the city level. On average, there are about 22 exporters and 11 importers transacting in a city, with about two times the number of small importers transacting in a city compared to large importers. We see that an average importer sources from about three cities, which is much lower than the average number of exporters sourced from, hinting at spatial clustering in buyer–seller matches. A small U.S. importer sources from under three Bangladeshi cities while a large U.S. importer sources from about five Bangladeshi cities. Our main variable of interest, the number of exporters in a city selling to a particular U.S. importer, is about 0.96 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 about 0.68 in the sample of small importers and increases to 2.14 when the importer is large.

4. Results

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

Table 3 presents the results from our baseline regression described in Eq. (2.8). We investigate the impact of the presence of firms that previously matched with a U.S. importer in the neighborhood (city) of a Bangladeshi exporter on the probability of a first-time match between the exporter and the same importer. We successively add time-varying importer and exporter controls and fixed effects in each column from column (1) through column (4). Column (1) includes year fixed effects only. Column (2) additionally includes time-varying exporter controls of total export value and total number of HS-10 digit products exported and time-varying importer controls of age and employment, all of which enter in logs. We argue that total export sales and the number of products exported are strongly correlated with exporter productivity (Bernard et al., 2014b) and can account for exporter-specific time-varying shocks. Similarly, importer age and employment are highly correlated with firm productivity (Foster et al., 2001) and subsequently profitability (Helpman et al., 2004). Column (3) includes importer-year and exporter-year fixed effects and column (4) includes pair, importer-year and exporter-year fixed effects, forming our baseline specification. The columns show the coefficient on the 'Neighbors $(t-1)$' variable, which captures the presence of neighbors that previously transacted with the same buyer. In all our tables, we report t-statistics based on standard errors that are clustered at the importer-city level.

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[18] See list of geo codes provided by the Bangladesh Bureau of Statistics at http://www.bbs.gov.bd/WebTestApplication/userfiles/Image/geocodeweb.pdf.

[19] 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 mile². For a map of the sub-districts of Bangladesh see http://www.fao.org/fileadmin/templates/faobd/img/Administrative_Unit_Map.jpg.

[20] World Bank, http://data.worldbank.org/indicator/EN.POP.DNST, accessed June 16, 2014.

Table 3
First match status, 2003–2009, role of neighbors.

	(1)	(2)	(3)	(4)	(5)	(6)	
	OLS	OLS	OLS	OLS	IV 2SLS	Propensity score matching average treatment effect on the treated	
						Kernel	3 nearest neighbor
Neighbors (t − 1)	0.000268***	0.000266***	− 0.00007	0.000196***	0.000488***	0.000747***	0.000696***
	(12.37)	(9.31)	(1.35)	(9.89)	(1.94)	(16.80)	(18.56)
Year fixed effect	Y	Y	–	–	–	Y	Y
Importer controls	–	Y	–	–	–	Y	Y
Exporter controls	–	Y	–	–	–	Y	Y
Importer × year fixed effect	–	–	Y	Y	Y	–	–
Exporter × year fixed effect	–	–	Y	Y	Y	–	–
Importer × exporter fixed effect	–	–	–	Y	Y	–	–
Observations	13,750,000	10,800,000	13,750,000	13,750,000	13,750,000	13,750,000	10,800,000
Adjusted R-squared	0.001	0.002	0.008	0.78	–	–	–

Notes: T-statistics reported in parentheses based on standard errors clustered at the importer-city level. Significance level if p-value: *<0.10, **<0.05; ***<0.01. 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. Number of observations rounded for disclosure avoidance. In column 2, importer controls include age and employment and exporter controls include total export value and total number of HS-10 digit products exported, all in logs. Column 6 displays the average treatment effect on the treated, ATT, based on propensity score matching where scores are generated using year, importer and exporter controls.

Column (1) includes year fixed effects only and thus represents a correlation between the neighbor variable and first-match status after accounting for annual shocks. We find a positive and significant coefficient on the neighbor variable, suggesting a positive relationship between the presence of neighbors that matched with a US importer in the previous period and the likelihood of a first-time match with that US importer in the current period. The coefficient remains positive and significant and similar in magnitude when we control for time-varying observed importer and exporter characteristics in column (2).

In column (3), we control for unobserved importer-year and exporter-year shocks using importer-year and exporter-year fixed effects to account for time-varying unobserved firm heterogeneity that can drive matching and sorting between importers and exporters (Dragusanu, 2014). For instance, an importer may experience a productivity shock in a particular year, making the importer more likely to match with Bangladeshi firms in that year. The exporter-year fixed effects account for any city specific shocks that may be correlated with both the presence of neighbors in the previous period and the likelihood of matching with a US importer, including, for example, infrastructure or technology shocks in the city. We find that once we control for such heterogeneity, the coefficient on our neighbor variable is close to zero and statistically insignificant.

Note that the specification in column (3) does not control for match quality. In other words, it does not account for unobservable factors that drive propensities between importers and exporters to match. This may include factors like city specific comparative advantage on the part of the importer (employees who have connections to a particular city), or importer specific comparative advantage on the part of the exporter (suitability to an importer's customization requirements). In column (4), we additionally include a set of importer–exporter or pair fixed effects to control for match quality to the extent that it does not vary over time. Once we control for match quality using pair fixed effects and exploit variation in the presence of neighbors within importer–exporter pairs, we find that the coefficient on the neighbor variable is positive and statistically significant, suggesting that not accounting for match quality may lead us to under-estimate the contribution of neighbors.[21] The magnitude of the coefficient suggests that a 1% increase in the number of exporters in the city that previously matched with the same importer is associated with an increase in the likelihood of a first-time match between a Bangladeshi exporter and a U.S. importer of 0.15%.[22]

Our results are consistent with the idea that the presence of neighboring exporters selling to a particular foreign buyer increases the likelihood of a firm starting to sell to the same buyer, lending support to our hypothesis that neighbors can spur matching by reducing match specific costs. In the context of the literature on export spillovers, our results indicate that gains specific to the trade partner are also important, and neighbors can help lower the cost of matching with particular importers that they already transact with.

4.2. Instrumental variables and matching estimation

Though our preferred specification in column (4) of Table 3 controls for time-invariant importer–exporter (pair) shocks and time-varying importer and exporter heterogeneity, it remains susceptible to the concern that unobserved importer-city shocks may be correlated with both the presence of neighbors and matching between the importer and exporter. For instance, the U.S. importer might have a city-specific comparative advantage in the form of inherent knowledge of the city through an employee who hails from that particular city. This would not be observable in our data and may influence both the number of neighbors in the city exporting to the importer and matching between the importer and exporters in the city.

To address such concerns, we adopt two separate strategies. First, we employ an instrumental variables strategy. For each US importer in a given year, we first calculate the average real exchange rate against the US dollar for each country from which it imports textile products other than Bangladesh, weighted by its imports from that country in the year preceding our sample, 2002.[23,24] We use 2002 import shares rather than contemporaneous ones because current import shares are likely to be endogenous. We argue that the import-weighted exchange rates generate exogenous variation in the importer's propensity to match with Bangladeshi exporters because a depreciation of rival currencies in a given year is likely to encourage US importers to substitute

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[21] We hence use the specification in column (4) with importer-year, exporter-year and pair fixed effects as our preferred specification in all subsequent regressions.
[22] Elasticities are calculated using the "margins" command in STATA.

[23] We obtain the nominal exchange rate to the US dollar for each country along with price levels (Price level of CGDPo (PPP/XR), price level of USA GDPo in 2005 = 1) from the Penn World Tables v8.1 accessed at http://www.rug.nl/research/ggdc/data/pwt/pwt-8.1 on February 2016. We then calculate the real exchange rate as the nominal exchange rate multiplied by the US price level divided by the exporter's price level in that year.
[24] For US importers who do not import textile products from any country other than Bangladesh in a year, we calculate a weighted average of the real exchange rate against the US dollar for all countries. We also conduct a robustness check where we exclude such US importers from the sample and ensure that our results are unchanged qualitatively.

away from Bangladesh to other rival exporting countries of textiles.[25] Besides, exchange rate movements are largely driven by global macro-economic conditions that are exogenous to Bangladesh. This idea of constructing firm specific exchange rate instruments has been exploited in previous studies in the literature (Park et al., 2010; Bastos et al., 2014).

Next, we interact the importer specific exchange rate variable with a weather-related shock — monsoon floods in Bangladesh in the years 2004 and 2007. Particularly, we generate a dummy variable that equals one for cities that experienced devastating monsoon floods.[26] Mirza (2011) documents the loss to overall Bangladeshi GDP growth in the flood years. He notes that in the 2007 fiscal year when the floods hit, Bangladeshi GDP growth was 6.1% relative to 6.4% in the previous year. Dewan (2015) notes the particular damage caused by these floods to garment factories in the affected regions, primarily due to disruption in infrastructure provision. We argue that the floods provide exogenous variation at the city level in the number of neighbors that US importers matched with in the flood years because they are a negative shock to exporter activity in the affected regions.

Hence, our instrument is a combination of a US importer (and year) specific negative shock driven by global exchange rate movements and a Bangladeshi city (and year) specific weather-related negative shock to matches with Bangladeshi exporters in the previous period in the neighborhood of a firm. The instrument, which varies at the importer-city-year level, can be calculated for each importer–exporter pair mx where exporter x is located in city c as,

$$IV_{mc,t-1} = \left[\sum_{k=1}^{n_m} \left(\frac{imports_{mk,2002}}{imports_{m,2002}} * realexchange\ rate_{k,t-1} \right) flood_{c,t-1}, \right]$$

(2.9)

where m denotes importer, k country ranging from 1 through n_m, the number of countries importer m imports from, t time and c denotes a city in Bangladesh.

This instrument is arguably exogenous to unobserved factors determining match status with the US importer in the current period. Our first stage results confirm the negative correlation between the instrument and our neighbor variable. The first stage is highly significant and we find a strong negative correlation between our instrument and the neighbor variable with a t-statistic of 40 (coefficient −0.000072). We present instrumental variables 2SLS results in column (5) of Table 3. We find that the coefficient on the neighbor variable is positive and significant, supporting our finding from the OLS estimation. The co-efficient on the neighbor variable from the IV estimation is larger than the OLS estimate. This may be due to omitted variable bias in the OLS specification. Omitted variables that lead to increases in the number of neighboring exporters selling to a particular buyer in the previous peri-od but lowers the probability of exporting to a buyer would lead to a downward bias in the OLS coefficients.

Second, we employ a propensity score matching estimation strategy. We calculate propensity scores (probability of treatment) for each importer–exporter pair based on observable characteristics of the im-porter and exporter, where we define treatment as the presence of at least one neighbor exporting to this importer in the previous period. We use the two-digit NAICS classification of the importer, year, import-er age and size and the total value and number of products exported by the exporter as observable characteristics to calculate propensity scores. We then match treated pairs with control pairs who did not receive the treatment but have similar propensity scores to treated pairs.[27] This allows us to calculate the average treatment effect on the treated (ATT) as the difference in the means of the likelihood of matching between the treatment and control groups. We find that the neighbor effect is positive and statistically significant, shown in column (6) of Table 3. The ATT is about 0.0007 using either kernel or nearest neighbor matching methods, indicating that our results hold up qualitatively from the propensity score matching procedure. Overall, our results sug-gest a robust relationship between the presence of neighbors exporting to a particular importer in the previous period and the likelihood of matching with this importer in the current period.

4.3. Isolating information and cost-sharing gains

The key idea we explore in this paper is that the presence of neigh-boring exporters selling to a particular importer increases the likelihood of a firm matching with that same importer by lowering the fixed costs of matching. We argue that fixed costs are lower because firms learn from their neighbors, and share costs with them in myriad ways. We cannot directly measure learning and cost-sharing and we hence look for evidence for this in two different ways. First, we explore alternate scenarios that might yield an association between exporter presence in the previous period and the likelihood of a first-time match, and show that these scenarios are unlikely. Second, we examine the argu-ment that if gains are due to learning, we can expect these gains to dis-sipate as the number of neighbors increases. This is because the extra information obtained from an additional neighbor over the previous one is likely to be lower as the number of neighbors rises. Our results show that this is indeed true. Taken together, our results are consistent with information and cost-sharing gains.

To begin, we ask if the neighbor effects we observe arise from the large U.S. importers who, when unable to complete their entire order with one Bangladeshi exporter, reach out to other Bangladeshi ex-porters in the neighborhood in the next period to do so. We note here that even if this were the case, there is no reason, a priori, to expect that the U.S. importer will seek exporters in the same city to fulfill its order. Nevertheless, under this scenario, neighbor effects would arise mainly from having small exporters in the neighborhood. We would not expect to see significant effects when exporters in the neighborhood are large, and are capable of completing orders from large U.S. importers themselves. In addition, we would not anticipate significant neighbor effects when the U.S. importer is small. A natural way to explore this idea is to decompose our key neighbor variable into two distinct mea-sures — one constructed using small exporters alone and the other con-structed using larger exporters alone.

Table 4, Panel A presents the results for our main specification, with the neighbor variable of interest decomposed into "small" and "large" neighboring exporters in rows (2) and (3) respectively. Exporters are first classified into three quantiles using their average value of total ex-port sales over the sample period. The top quantile is classified as "large" and the rest as "small". Row (2) presents coefficients for the neighbor

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[25] We conduct one additional robustness check of our IV 2SLS results. It is possible that Bangladeshi textile exports are not close substitutes for exports from advanced countries. In other words, a US importer might import completely different products from Bangladesh compared to Italy, for example. This means that a weighted average exchange rate that includes advanced economies might not be ideal to capture the availability of substitutes to Bangladeshi exports. To account for this, we restrict trading partners to middle- and low-income countries using the World Bank country classification in 2009. Our results hold up to this alternate version of the instrument.

[26] See flood maps and details at http://www1.american.edu/ted/ice/Bangladesh.html, http://coolgeography.co.uk/A-level/AQA/Year%2012/Rivers_Floods/Flooding/Bangladesh/Bangladesh.htm, http://reliefweb.int/report/bangladesh/bangladesh-monsoon-floods-2004-post-flood-needs-assessment-summary-report for regions most affected by the 2007 and 2004 floods respectively. Dhaka and Comilla were the worst affected during the 2004 floods. We effectively consider the entire country as affected in 2007 due to the severity of the floods in the Dhaka region and mudslides that affected the Chittagong region, disrupting road infrastructure near Chittagong port, Bangladesh's predominant port.

[27] We explore both the nearest neighbor and kernel matching techniques to assign treat-ment and control pairs. We impose the common support condition in both cases and em-ploy caliper matching to implement the 'three nearest neighbor' in order to reduce risk of bad matches if the closest neighbor is far away (Caliendo and Kopeinig, 2008). We have experimented with one and five nearest neighbor matching and results remain qualita-tively similar. Tests for balance between treatment and control pairs show very low per-centage bias (between 2 and 3%), indicating that pairs are well balanced (in other words, similar) between treatment and control groups.

Table 4
First match status, 2003–2009, ruling out alternative explanations.

Panel A: neighbor effects by size				
	All importers	Small importers	Large importers	Large importers
	(1)	(2)	(3)	(4)
Neighbors (t − 1)	–	–	–	0.000197***
				(7.34)
Neighbors (t − 1)				
Small exporters	0.000047	−0.00004	0.000069	–
	(0.67)	(0.93)	(0.83)	
Large exporters	0.000261***	0.000255***	0.000265***	–
	(10.90)	(8.36)	(7.48)	
Importer × year fixed effect	Y	Y	Y	Y
Exporter × year fixed effect	Y	Y	Y	Y
Importer × exporter fixed effect	Y	Y	Y	Y
Observations	13,750,000	11,000,000	2,600,000	2,600,000
Adjusted R-squared	0.78	0.80	0.75	0.75

Panel B: neighbor effects, product heterogeneity and the MFA			
	Exclude complex products	Multi-product cities	Sample period 2007–2009
	(1)	(2)	(3)
Neighbors (t − 1)	0.000217***	0.000195***	0.000086***
	(12.30)	(9.30)	(4.14)
Importer × year fixed effect	Y	Y	Y
Exporter × year fixed effect	Y	Y	Y
Importer × exporter fixed effect	Y	Y	Y
Observations	9,680,000	12,800,000	7,600,000
Adjusted R-squared	0.76	0.77	0.86

Notes: T-statistics reported in parentheses based on standard errors clustered at the importer-city level. Significance level if p-value: *<0.10, **<0.05; ***<0.01. 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. Number of observations rounded for disclosure avoidance. In Panel A, 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. Exporters are first classified into three quantiles using average value of total export sales over the sample period. The top quantile is classified as "Large" and the rest as "Small". Panel B, column (1) excludes exporters exclusively exporting products in the top quantile of the Product Complexity Index (Hausmann et al., 2011) after products are divided into three quantiles. Column (2) only considers observations for cities above the 25th percentile of the distribution of the number of six-digit HS products produced in a city in a given year. Column (3) only considers observations between 2007 and 2009.

variable defined as the number of small exporters in the city exporting to the same importer *m*, and row (3) presents coefficients for the neighbor variable defined as the number of large exporters in the city exporting to the same importer *m*. Columns break the sample into "small" and "large" importers.[28] Column (2) presents results for the sample of small importers and column (3) for the sample of large importers. "Small" ("large") importers are those that employ an average of 1–249 (250 or more) employees over the sample period. Column (1) presents results for the full sample.

We see from column (3) that neighbor effects exist, and are statistically significant when exporters in the neighborhood are large. In fact, we do not see significant effects when exporters in the neighborhood are small. Neighbor effects appear to emanate from relatively large neighbors. Additionally, from column (2), we see that neighbor effects exist even when the U.S. importer is small and the Bangladeshi exporter is large and is more likely to have its entire order fulfilled by the exporter. This reassures us that our results are not solely driven by lack of exporter capability to fulfill large orders.

In addition, the results in Table 4, Panel A help us rule out one other scenario. Consider the case where a large U.S. importer first matches with a Bangladeshi exporter, who then becomes a specialized supplier. This exporter then develops expertise in products customized for this large U.S. importer, generating a barrier to entry for other potential exporters hoping to supply to the U.S. importer. In this case, our results would be an under-estimate, since this scenario would generate a negative relationship between exporter presence (specifically, large exporter presence) in the neighborhood and the likelihood of a first-time

match with a large U.S. importer. However, from Table 4, we observe a positive and significant coefficient in row (3), column (3), suggesting that the presence of large exporters in the neighborhood exporting to a large U.S. importer is associated with greater likelihood of a first-time match with this large importer. Thus, we deem this scenario unlikely as well.

Next, it is possible that U.S. importers gradually expand their presence in the Bangladeshi market, as they test a few relationships with exporters in the initial period, and then recruit an increasing number of exporters in subsequent periods. This type of gradual expansion strategy into a foreign market could induce a positive association between exporter presence in one period, and the likelihood of a match in the next period. However, note that our results show that a U.S. importer is more likely to match with an exporter if there is a greater presence of exporters that it matched with in the previous period, in the city that this exporter is located in.

If our results purely reflected U.S. importers' expansion strategy, we would not anticipate this propensity by importers to match in the neighborhood of previous partners. This is especially true for large U.S. importers, who typically operate in more than one Bangladeshi city, and can select exporters from other cities. In column (4), we restrict our estimation sample to large U.S. importers only. We find a positive coefficient on the key neighbor variable which is statistically significant and similar in magnitude to our baseline effect, indicating that even large importers, who can potentially match with exporters in any Bangladeshi city, display greater likelihood of matching with an exporter in the same neighborhood of other exporters they have previously transacted with.

In Panel B, we address a different set of concerns. In column (1), we exclude exporters who exclusively export complex products in our sample period. Complex products are products that fall in the top third

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[28] We note here that observations in columns (2) and (3) do not add up to observations in column (1) due to the imperfect match between LFTTD-IMP and the LBD that provides importer size information.

quantile of the product complexity index calculated by Hausmann et al. (2011) and broadly categorize products as complex if not many countries produce them.[29] Our argument is that such products are more likely to be unique and specialized and U.S. importers importing such products might have little or no option to export them from any other exporter. The association we observe between neighbors matching in the previous period and the importer–exporter pair matching in the current period might simply reflect such a specialized relationship. However, our results in column (1) for exporters of less complex products are qualitatively similar to our baseline.

In column (2), we test whether the impact of a larger number of neighbors that previously matched with the same U.S. importer remains significant when we only consider cities where multiple products are produced. We compute the number of six-digit HS products exported from each city for every year in the sample. Over our sample period, the 25th percentile corresponds to cities that export ten products. Presumably, cities in the 25th percentile and below are more specialized. Thus, we restrict our sample to cities that are above the 25th percentile of the distribution of the total number of six-digit HS products exported from a city in a given year. We find results quantitatively and qualitatively similar to results from our preferred specification in column (4), Table 3.

Finally, we note that the final phase of the removal of textile and apparel quotas under the Multifiber Arrangement (MFA) overlaps with the beginning of our sample period. The MFA phase-down began in 1997 and all quotas were removed in the beginning of 2005. It is possible that the final removal of the MFA quotas in 2005 caused a surge in new matches between U.S. importers and Bangladeshi exporters transacting in previously quota-restricted products and resulted in an increasing number of new matches in subsequent years. This might induce a positive correlation between matches to particular importers in the previous period and the likelihood of a first-time match in the current period, especially in the years immediately after the quota removal. To ensure that our results are not predominantly being driven by the MFA quota removal, we focus only on the 2007–2009 sample period well after the quota removals were in place and any MFA induced shocks had likely dissipated. In this reduced sample, we find that the results, presented in column (3) of Panel B, Table 4, remain robust. Together, these results lend further credence to the idea of information gains and cost-sharing through the network of neighbors.

We now explore the idea that neighbor effects dissipate as the size of the neighbor network becomes large. If indeed the gains from neighbors are related primarily to obtaining information on the trade partner, we expect the additional information gained from an extra neighbor to be lower as the number of neighbors increases. In column (1) of Table 5, the first four rows provide coefficients for interactions of the neighbor variable with dummies that indicate where the value of the variable falls in the distribution. The quantile dummies are created by dividing the neighbor variable into four quantiles using only the non-zero values of the variable.[30] Results indicate that the magnitude of the neighbor effect decreases as the neighbor variable takes higher values. Thus, we find that when the number of exporters in the neighborhood exporting to a U.S. buyer increases, effects weaken, consistent with gains from learning.

Column (2) employs an indicator variable capturing the presence of at least one neighbor in the neighborhood exporting to the importer in the previous period. We find that the magnitude of this coefficient is much larger than our baseline estimate. In column (3), we include both the indicator variable capturing the presence of at least one

neighbor and our neighbor variable, capturing the size of the neighbor network. This helps us tease out the effect of the presence of a neighbor from the effect of network size. We find that the coefficient on the indicator variable is much larger than that on the neighbor variable, though controlling for the presence of at least one neighbor, the size effect is still positive and significant.[31] Again, this is consistent with the idea of gains from neighbors operating via information sharing and learning. Finally, in column (4) we test whether the impact of neighbors that previously matched with the same U.S. importer remains significant when the sample is restricted to observations for which the number of neighboring exporters exporting to the same importer is greater than one, an exercise similar to Koenig et al. (2010). The purpose is to ensure that the observed 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. Our results confirm that the impact of neighbors remains positive and significant.

4.4. Robustness checks

In this section, we carry out robustness checks of our baseline results presented under column (4) in Table 3. Results are presented in Table 6. In column (1) of Panel A, we restrict the sample to exporters who begin exporting to the U.S. in 2002 and after. We first create a list of all Bangladeshi textile exporters between 1992 and 2009 since the LFTTD-IMP is available beginning in 1992. We then only keep the exporters who appear in the data for the first time in 2002 and after.[32] This is to address the concern that the first-time matches we observe in our data actually took place before 2002, with a gap between 2002 and the first year in which we observe them in our sample period. This would lead us to erroneously classify continuing relationships as a first-time match. Our main result remains qualitatively similar to results in column (4), Table 3 using this stricter definition of first-time matches.

Finally, we address the concern that a large share of exporters in our sample may be multi-plant exporters. In case of multi-plant exporters, 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 the ones typically associated with multi-unit status.[33] Second, we rerun our baseline regressions on a restricted sample of small exporters, 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 is disproportionately driving our results, we would expect neighbor effects to exist only for large exporters. Our results suggest otherwise. In column (2), we restrict our sample to small exporters. Small exporters are exporters in the bottom two quantiles of the distribution of average value of total export sales over the sample period. The coefficient is still positive and significant, though smaller in

[29] "The Atlas of Economic Complexity," Center for International Development at Harvard University, http://www.atlas.cid.harvard.edu accessed at http://atlas.media.mit.edu/en/rankings/hs02/?depth=6 on March 3, 2016.
[30] In our estimation, the neighbor variable, which captures the effect for the omitted category is dropped, since it consists solely of zero values.
[31] In fact, the coefficient on the indicator variable is almost two times the coefficient on the neighbor variable, which is similar in magnitude to our baseline coefficient in Table 3, column (4), suggesting that the baseline more closely reflects the effect of the neighbor variable at higher values.
[32] If any of these exporters had exported to the U.S. pre-1992 we would not be able to capture that information.
[33] Kim (1999) documents that the number of employees per manufacturing establishment of U.S. firms is 7 to 10 times larger for multi-unit compared to single-unit firms (Table 4).

Table 5
First match status, 2003–2009, consistency checks.

	(1)	(2)	(3)	(4)
Neighbors (t − 1)				
Quantile 1	0.000399***	–	–	–
	(6.96)			
Quantile 2	0.000307***	–	–	–
	(6.78)			
Quantile 3	0.000256***	–	–	–
	(8.90)			
Quantile 4	0.000197***	–	–	–
	(9.90)			
Indicator neighbors (t − 1) > 0	–	0.000883***	0.000429***	–
		(15.60)	(6.56)	
Neighbors (t − 1)	–	–	0.000185***	0.000196***
			(8.61)	(9.69)
Importer × year fixed effect	Y	Y	Y	Y
Exporter × year fixed effect	Y	Y	Y	Y
Importer × exporter fixed effect	Y	Y	Y	Y
Observations	13,750,000	13,750,000	13,750,000	13,400,000
Adjusted R-squared	0.78	0.78	0.78	0.77

Notes: T-statistics in parentheses based on standard errors are clustered at the importer-city level. Significance level if p-value: *<0.10, **<0.05; ***<0.01. 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. Number of observations rounded for disclosure avoidance. In column (1), the neighbor variable is interacted with five dummies. The omitted category is where the neighbor variable takes a value of zero. Non-zero values are then divided into four quantiles, each represented by a quantile indicator. In columns (2) and (3), Indicator Neighbors (t − 1) > 0, is a dummy variable that takes on a value of 1 if there is at least one neighbor and 0 otherwise. In column (4), we restrict the sample to observations for which the number of neighboring exporters exporting to the same importer is greater than one.

magnitude, suggesting that neighbor effects are smaller for small exporters. We explore this further in a subsequent section.

In Panel B of Table 5, we explore alternative measures of our neighbor variable. Columns (1) and (2) present measures of exporter presence in the neighborhood, normalized by the total number of exporters and importers in the city in the previous period, respectively. These measures establish the robustness of our qualitative result after accounting for the fact that exporter density might capture neighbor effects better than the number of exporters in the neighborhood. We find

that greater density of firms in the neighborhood exporting to a U.S. importer is associated with a higher likelihood of matching with the same importer, and that these effects are statistically significant. Column (3) explores an alternative lag structure to our baseline neighbor measure. We measure the number of exporters in city c selling to importer m at time $t − 2$. Results show that the neighbor effect is positive and significant, but smaller than our baseline effect. This points to evidence for time decay in the neighbor effect.

Table 6
First match status, 2003–2009, robustness checks.

Panel A: alternative samples

	First year > = 2002	Small exporters
	(3)	(4)
Neighbors (t − 1)	0.000213***	0.000092***
	(11.07)	(3.78)
Importer × year fixed effect	Y	Y
Exporter × year fixed effect	Y	Y
Importer × exporter fixed effect	Y	Y
Observations	9,190,000	5,800,000
Adjusted R-squared	0.82	0.93

Panel B: alternative spillover measures

	(1)	(2)	(3)
Neighbors/total exporters (t − 1)	0.314036***	–	–
	(7.47)		
Neighbors/total importers (t − 1)	–	0.457183***	–
		(9.89)	
Neighbors (t − 2)	–	–	0.000128***
			(5.54)
Importer × year fixed effect	Y	Y	Y
Exporter × year fixed effect	Y	Y	Y
Importer × exporter fixed effect	Y	Y	Y
Observations	13,750,000	13,750,000	13,750,000
Adjusted R-squared	0.78	0.78	0.78

Notes: T-statistics reported in parentheses based on standard errors clustered at the importer-city level. Significance level if p-value: *<0.10, **<0.05; ***<0.01. 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. Number of observations rounded for disclosure avoidance. In Panel A, the samples are restricted in column (1) to exporters who first appear in the LFTTD-IMP in 2002 and after between 1992 and 2009; and in column (2) to "small" exporters. Exporters are first classified into three quantiles using average value of total export sales over the sample period. The top quantile is classified as "large" and the rest as "small".

4.5. Extensions

Our goal thus far has been to establish that greater presence of exporters in the neighborhood that matched with a particular importer is associated with a greater probability of matching with the same importer. We argue that greater exporter presence in the neighborhood lowers the fixed costs of matching through information and cost-sharing gains. To this end, we demonstrate that alternate scenarios that might yield observationally equivalent empirical results are unlikely. We also ascertain that our results are robust to alternate measures of exporter presence. In this section, we explore the nature of neighbor effects further.

First, we ask if these effects differ for large and small importers and exporters, motivated by considerable heterogeneity in exporter and importer sizes observed in the data. The average annual value of a transaction between a trade pair in our sample is a little over half a million U.S. dollars. Roughly three-quarters of annual Bangladeshi textile export transactions are valued at less than $500,000. We expect that small Bangladeshi exporters might benefit from neighbors differently from large exporters. On the one hand, they might not have the resources to devote to activities that generate matches with foreign buyers and thus may rely more on neighbors to surmount the fixed costs of matching. Hence, neighbors might matter more for them. Alternatively, in order to assimilate and exploit information, exporters may need some minimum capacity. Small exporters may lack the requisite capabilities to translate any information they gain from neighbors into a match. This idea is akin to that prevalent in the literature on multinational firms and technology transfer to domestic firms, where only domestic firms with sufficient absorptive capacity can gain from spillovers (Blalock and Gertler, 2009). Alternatively, if the importer is primarily responsible for initiating and finalizing the match, it is possible that larger exporters in the neighborhood are more visible to both the

Table 7
First match status, 2003–2009, heterogeneous effects.

	(1)	(2)	(3)
Neighbors (t − 1)	0.000089***	0.000195***	0.000575***
	(2.20)	(8.12)	(12.08)
Large Exporter	0.000164***	–	–
	(3.75)		
Large Importer	–	0.000002	
		(0.07)	
(Exporters/Importers) (t − 1)	–	–	−0.000258***
			(7.98)
Importer × year fixed effect	Y	Y	Y
Exporter × year fixed effect	Y	Y	Y
Importer × exporter fixed effect	Y	Y	Y
Observations	13,750,000	13,750,000	13,750,000
Adjusted R-squared	0.78	0.78	0.78

Notes: T-statistics in parentheses based on standard errors are clustered at the importer-city level. Significance level if p-value: *<0.10, **<0.05; ***<0.01. 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. Number of observations rounded for disclosure avoidance. In columns (1) and (2), "Large Exporter" and "Large Importer" are indicator variables. 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. Exporters are first classified into three quantiles using average value of total export sales over the sample period. The top quantile is classified as "Large" and the rest as "Small". In column (3), the neighbor variable is interacted with a lagged measure of the total number of exporters per importer in the city.

importer and the exporters who matched with the importer in the previous period.

On the importer side, evidence suggests that there is substantial heterogeneity within U.S. trading firms in terms of size (Bernard et al., 2010). In our analysis sample, we find that the average export value and number of exporters per importer display variation 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 ask if neighbor effects differ across importer 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. Additionally, on the Bangladeshi side, exporters might find it more difficult to search and match with smaller U.S. buyers.

In column (1) of Table 7, we interact our key neighbor variable with a dummy that equals one when the exporter in the match is large. Similarly, in column (2), we interact our key neighbor variable with a dummy that equals one when the importer in the match is large. When included with the main neighbor variable, these interaction terms capture differential effects for large exporters and importers, respectively. Results in column (1) of Table 6 indicate that neighbor effects are much stronger for large exporters, consistent with the idea of absorptive capacity or greater visibility of larger exporters. We note here that these explanations are speculative, and firmly establishing them will require further work that is beyond the scope of this paper. From column (2), we see that the neighbor effect for larger importers is not statistically different than for small importers, suggesting little heterogeneity in neighbor effects by importer size

In column (3), we examine differential neighbor effects in cities where the number of total Bangladeshi exporters per U.S. importer in the previous period is large. The idea is to ask if neighbor effects differ by intensity of competition in the neighborhood. We interact the neighbor variable with the total number of Bangladeshi exporters per U.S. importer in a city in the previous period. Results show a negative and statistically significant coefficient on the interaction term, that neighbor effects are weaker in cities with more intense competition for importers. This suggests that exporters might guard information more carefully in more competitive environments.

In summary, our results suggest that a 1% increase in the number of textile exporters that previously matched with a U.S. importer in the Bangladeshi city that an exporter is located in is associated with a 0.15% increase in the likelihood of a match between that exporter and the same importer for the first time. We present evidence consistent with exporter presence in the neighborhood lowering partner-specific fixed costs of matching, and facilitating information and cost sharing. We also present evidence that these effects vary with exporter characteristics. We find that neighbor effects are weaker in more competitive environments and dissipate as exporter presence increases.

5. Conclusion

This paper finds a statistically positive and economically significant role for exporters in the neighborhood of a firm, that have previously matched with a particular importer, in improving the likelihood of that firm matching with the same importer for the first time. Our study contributes to nascent investigations in the international trade literature on matches between buyers and sellers and their determinants. We also build on the existing empirical body of evidence that documents network effects in trade and show that a network of neighboring exporters can help matching between buyers and sellers by potentially lowering the partner-specific fixed costs of matching.

Our results also establish the importance of isolating the partner-specific component of export spillovers and recognizing that gains may depend on exporter and importer characteristics. Earlier studies, such as Koenig et al. (2010), have underscored the role of neighbors in bringing about learning 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 that neighbors can help matching by disseminating information on individual buyers and sellers in the foreign country, their requirements, strengths and capabilities, thus spurring trade relationships. In light of initiatives aiming to improve access to information about exporting in destination markets, our findings suggest that information on individual buyers and sellers can also play a key role. 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.

Appendix A

Table A1
Examples of manufacturer id construction

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

Notes: This table provides examples of MID constructions based on fictitious exporter names and addresses and is for illustrative purposes only.

A.1. 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). We 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.[34] Close inspection of the three-letter city list indicates that cities conform roughly to sub-districts (*upazilas*), the third lowest level of

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[34] See http://www.bbs.gov.bd.

geographic administrative divisions. There are 282 cities in our analysis sample.

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 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 Manufacturers 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.[35] 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.[36] 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.[37]

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.

Additionally, among the three-letter city codes reported in the data, we find that one three-letter code represents about 45% of exporters in the sample, leading us to suspect that this particular code corresponds to a district. We thus re-estimate our baseline specification excluding observations corresponding to this code, so that our measure of neighboring exporters corresponds to comparable geographic areas. We find that our coefficient remains positive and significant. Results for both sets of robustness checks are available upon request.

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[36] See http://www.bgmea.com.bd/home/pages/AboutBGMEAT#.UnEBd6yAqSo.

[37] See http://siteresources.worldbank.org/INTPSD/Resources/336195-1092412588749/00–Bangladesh–1-78.pdf for detailed discussion.