Assortative Matching of Exporters and Importers

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This Version: December 2014

First Version: November 2013

Abstract: This paper examines the mechanism behind matching of exporting firms and importing firms. From transaction data of Mexican textile/apparel exports to the US, we report two new facts on exporter-importer matching at the product level. First, matching is approximately one-to-one. Second, in response to the entry of Chinese exporters into the US induced by the end of the Multi-Fiber Arrangement, US importers switch their Mexican partners to those with higher capability while Mexican exporters switch their US partners to those with lower capability. To explain these facts, we present a model combining Becker-type positive assortative matching of final producers and suppliers with the standard Melitz-type model. The model interprets the observed changes in matching as evidence for a previously undocumented source of gains from trade associated with firm heterogeneity.

Keywords: Firm heterogeneity, assortative matching, two-sided heterogeneity, trade liberalization

Acknowledgments: We thank Bernardo Blum, Kerem Cosar, Don Davis, Swati Dhingra, Daniel Halvarsson, Keith Head, Mathias Iwanowsky, Nina Pavcnik, Esteban Rossi-Hansberg, Peter Schott, Heiwai Tang, Catherine Thomas, Yuta Watabe, Shintaro Yamaguchi and seminar participants at Hitotsubashi Conference on International Trade and FDI, Yokohama National University, Kyoto University, Tohoku University, PEDL research workshop in London, Université catholique de Louvain, Stockholm University, RMET, NOITS, LACEA-TIGN Meeting, CEA, Econometric Society NASM, APTS, IEFS Japan Annual Meeting, Keio University, NEUDC, and LSE for their comments. We thank Secretaría de Economía of México and the Banco de México for help with the data. Financial supports from the Private Enterprise Development in Low-Income Countries (PEDL) and the Wallander Foundation are gratefully acknowledged. Francisco Carrera, Diego de la Fuente, Carlos Segura and Stephanie Zonszein provided excellent research assistance.

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1 Introduction

The last decade has witnessed a rise in research on heterogeneous firms and trade. A robust finding that only firms with high capability (productivity/quality) engage in exporting and importing has developed new theories emphasizing gains from trade associated with firm heterogeneity (Melitz, 2003; Bernard, Eaton, Jensen, and Kortum, 2003).[1] The key mechanism linking trade and industry performance in these theories is that trade liberalization improves the aggregate industrial performance by shifting resources to more capable firms within industries as empirical studies observe (e.g. Pavcnik, 2002). These "new new" trade theories have been applied for various issues and centered in the trade research of the last decade.[2]

In contrast to the level of our knowledge about which firms participate in trade, we know little about which exporters trade with which importers, i.e. matching of exporters and importers, in a product market. Do exporters and importers match based on their capability? Does trade liberalization change matching in any systematic way? Does matching matter for the aggregate industrial performance? This paper is one of the first attempts to answer these questions empirically.

Workhorse trade models consider types of international trade where considering matching of exporters and importers do not play an important role. Perfectly competitive models such as the Ricardian and Heckscher-Ohlin models do not predict any systematic matching pattern because in equilibrium exporters and importers are indifferent on whom they trade with.[3] The love of variety model also abstracts away from matching, predicting that all exporters trade with all importers.

Actual matching patterns are very different from what these workhorse trade models predict. The two graphs in Figure 1 show how Mexican exporters trade with US importers in two HS 6 digit textile/apparel product markets. Each small dot in the left side represents a Mexican exporter, while each small dot in the right side represents a US importer. Product A has typical numbers of exporters and importers among textile/apparel products that Mexico exports to the US, while Product B has somewhat larger numbers. Each line connecting an exporter and an importer represents a "match" where the exporter and the importer transact the product during June-December 2004. Both graphs clearly show that most firms trade with only one firm, that is, matching is approximately one-to-one. Though the graphs show some deviations from one-to-one matching, these deviations account for only a small share of the aggregate trade volume. In section 2, we show that the trade volume by "main-to-main" matches, defined as matches where the exporter and the importer are both the largest main partner of each other, accounts for approximately 80 percent of the aggregate Mexican textile/apparel exports to the US. This means that one-to-one matching of the main partners is a good approximation of trade relationships in a given

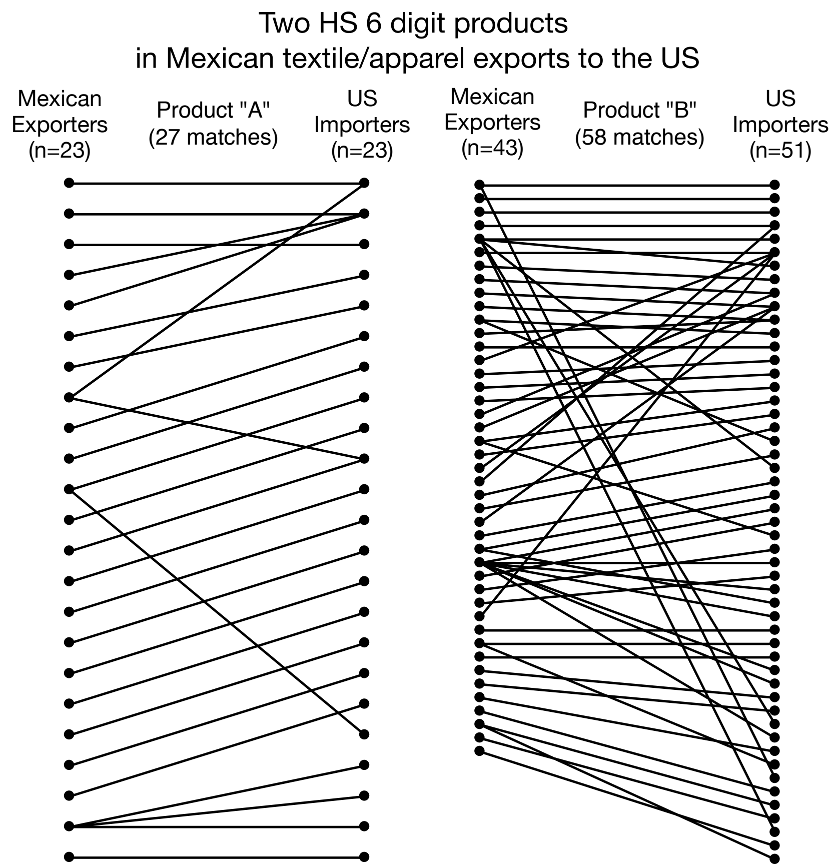
[1] See, for example, Bernard and Jensen (1995, 1999) for such findings that motivated the theories.

[2] See survey papers e.g. Bernard, Jensen, Redding, and Schott (2007; 2012) and Redding (2011) for more papers on the literature.

[3] Because of this prediction, perfectly competitive models are sometimes called "anonymous market" models.

product market. Thus, understanding firms' choice of main partner is crucial for understanding product-level trade.

Figure 1: Exporter-Importer Matching Graphs



Note: Small dots in the left side and the right side of lines represent Mexican exporters and US importers, respectively. Each solid line connecting an exporter and an importer indicates that they transact the product during June to December 2004.

To examine the mechanism behind how importers and exporters choose their main partners, we develop a model combining a canonical one-to-one matching model of Becker (1973) with a standard Melitz-type heterogeneous firm trade model. The model has final producers (importers) and suppliers (exporters) both of which are heterogeneous in capability. A final producer and a supplier form a team under prefect information. Since team-level capability depends on team members' capabilities, a resulting matching determines the distribution of team capability. Finally, teams compete in a monopolistically competitive market as firms do in Melitz-type models. In our benchmark case where member's capability exhibits complementarity within teams, stable matching becomes positive assortative by capability where high capable exporters match with high capable importers, while low capable exporters match with low capable importers.

We then analyze trade liberalization that allows more foreign suppliers to enter the final producer country. The model exhibits a new adjustment mechanism of industries to trade liberalization. The Becker-type matching model determines positive assortative matching as a market outcome that depends on the capability distributions of final producers and suppliers. Trade liberalization allows foreign suppliers to enter the market and changes the capability distribution of suppliers available for final producers in the market. Existing matching becomes unstable since some final producers switch to foreign suppliers. Then, existing firms systematically change partners so that the new matching becomes positive assortative under the new capability distribution. Final producers switch partners to ones with higher capability, while incumbent suppliers switch partners to ones with lower capability. This change in matching toward assortative matching leads to an efficient use of technology exhibiting complementarity and improves the aggregate industrial performance at the world level under normal circumstances. In short, the model identifies re-matching of buyers and suppliers as a new source of gains from trade liberalization associated with firm heterogeneity.

We test the implication of Becker-type positive assortative matching by investigating how matching of US importers and Mexican exporters responds to the entry of Chinese suppliers in the US, induced by the end of the Multi-Fiber Arrangement (MFA) in 2005. The end of the MFA in 2005 provides an ideal experiment because the US removed import quotas and saw the increase in Chinese exporters for some textile/apparel products but not for others. Using firm's pre-shock trade volume in 2004 as a proxy for capability, we find that in products for which the US had binding quotas on imports from China, US importers more frequently switched their Mexican main partners to ones with higher capability and Mexican suppliers more frequently switched their US main partners to ones with lower capability than in other textile products without binding quotas. We do not find systematic partner changes in other directions. These findings strongly support the Becker-type positive assortative matching. We also present a number of additional analysis to support the robustness of our results and to reject possible alternative explanations.

Our empirical results have implications for several strands of the theoretical trade literature. First, we provide the first evidence from transaction data for models of trade in intermediate goods formulating it as the Becker-type positive assortative matching (e.g. Antràs, Garicano and Rossi-Hansberg, 2006; Sugita 2014).[4] Second, our finding is related to a recent debate over the size of gains from trade associated with firm heterogeneity (e.g. Arkolakis, Costinot, and Rodriguez-Clare, 2012; Melitz and Redding, 2014a, 2014b). Though the current debate has focused mainly on gains from reallocation of production factors among firms (e.g Melitz, 2003; Bernard et al. 2003), our finding suggests another type of gains from

[4] Antràs et al. (2006) presents a model where heterogeneous workers match internationally, while Sugita (2014) presents a model where heterogeneous firms of Melitz-type match internationally. Our model is basically a partial equilibrium version of Sugita (2014). Sugita (2014) also shows that the positive assortative matching of exporters and importers explains stylized facts on exporters, importers, and unit prices in a unified framework.

trade associated with firm heterogeneity.[5] Third, our finding supports theories regarding international trade as non-anonymous transactions. Casella and Rauch (2002), Rauch and Casella (2003), and Rauch and Trindade (2003) analyze information frictions making matching of exporters and importers difficult. Our finding confirms that matching is an important problem for exporters and importers. While these models consider that firms match based on horizontally differentiated characteristics, we find that firms match based on vertically differentiated capability. Importers with high capability are "good importers" that all exporters prefer to trade, but only those with high capability can trade with them. This finding justifies policy discussions emphasizing the importance of encouraging domestic firms not only to start exporting, but also to export to high capable importers. The view that all importers are not equally valuable to exporters is also shared by a recent random network model of Chaney (2014).

Our paper is also related to the growing empirical literature studying matching of exporters and importers using customs transaction data. As pioneering studies, Blum, Claro, and Horstmann (2010, 2011) and Eaton, Eslava, Jinkins, Krizan, and Tybout (2012) document characteristics of exporter-importer matching in Chile-Colombia trade, Argentina-Chile trade, and Colombia-US trade, respectively. Bernard, Moxnes, and Ulltveit-Moe (2013) and Carballo, Ottaviano, and Volpe Martincus (2013) study exports from one country to multiple destinations in Norwegian customs data and in the customs data of Costa Rica, Ecuador, and Uruguay, respectively. These studies mainly define exporter-importer matching at the country pair level and document cross-sectional facts on the number of exporters for an importer and the number of importers for an exporter. We define matching more narrowly at the product level and identify a theoretical mechanism behind product-level matching by examining the response of matching to a trade liberalization shock. In section 2, we show that our finding is compatible with their findings by replicating some of their key findings under their definition of matching. Benguria (2014) and Dragusanu (2014) find positive correlations of firm-level variables (employment, revenue, etc.) of exporters and importers for France-Colombia trade and India-US trade, respectively. None of them relates observed correlations to the Becker-type positive assortative matching. In Section 4.4, we compare these correlation tests and our empirical test. Finally, regarding dynamic characteristics of matching, Eaton et al. (2012) and Machiavello (2010) are pioneering studies on how new exporters acquire or change buyers in Colombian exports to the US and in Chilean exports of wine to the UK, respectively. While these two studies consider steady state dynamics, we focus on how matching responds to a specific shock to a market. The above mentioned empirical studies propose different theoretical mechanisms to explain their findings, but none of them proposes the Becker-type positive assortative matching. Note that our treatment-control groups comparison can identify only the existence of the Becker-type mechanism and is silent about whether other mechanisms also exist or not.

The rest of the paper is organized as follows. Section 2 explains our data set and shows statistics

[5] Our mechanism is also different from Melitz and Redding (2014a) where the reallocation of production factors among firms occurs in each of multiple production stages.

indicating that exporter-importer matching at the product level is approximately one-to-one. Section 3 develops a model of matching of exporters and importers and derive predictions that will be confirmed in later sections. Section 4 explains our empirical strategies. Section 5 presents the main empirical results and additional results for checking the robustness of the main results. Section 6 concludes the paper.

2 Approximately One-to-One Matching

2.1 Matched Exporter-Importer Data

We constructed matched exporter-importer data for Mexican textile/apparel exports to the US from the administrative records on every transaction (shipment) crossing the Mexican border from June 2004 to December 2011. Appendix explains how we constructed the data set. The data set contains the following information for each pair of Mexican exporter and US importer that trade a HS 6 product in a year: (1) exporter-ID; (2) importer-ID; (3) the year of transaction; (4) the 6 digit HS product code (we use from HS50 to HS63); (5) the value of annual shipment (in US dollars); (6) the quantity and unit; (7) an indicator on whether their trade is processing re-export (Maquiladora/IMMEX) or not; and other information.

We dropped some information from the data set. First, we dropped exporters who are individuals or courier companies (e.g. FedEx, UPS, etc.) since our focus is on firm-to-firm matching. Second, we dropped products traded by either only one exporter or only one importer in 2004 since these products do not have any matching problem of US importers and Mexican exporters. Third, since the data set contains information only from June to December for 2004, we dropped observations from January to May for other years to make the information of each year comparable to each other. We conducted all empirical exercises in the paper without conducting the latter two operations and obtained similar results.

Finally, we dropped transactions by exporters that do not report importer information for most transactions. For a given HS6 product and a given year, we dropped an exporter from the data if the total value of transactions without importer information accounts for more than 20 percent of the exporter's annual export value. This results in dropping around 30-40 percent of exporters and around 60-70 percent of export values. Almost all of these dropped exporters engage in processing re-exports called Maquiladora/IMMEX exports. This is because Mexican customs do not mandate Maquiladora/IMMEX exporters to report the information of importers.[6] However, in practice and in our data, many Maquiladora/IMMEX

[6]The Maquiladoras program is a government export-promotion program and replaced by the IMMEX (Industria Manufacturera, Maquiladora y de Servicios de Exportacion) program in 2006. In the Maquiladoras/IMMEX program, firms in Mexico can import materials and equipments for duty free if the firms export products assembled using them. Maquiladora/IMMEX exports are mostly outsourcing contracts between Mexican manufacturers and foreign (in most cases US) buyers. To be eligible for the Maquiladora/IMMEX programs, exporters must register the information of foreign buyers in advance. Because of this registration, exporters do not need to report the information of foreign buyers for each shipment. We show in Section 2.2.2 that Non-Maquiladora trade and Maquiladora trade show very similar patterns on the Main-to-Main trade shares in Table 2. The patterns are also similar for the number of partners. These suggest that the sample selection problem that could potentially arise

exporters report the information of importers, which allows us to compare Maquiladora/IMMEX exporters and other normal exporters.

2.2 Exporter-Importer Matching at Product Level

2.2.1 Summary Statistics

Table 1 reports summary statistics on matching of Mexican exporters and US importers for HS 6 digit level textile/apparel products. Rows (1) and (2) report statistics on the number of exporters and importers in one product market (HS6 digit level), respectively. Rows (3) and (4) are statistics on the number of exporters selling a product to an importer and the number of importers buying a product from an exporter, respectively.

Table 1 shows that matching of exporters and importers is very different from the prediction from the conventional love of variety model. Since the model predicts that all exporters sell to all importers, numbers in Rows (1) and (2) can be interpreted as the model's predictions on the number of exporters selling to a typical importer and on the number of importers buying from a typical exporter, respectively. Compared with predicted numbers, the actual numbers in Rows (3) and (4) are extremely small. While the predicted numbers are 30-38 sellers and 39-50 buyers for the mean (16-21 sellers and 22-29 buyers for the median), more than half of exporters and importers trade with only one partner. Furthermore, though there are some firms trading with multiple partners, trade with the main partner is very important. Rows (5) and (6) show that even these firms transact around 75 percent of trade with one single main partner. Overall, Table 1 shows that product-level matching of exporters and importers is approximately one-to-one.

Table 1: Summary Statistics of Product-Level Matching for Mexico's Textile/Apparel exports to the US

HS 6 digit product level statistics	2004	2005	2006	2007
(1) N of Exporters, mean (median)	38.1 (21)	36.6 (19)	33.1 (17)	30.0 (16)
(2) N of Importers, mean (median)	49.7 (29)	47.9 (28)	43.3 (26)	39.3 (22)
(3) N of Exporters Selling to an Importer, mean (median)	1.1 (1)	1.1 (1)	1.1 (1)	1.1 (1)
(4) N of Importers Buying from an Exporter, mean (median)	1.5 (1)	1.5 (1)	1.4 (1)	1.4 (1)
(5) Value Share of the Main Exporters (Exporters>1)	0.76	0.77	0.76	0.77
(6) Value Share of the Main Importer (Importers>1)	0.74	0.76	0.77	0.76

Note: Each row reports mean statistics of variables indicated from 2004 to 2007 and median statistics in parenthesis. Rows (1) and (2): the numbers of Mexican exporters and US importers of a given product, respectively. Row (3): the number of Mexican exporters selling a given product to a given US importer. Row (4): the number of US importers buying a given product from a given Mexican exporter. Products are HS digit products. Row (5): the share of imports from the main Mexican exporters in the importer's product import volume. Row (6): the share of exports to the main US importers in the exporter's product export volume. Statistics in Rows (5) and (6) are calculated only for firms with multiple partners.

from the exclusion of data is likely to be small.

2.2.2 Main-to-Main Shares

It is well established that exports by a few large firms account for a large share of industrial exports. Figure 1 and Table 1 do not take into account this fact. Even though more than half of firms trade with just one partner, trade by these firms may account for a small fraction of the aggregate trade volume.

To take into account this heterogeneity in trade volume, we construct a new measure "main-to-main share". For each product-year combination, we identify the "main partner" of each firm, with whom the firm makes the largest trade volume. Then, we define "main-to-main trade" as trade in which the exporter is the main partner of the importer and at the same time the importer is the main partner of the exporter. Finally, we define "main-to-main share" as the share of main-to-main trade to the total trade volume.

The "main-to-main share" expresses to what extent the overall transaction in one product market is quantitatively close to one-to-one matching. If all exporters and importers trade with only one partner, this share takes the maximum value equal to one. If all n_x symmetric exporters trade with n_m symmetric importers as in the love of variety model of trade in intermediate goods with symmetric firms, this share takes the minimum value equal to $\min\{1/n_m, 1/n_x\}$. Even if some large firms trade with multiple partners, main-to-main share becomes close to one when these firms concentrate their trade with those with their respective main partners.

Column (1) in Table 2 reports the main-to-main share for Mexico's textile/apparel exports to the US. The main-to-main share is around 80 percent and stable across years. Trade within one-to-one matches of the main partners accounts for 80% of textile/apparel trade volume. This means that understanding the mechanism behind one-to-one matching between main partners leads to understanding the mechanism behind 80 percent of the aggregate trade volume. In the rest of the paper, we provide theory and evidence for the mechanism of how firms choose their main partners.

Given that we are analyzing trade between Mexico and US, some might think that our result might be driven by processing re-exports through Maquiladora/IMMEX programs because of the nature of these processing trade. For instance, to be eligible for Maquiladora/IMMEX, exporters must register importers in advance and costs of registration lead firms to trade with only a small number of partners.

In our data, we can identify transactions under these programs. In those programs, sellers register buyers in advance, therefore the cost of registration may lead firms to trade with only a small number of partners. Very few firms engage in both non-Maquiladora exports and Maquiladora exports.

Columns (2) and (3) report the main-to-main share for Maquiladora/IMMEX trade and other normal trade, respectively. These two types of trade show very similar main-to-main shares. So approximately one-to-one matching is not specific to processing trade.

Columns (4) to (6) in Table 2 present "main2-to-main2 share", a measure on how the overall transaction is close to "two to two" matching. We identify the second main partner for each firm with whom the firm makes the second largest trade volume for a given product-year combination. Then we calculate "main2-to-main2 trade" where the exporter is the main partner or the second main partner of the importer and the importer is the main partner or the second main partner of the exporter. Columns (4) to (6) show that main2-to-main 2 share accounts for more than 90 percent of the aggregate trade volume.

Table 2: "Main-to-Main" Shares in Mexico's Textile/Apparel exports to the US

	Main-to-Main Share			Main2-to-Main2 Share		
Year	All	Maquila	Non-Maquila	All	Maquila	Non-Maquila
	(1)	(2)	(3)	(4)	(5)	(6)
2004	0.77	0.77	0.78	0.92	0.92	0.92
2005	0.79	0.79	0.79	0.93	0.92	0.95
2006	0.80	0.80	0.83	0.95	0.95	0.95
2007	0.83	0.83	0.83	0.94	0.94	0.97

Note: Each column reports the volume share of a type of transactions in the total export volume for Mexico's Textile/Apparel (HS50-63) exports to the US. In a "Main-to-Main" transaction, the exporter and the importer trade in the product by the largest volume with each other. In a "Main2-to-Main2" transaction, the exporter and the importer trade in the product by the largest or the second largest volumes with each other.

2.2.3 Comparison with Previous Studies

The last years have seen a rise in the literature on matching of exporters and importers using customs transaction data. Previous studies by Blum et al. (2010, 2011), Eaton et al. (2012), Bernard et al. (2013), and Carballo et al. (2013) commonly find that the number of partners is an important margin for explaining firm heterogeneity in trade volume. Does our finding of approximately one-to-one matching contradict with these studies that emphasize "partner margins"?

Our finding is actually compatible with the previous studies mentioned above. First of all, these studies except Carballo et al. (2013) and our study use a different definition of matching. They define a match at the country level, while we define it at the product-country level.[7] More precisely, in their definition, an exporter and an importer form a match in a given country if they trade some product with each other, while in our definition, an exporter and an importer form a match in a given product and a given country pair if they trade the product with each other. If every firm traded only one product, these two definitions would identify an identical set of matches. Since a number of firms trade multiple products in reality, our definition of matching is strictly narrower than the one in these studies and identifies fewer partners for firms trading multiple products.

Second, if we define a match at the country level as the previous studies do, we are able to replicate previous findings with our data. First, in Table 1, we find lower mean numbers of exporters selling to an importer and of importer buying from an exporter than the ones observed by Blum et al. (2010,

[7]Carballo et al. (2013) also examines the number of buyers per exporter at the product-destination level. They primarily focus on the number of buyers for exporters and the share of the main buyers for exporters. However, they do not analyze the number of sellers for importers.

2011), Bernard et al. (2013), and Carballo et al. (2013). When we calculate these numbers under their definitions, the numbers increase and become similar to theirs. Second, Blum et al. (2010, 2011) and Bernard et al. (2013) find a negative correlation between the number of partners per exporter and the number partners per importer.[8] Following Table 3.2 in Blum et al. (2010) and Figure 5 in Bernard et al. (2013), we calculate for each Mexican exporter: (X) the number of US buyers the exporter trade with and (Y) the average number of Mexican partners among these US buyers. Then, we run a regression of (Y) on (X) with the constant term. We find a significant negative slope, -0.115 (s.e. 0.018), for 2004, which is comparable to that of -0.13 (s.e. 0.01) for Norwegian exporters by Bernard et al. (2013).[9] Therefore, our analysis of one-to-one matching of exporters and importers at the product-country level has no conflict with the previous analysis of partner margins at the country level.

3 The Model

This section has three aims. The first is to develop a model combining a canonical Becker (1973) model of one-to-one matching with a standard Melitz-type heterogeneous firm trade model. The second is to explain the model's implication for the novel effect of trade liberalization on the aggregate industrial performance. The third is to derive predictions from the model that will be tested in later sections of the paper.

3.1 A Matching Model of Exporters and Importers

We set up a matching model of global supply chains producing differentiated final goods.[10] There are three types of firms, US final producers, Mexican suppliers and Chinese suppliers. A US final producer matches with a supplier either from Mexico or China to form a team that produces one variety of final goods. Once teams are formed, suppliers tailor intermediate goods for a particular variety of final goods; therefore, firms transact intermediate goods only within their team. Each firm joins only one team.

Firms are heterogeneous in their capability. Capability expresses either productivity or quality, depending on other parameters of the model. Let x and y be the capability of final producers and suppliers, respectively. There are fixed mass M_U of final producers in the US, M_M of suppliers in Mexico and M_C of suppliers in China. The c.d.f. (cumulative distribution function) for the capability of US final producers is $F(x)$ with support $[x_{min}, x_{max}]$. The capability of Mexican suppliers and that of Chinese

[8]Bernard et al. (2013) call this negative correlation of the number of partners "negative assortative matching." Again, their definition of assortative matching is different from ours. We follow Becker's definition of assortative matching with respect to agent's given abilities.

[9]When we we define a match at the product level and run a similar regression with product fixed effects, the negative correlation becomes much weaker and becomes insignificant for some years. For instance, the slope of the regression for 2004 is -0.036 (s.e. 0.029).

[10]Our model is a partial equilibrium version of Sugita (2014) where firm entry is endogenous and international matching arises from Ricardian comparative advantage in a two country general equilibrium model.

suppliers follow an identical distribution and the c.d.f. is $G(y)$ with support $[y_{min}, y_{max}]$.[11] The identical capability distribution of Chinese and Mexican suppliers is assumed for the graphical expositions of comparative statics results. For simplicity, a Chinese supplier is a perfect substitute for a Mexican supplier with the same capability.

The model has two stages. In Stage 1, final producers and suppliers form teams under perfect information. After teams are formed, in Stage 2, teams compete in the US final good market in a monopolistically competitive fashion.

Teams are heterogeneous in team capability. Team capability $\theta(x, y)$ is an increasing function of team member's capability, $\theta_1 \equiv \partial\theta(x, y)/\partial x > 0$ and $\theta_2 \equiv \partial\theta(x, y)/\partial y > 0$. Matching endogenously determines the distribution of team capability.

The representative consumer in the US maximizes the following utility function:

$$U = \frac{\delta}{\rho}\ln\left[\int_{\omega\in\Omega}\theta(\omega)^{\alpha}q(\omega)^{\rho}d\omega\right] + q_0 \text{ s.t. } \int_{\omega\in\Omega}p(\omega)q(\omega)d\omega + q_0 = I.$$

where Ω is a set of available differentiated final goods, ω is a variety of differentiated final goods, $p(\omega)$ is a price of ω, $q(\omega)$ is consumption of ω, $\theta(\omega)$ is capability of a team producing ω, $\alpha \geq 0$ is a parameter on how demand responds to capability (product quality), q_0 is consumption of a numeraire good, I is an exogenously given income, and δ expresses industry-wide demand shocks. Consumer's demand for a variety with price p and capability θ is derived as

$$q(p, \theta) = \frac{\delta\theta^{a\sigma}p^{-\sigma}}{P^{1-\sigma}}, \tag{1}$$

where $\sigma \equiv 1/(1-\rho) > 1$ is the elasticity of substitution and $P \equiv \left[\int_{\omega\in\Omega}p(\omega)^{1-\sigma}\theta(\omega)^{\alpha\sigma}\,d\omega\right]^{1/(1-\sigma)}$ is the price index.

Production technology is of Leontief type. When a team produces q units of final goods, the supplier in the team produces q units of intermediate goods with costs $c_y\theta^{\beta}q + f_y$; then, using them, the final producer assembles final goods with costs $c_x\theta^{\beta}q + f_x$. The total costs for team with capability θ producing q units of final goods are

$$c(\theta, q) = c\theta^{\beta}q + f, \tag{2}$$

where $c \equiv c_x + c_y$ and $f \equiv f_x + f_y$. The marginal cost of each firm is assumed to depend on team's capability. This assumption is mainly for simplicity, but it also aims to express externality within teams that makes firms' marginal costs to depend on team capability as well as their own.[12]

Team capability θ may represent productivity and/or quality, depending on parameters α and β. For

[11] The maximums x_{max} and y_{max} may be positive infinite (e.g. F and G may be Pareto distributions).

[12] An example for within team externality is costs of quality control. Producing high quality final goods might require extra costs of quality control at each production stage because even one defective component can destroy the whole product (Kremer, 1993). Another example is productivity spillovers through teaching and learning (e.g. joint R&D) within a team.

instance, when $\alpha = 0$ and $\beta < 0$, all teams face symmetric demand functions, while a team with high capability has lower marginal costs. Teams behave as firms in the Melitz model and θ may be called productivity. When $\alpha > 0$ and $\beta > 0$, a team with high capability faces a large demand at a given price and at the same time pays high marginal costs. Teams behave as firms in Baldwin and Harrigan (2011) and Johnson (2012) and θ may be called quality.

We obtain an equilibrium by backward induction.

Stage 2 Team's optimal price is $p(\theta) = c\theta^{\beta}/\rho$. Hence, team's revenue $R(\theta)$, total costs $C(\theta)$, and joint profits $\Pi(\theta)$ are

$$R(\theta) = \sigma A \theta^{\gamma},\ C(\theta) = (\sigma - 1) A\theta^{\gamma} + f,\ \text{and}\ \Pi(\theta) = A\theta^{\gamma} - f, \tag{3}$$

where $A \equiv \frac{\delta}{\sigma}\left(\frac{\rho P}{c}\right)^{\sigma-1}$. Parameter $\gamma \equiv \alpha\sigma - \beta(\sigma - 1)$ summarizes how capability affects team profits. Since comparative statics on parameters α, β, and σ is not our main interest, we normalize $\gamma = 1$ by choosing the unit of θ. This normalization greatly simplifies the calculations below.

Stage 1 Firms choose their partners and decide how to split team profits, taking A as given. Profit schedules, $\pi_x(x)$ and $\pi_y(y)$, and matching functions, $m_x(x)$ and $m_y(y)$, characterize equilibrium matching. A final producer with capability x matches with a supplier with capability $m_x(x)$ and receives the residual profit $\pi_x(x)$ after paying profits $\pi_y(m_x(x))$ for the partner. Let $m_y(y)$ be the inverse function of $m_x(x)$ where $m_x(m_y(y)) = y$ and a supplier with capability y matches with a final producer with capability $m_x(x)$.

We focus on stable matching that satisfies two conditions: (i) (*individual rationality*) all firms earn non-negative profit, $\pi_x(x) \geq 0$ and $\pi_y(y) \geq 0$ for all x and y; (ii) (*pair-wise stability*) each firm is the optimal partner for the other team member:[13]

$$\begin{aligned} \pi_x(x) &= A\theta(x, m_x(x)) - \pi_y(m_x(x)) - f = \max_y A\theta(x, y) - \pi_y(y) - f \\ \pi_y(y) &= A\theta(m_y(y), y) - \pi_x(m_y(y)) - f = \max_x A\theta(x, y) - \pi_x(x) - f. \end{aligned} \tag{4}$$

The first order conditions for the maximization in (4) are

$$A\theta_2(x, m_x(x)) = \pi_y'(m_x(x)) \text{ and } A\theta_1(m_y(y), y) = \pi_x'(m_y(y)).$$

[13] Parameter A is given to individual firms, but endogenous at the market level. Therefore, stable matching considered here is a $f-$core of an economy with wide spread externality of Hammond, Kaneko, and Wooders (1989). See this paper for the existence of f-core.

Using $m_x(x) = y$ and $m_y(y) = x$, the above first order conditions become:

$$\pi_x'(x) = A\theta_1(x, m_x(x)) > 0 \text{ and } \pi_y'(y) = A\theta_2(m_y(y), y) > 0 \tag{5}$$

and prove that profit schedules are increasing in capability.

Trade volume within a match $T(x, y)$ is equal to supplier's costs plus supplier's profit. From (3) with $\gamma = 1$ and (5), $T(x, y)$ turns to be increasing in member's capability :

$$\begin{aligned} T(x, y) &= \left[\frac{c_x}{c} C(\theta(x, y)) + f_x\right] + \pi_y(y); \\ \frac{\partial T}{\partial x} &= \frac{c_x}{c}(\sigma - 1) A\theta_1 > 0 \text{ and } \frac{\partial T}{\partial y} = \frac{c_x}{c}(\sigma - 1) A\theta_2 + \pi_y'(y) > 0. \end{aligned} \tag{6}$$

Because of fixed costs, there exists a cut-off level of team capability θ_L such that only teams with capability $\theta \geq \theta_L$ produce on the market. At the same time, there are capability cut-offs x_L and y_L such that only final producers with $x \geq x_L$ and suppliers with $y \geq y_L$ participate in the matching market, i.e. in international trade. These cut-offs satisfy

$$\pi_x(x_L) = \pi_y(y_L) = 0 \text{ and } M_U[1 - F(x_L)] = (M_M + M_C)[1 - G(y_L)]. \tag{7}$$

The second condition in (7) expresses that the mass of suppliers in the matching market is equal to that of final producers.

It is known that the sign of the cross derivative of team's joint profits, which is the sign of the cross derivative θ_{12}, determines the sign of sorting in stable matching (e.g. Becker, 1973). For simplicity, we consider three cases where the sign of θ_{12} is constant: (1) Case-C (Complement) $\theta_{12} > 0$ for all x and y (i.e. θ is strict supermodular); (2) Case-I (Independent) $\theta_{12} = 0$ for all x and y (i.e. θ is additive separable); (3) Case-S (Substitute) $\theta_{12} < 0$ for all x and y (i.e. θ is strict submodular).[14] In Case-C, we have positive assortative matching (PAM) ($m_x'(x) > 0$): high capable firms match high capable firms while low capable firms match low capable firms. In Case-S, we have negative assortative matching (NAM) ($m_x'(x) < 0$): high capable firms match low capable firms. In Case-I, we cannot determine a matching pattern ($m_x(x)$ cannot be defined as a function) since each firm is indifferent about partner's capability. Therefore, we assume matching is random in Case-I.[15]

[14] An example for Case-C is the complementarity of quality of tasks in a production process (Kremer, 1993; Kugler and Verhoogen, 2012; Sugita, 2014). For instance, a high quality car part is more useful when it is combined with other high quality car parts. An example for Case-S is technological spillovers through learning and teaching. Gains from learning from high capable partners might be greater for low capable firms. See Grossman and Maggi (2000) for further examples.

[15] See e.g. Legros and Newman (2007) for a proof of this result. To understand the intuition, consider matching among two final producers $\{X, X'\}$ and two suppliers $\{Y, Y'\}$. Let their capability be x, x', y and y' where $x > x'$ and $y > y'$. Then, consider how much extra team profits each final producer can produce by switching the supplier from Y' to Y. In Case C, final producer X can produce more extra team profits than X' because $\theta_{12} > 0$. Therefore, X can make a better offer to Y than X' does and matches with Y (PAM). In Case S, final producer X' can produce more extra team profits than X because $\theta_{12} < 0$. Therefore, X' can make a better offer to Y than X does and matches with Y (NAM). In Case I, both final producers

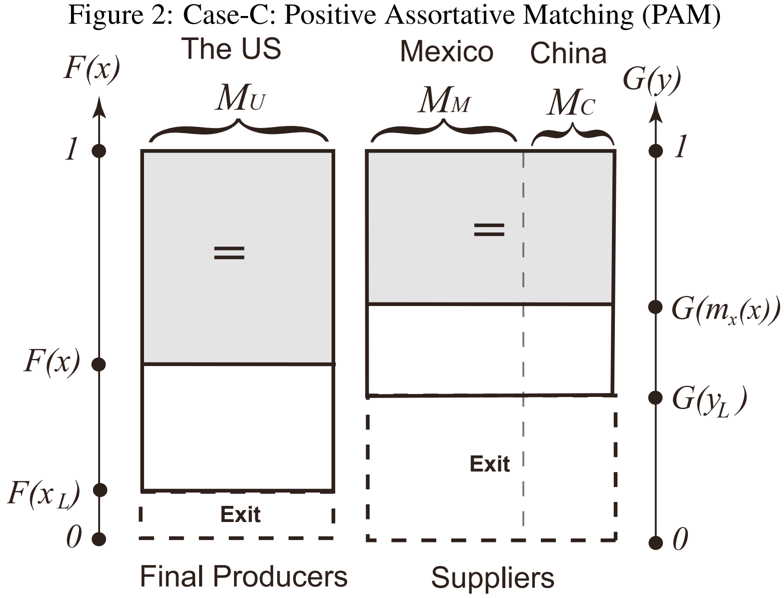
We focus on Case-C and Case-I in the main text of the paper and discuss Case-S in Appendix for three reasons. First, our empirical analysis supports Case-C and rejects Case-I and Case-S. Second, Case-I is a useful benchmark since it nests traditional Melitz-type models with firm heterogeneity only in one side of the market, i.e. either among suppliers ($\theta_1 = \theta_{12} = 0$) or among final producers ($\theta_2 = \theta_{12} = 0$). Finally, the analysis of Case-S turns out to be much more complex than the analysis of other two cases.

In Case-C, matching function $m_x(x)$ is determined to satisfy the following "matching market clearing" condition.

$$M_U [1 - F(x)] = (M_M + M_C) [1 - G(m_x(x))] \text{ for all } x \geq x_L, \tag{8}$$

The left hand side of (8) is the mass of final producers that have higher capability than x and the right hand side is the mass of suppliers who match with them. Under PAM, they are suppliers with higher capability than $m_x(x)$. Figure 2 describes how matching function $m_x(x)$ is determined for a given $x \geq x_L$. The width of the left rectangle is equal to the mass of US final producers, while the width of the right rectangle is equal to the mass of Mexican and Chinese suppliers. The left vertical axis expresses the value of $F(x)$ and the right vertical axis does the value of $G(y)$. The left gray area is equal to the mass of final producers with higher capability than x and the right gray area is the mass of suppliers with higher capability than $m_x(x)$. The matching market clearing condition (8) requires the two areas to have the same size for all $x \geq x_L$.

Figure 2: Case-C: Positive Assortative Matching (PAM)



An equilibrium is obtained as follows (see Appendix for calculation). First, the matching market

can produce exactly the same extra team profits because $\theta_{12} = 0$. For matching to be stable, the difference in profits between Y and Y' must be equal to this extra profits so that both X and X' are indifferent between Y and Y'.

clearing condition (8) determines matching function $m_x(x)$ for each x. Let $\theta(x, y) \equiv \theta^x(x) + \theta^y(y)$ for additive separable Case-I. Using m_x, the index A is obtained as

$$A = \frac{\delta}{\sigma\Theta}, \text{ where } \Theta = \begin{cases} M_U \int_{x_L}^{\infty} \theta\left(x, m_x(x)\right) dF(x) & \text{for Case-C} \\ M_U \int_{x_L}^{\infty} \theta^x(x) dF(x) + (M_M + M_C) \int_{y_L}^{\infty} \theta^y(y) dG(y) & \text{for Case-I.} \end{cases}$$

Using A in the last equation, equation (7) and the cut-off condition for teams, $A\theta\left(x_L, y_L\right) = f$, determine two cut-offs x_L and y_L.[16]

3.2 Matching as a Market Outcome

The Becker-type matching model explains assortative matching as a market outcome that depends on the capability distributions of final producers and suppliers. With this property, the model sheds a new light on the effect of trade liberalization on the aggregate industrial performance.

To see this point more clearly, focus on Case-C positive assortative matching. Trade liberalization allows foreign suppliers to enter and changes the capability distribution of suppliers available for final producers. Some final producers prefer to switch partners to foreign entrants (this is the reason why foreign suppliers enter) and the old matching becomes unstable. Firms change their partners so that the new matching becomes positive assortative under the new capability distribution. Because technology θ exhibits complementarity, this re-matching toward positive assortative matching leads to an efficient use of technology and improves the aggregate industrial performance at the world level (e.g. the world profits) under normal circumstances.[17]

In the rest of the paper, we empirically test this implication of the Becker-type positive assortative matching for the adjustment of matching to trade liberalization. More specifically, we consider what happens to matching of US final producers and Mexican suppliers when the mass of Chinese suppliers increases ($dM_C > 0$). We continue to focus on Case-I versus Case-C. We discuss Case-S in Appendix and some alternative models in empirical section 5.3. For simplicity, we assume positive but negligible costs of switching partners so that a firm changes its partner only if it strictly prefers the new match to the current match.

When the mass of Chinese suppliers increases, some Mexican suppliers stop exporting to the US. Some US final producers stop importing from Mexico to import from China. Others remain in the

[16] Profits of individual firms can be obtained by integrating the first order conditions (5) with initial conditions (7):

$$\pi_x(x) = A \int_{x_L}^{x} \theta_1(t, m_x(t)) dt \text{ and } \pi_y(y) = A \int_{y_L}^{y} \theta_2(m_y(t), t) dt.$$

The stability condition alone determines the distribution of profits within teams. This is a virtue of this class of matching models with continuum of agents (Sattinger, 1979). We do not need to specify "bargaining power parameters" on how to split the matching surplus within matches.

[17] Under these circumstances, the change in the market condition A does not offset the efficiency gain of re-matching.

Mexico-US trade. We introduce the names of these groups of firms.

Definition 1. Consider Mexican suppliers and US final producers that trade with them before the event of an increase in Chinese suppliers occurs. (1) US final producers are called *continuing importers* if they continue importing from Mexico after the event, and *exiting importers* if they stop importing from Mexico after the event. (2) Mexican suppliers are called *continuing exporters* if they continue exporting to the US after the event, and *exiting exporters* if they stop exporting to the US.

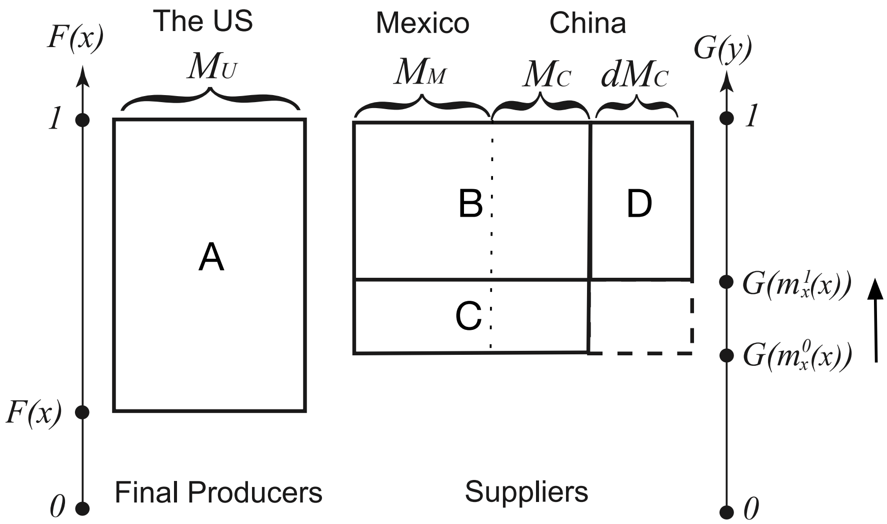
In the following, we focus on how continuing importers and continuing exporters change their partners in response to the Chinese entry.

In Case-I, firms are indifferent about partner's capability. Even negligible switching costs prohibit any change in matching. Continuing exporters and importers do not change their partners since all incumbent firms are indifferent to them.

Proposition 1. *Suppose that the mass of Chinese suppliers increases in Case-I. US continuing importers and Mexican continuing exporters do not change their partners.*

In Case-C, continuing importers and exporters systematically change matching to satisfy the matching market clearing condition (8). Let $m_x^0(x)$ and $m_x^1(x)$ be matching functions in an old equilibrium and in a new equilibrium, respectively. Figure 3 describes how a US importer with capability x changes the partner. Area A in Figure 3 expresses US importers with higher capability than x. They initially match with suppliers with higher capability than $m_x^0(x)$ expressed by Areas $B + C$. After the entry of Chinese exporters, more suppliers at any given capability level are available for US final producers. The old matching becomes unstable since some US final producers are willing to match with new Chinese exporters. In the new matching, final producers in Area A matches with Areas $B + D$ that has an equal mass and represents suppliers with higher capability than $m_x^1(x)$. The figure shows that a US final producer with given capability x switches the main partner from the one with capability $m_x^0(x)$ to the one with higher capability $m_x^1(x)$. We call this change "partner upgrading". This in turn implies "partner downgrading" for Mexican suppliers. The same figure also shows that Mexican suppliers with capability $m_x^1(x)$ used to match with final producer with strictly higher capability than x before the entry of Chinese suppliers.

Figure 3: Case-C: the Response of Matching to an Entry of Chinese Exporters ($dM_C > 0$)



Proposition 2. *Suppose that the mass of Chinese suppliers increases in Case-C. (1) US continuing importers switch their Mexican partners to those with higher capability (partner-upgrading). (2) Mexican continuing exporters switch their US partners to those with lower capability (partner-downgrading).*

We will test Propositions 1 and 2 in the rest of the paper.[18]

4 Empirical Strategies

We need three types of data to empirically test Propositions 1 and 2. First, we need an event that increases the number of Chinese exporters in the US market. Second, we need rankings of capability at the firm-product level. Finally, we need to track partner changes for US importers and Mexican exporters. In this section, we explain how we obtain these data and formulate an implementable test of Propositions 1 and 2. We also explain the advantage of our test over the "correlation test" of assortative matching.

4.1 The End of the Multi-Fiber Arrangement

The end of the Multi-Fiber Arrangement (MFA) in 2005 provides an exact shock that we analyzed in the last section, a sudden increase in Chinese exporters with various capability levels to the US textile/apparel product markets ($dM_C > 0$).

[18] We have assumed the identical capability distributions of Chinese and Mexican suppliers to derive Proposition 2 using the diagram. We remark that Proposition 2 holds without this assumption. Under the general distribution, if some US final producer with capability x that used to match with a Mexican supplier with capability y switches to some Chinese supplier, then Proposition 2 holds for all US continuing importers with weakly lower capability than x and all Mexican continuing exporters for weakly lower capability than y.

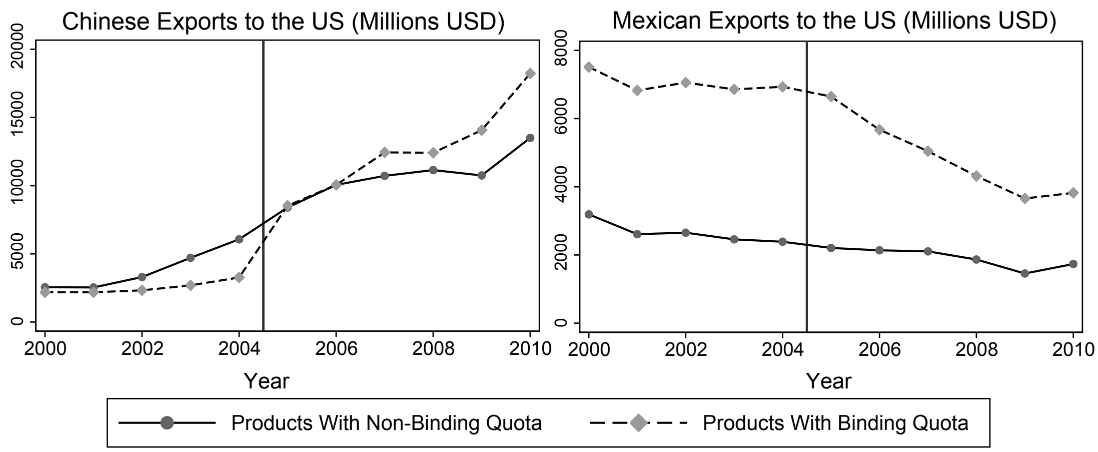
The MFA and its successor, the Agreement on Textile and Clothing, are agreements on quota restrictions on textile/apparel imports among the GATT/WTO member countries. At the GATT Uruguay round, the US (together with Canada, EU and Norway) promised to abolish their quotas in four steps. On January 1, 1995, 1998, 2002, and 2005, the US removed import quotas. In each removal, liberalized products account for 16, 17, 18, and 49% of imports in 1990, respectively.

The end of the MFA in 2005 is product-level liberalization of the US textile/apparel markets. Quotas had already been removed for a roughly half of the products before 2002, while the other half was liberalized in 2005. Many HS 2 digit chapters contain products liberalized in 2005 and those that had been already liberalized and therefore did not experience any change in 2005. This allows us to construct a treatment group (products liberalized in 2005) and to compare it to a control group (other products) within HS 2 digit chapters.

The Surge in Chinese Exports to the US The quota removal of 2005 triggered a surge in imports to the US, mostly from China. Brambilla, Khandelwal, and Schott (2010) estimate that US imports from China disproportionally increased by 271% in 2005, while imports from almost all other countries decreased.[19] The left panel in Figure 4 draws Chinese exports to the US for textile and apparel products (Chapters 50 to 63 of the Harmonized System Codes) from 2000 to 2010. The vertical line in year 2005 represents the year of the MFA quota removal. The dashed line expresses the aggregate export volume of products on which the US had imposed binding quotas against Chinese exports until the end of 2004 (the treatment group), while the solid line expresses that of other textile/apparel products (the control group). After the quota removal in 2005, exports of quota-removed products shown by the dashed line increased much faster than those of other products shown by the solid line.

[19]Seeing this huge import growth, the US and China had agreed to impose new quotas until 2008, but imports from China never went back to the pre-2005 level. The new quota system covered fewer product categories than the old system (Dayaranta-Banda and Whalley, 2007) and the level of quotas is substantially greater than the MFA level (see Table 2 in Brambilla et al., 2010).

Figure 4: Impacts of the end of the MFA on Chinese and Mexican textile/apparel exports to the US



Note: The left panel shows export values in million US dollars from China to the US for two groups of textile/apparel products from 2000 to 2010. The dashed line represents the sum of the export value of all the products on which US had imposed binding quotas against China until the end of 2004, while the solid line represents that of the products with non-binding quotas. The right panel expresses the same information for exports from Mexico to the US.

Exports by New Chinese Entrants with Various Capability Khandelwal, Schott, and Wei (2013) use Chinese customs transaction data to decompose the increases in Chinese exports to US, Canada and EU after the quota removal into intensive and extensive margins. The authors find that the increases in Chinese exports of quota constrained products were mostly driven by the entry of Chinese exporters who had never exported the products. Furthermore, these new exporters are much more heterogeneous in capability than incumbent exporters. Many new exporters are more capable than incumbent exporters.[20] In our model, this entry of new exporters at various levels of capability corresponds to an increase in the mass of Chinese suppliers $dM_C > 0$ analyzed in the last section.

Mexican Exports Facing Competition from China The removal of the MFA quotas had a huge impact on Mexican exports. Mexico had already had tariff-and-quota free access to the US market through the North American Free Trade Agreement (NAFTA).[21] At the end of the MFA, Mexico lost its advantage to third country exporters and faced an increase in competition with Chinese exporters in the US market. The right panel in Figure 4 shows Mexican exports to the US for quota-removed products by the dashed line (the treatment group) and other textile/apparel products by the solid line (the control

[20] Khandelwal et al. (2013) show two pieces of evidence. First, while incumbent exporters are mainly state-owned firms, new exporters include private and foreign firms. Private and foreign firms are typically more productive than state-owned firms. Second, the distribution of unit prices of new entrants has a lower mean but a greater support than that of unit prices of incumbent exporters. Khandelwal et al. (2013) show that these findings contradict with the predictions of optimal quota allocation and suggest inefficient quota allocations.

[21] Under the NAFTA, the US market was liberalized to Mexican exports in 1994, 1999, and 2003.

group) from 2000 to 2010. The figure shows that the two series had moved in a parallel manner before 2005, while exports of quota-removed products exhibits a much larger decline after 2005. The parallel movement of the two series before 2005 shows that there were no underlying differential trends between Mexico-US trade of quota-removed products and those of other products. This suggests that the choice of products for quota removal in 2005 was exogenous to Mexican exports to the US.[22]

In summary, the end of the MFA in 2005 provides an ideal natural experiment for testing Propositions 1 and 2. It induced a large and arguably exogenous increase in the mass of Chinese exporters with various capability levels in the US market for roughly half of textile/apparel products but not for the rest of textile/apparel products.

4.2 Proxy for Capability Rankings

We need rankings of capability for US final producers and Mexican suppliers in each product to test Propositions 1 and 2. One might think of estimating conventional capability measures such as total factor productivity (TFP). However, estimating it at the firm-product level is not feasible even if we had linked the current data set to typical firm-level data with which researchers estimate TFP . As we will explain in Section 4.4, it would require currently unavailable data and estimation methodology. Therefore, we take a different approach.

Notice that in Case-I no firm should change their partners. If Case-I holds in data, this prediction can be confirmed regardless of how we estimate capability rankings of firms. Therefore, to test Case-C versus Case-I, it is sufficient to find proxies of capability rankings that work if Case-C holds in data.

We use a property of our model that the trade volume of a firm is increasing in its capability in Case-C. Remember that trade volume within a match $T(x, y)$ is increasing in capability x and y (see (6)). In Case-C matching is positive assortative and matching functions are increasing, i.e. $m'_x(x) > 0$ and $m'_y(y) > 0$. Therefore, import volume by US final producers $I(x) = T(x, m_x(x))$ is increasing in own capability x as well as exports volume by Mexican suppliers $X(y) = T(m_y(y), y)$ is increasing in own capability y.

Using this monotonicity, for each product, we create the ranking of US continuing importers by their imports from the main partner in 2004. From the monotonicity of import volume and capability ($I'(x) > 0$), this ranking should agree with the true capability ranking of US continuing importers. Similarly, we create for each product the ranking of Mexican continuing exporters by their exports to the main partner in 2004, which should also agree with the true capability ranking of Mexican exporters in Case-C.

We assume that the capability ranking in a fixed set of firms is stable during our sample period 2004-2007. Then, we use the rank measured from 2004 data for the same firm throughout our sample

[22] We further investigate this parallel underlying trend assumption in Section 5.2.1.

period 2004-2007. We measure the capability rankings only for Mexican continuing exporters and US continuing importers that engaged in the Mexico-US trade in 2004 and 2007.

As robustness checks, we also create rankings based on total product trade volume in 2004 aggregated across partners and rankings based on unit prices.[23]

4.3 Specification

Finally, we need to track the partners changes of US importers and Mexican exporters and to isolate partner changes due to the Chinese entry from the ones due to other reasons. We simply estimate the following four regressions:

$$\begin{aligned} Upgrading_{igs}^{US} &= \beta_1 Binding_{gs} + \lambda_s + \varepsilon_{igs}^{m} \\ Downgrading_{igs}^{US} &= \beta_2 Binding_{gs} + \lambda_s + u_{igs}^{m} \\ Upgrading_{igs}^{Mex} &= \beta_3 Binding_{gs} + \lambda_s + \varepsilon_{igs}^{u} \\ Downgrading_{igs}^{Mex} &= \beta_4 Binding_{gs} + \lambda_s + u_{igs}^{u}. \end{aligned} \tag{9}$$

where i, g and s index a firm, a HS 6 digit product and a sector (HS 2 digit chapters), respectively.

We define dummy variables $Upgrading_{igs}^{c}$ and $Downgrading_{igs}^{c}$ as follows: $Upgrading_{igs}^{c} = 1$ $(c = US, Mex)$ if during 2004-07 firm i in country c switched the main partner of product g to a firm with a higher capability rank; $Downgrading_{igs}^{c} = 1$ $(c = Mex, US)$ if during 2004-07 firm i in country c switched the main partner of product g to a firm with a lower capability rank. By construction, $Upgrading_{igs}^{c}$ and $Downgrading_{igs}^{c}$ are defined only for US continuing importers and Mexican continuing exporters during 2004-07. Our sample for the regression analysis drops exiting importers and exporters. In subsection 5.3.2, we will consider cases where the exclusion of these firms could affect the interpretation of estimated β_i. We choose the sample period for 2004-2007 because Lehman crisis in 2008 led to reductions in Mexican exports to the US, potentially confounding the impact of the end of the MFA.

$Binding_{gs}$ is a dummy variable indicating whether Chinese exports of product g to the US had faced a binding quota in 2004. Brambilla et al. (2010) constructed an indicator on binding quota for Chinese exports for each HS 10 digit category for the US.[24] Since HS product categories of Mexico and the US are same only up to the first 6 digits, we aggregated their indicator up to the HS 6 digit level.[25] λ_s are

[23] We prefer to use firms' trade volume with the main partners rather than firm-level total product trade volume aggregated across partners. This is because the latter measure may not capture the ranking of profit opportunities for the partners. For instance, consider two importers. One makes large imports by buying small amounts from each of many partners. The other makes smaller total imports but imports greater amounts from each seller. We think a typical exporter will regard trade with the latter importer more profitable.

[24] A quota is defined binding if the fill rate, realized imports value over the quota value, is bigger than 0.8. Our results are robust to the choice of other cut-offs.

[25] We constructed our indicator as follows. Let x_{g2004}^{m} be US imports of HS 10 digit product g from Mexico in 2004. Let j

HS 2 digit-level sector fixed effects that control for unobservable and observable shocks for the period at the broad sector level. u^c_{igs} and ε^c_{ijs} are error terms.

The coefficients of interest in (9) are β_i for $i = 1, ..., 4$. With HS 2 digit product fixed effects, these coefficients are identified by the comparison of the treatment group and the control group within the same HS 2 digit sector level. The treatment is the removal of binding quotas on Chinese exports to the US ($Binding_{gs} = 1$). The coefficient β_i estimates its impact on the probability that firms switch their main partners to those with higher or lower capabilities.

Proposition 1 for random matching in Case-I predicts that in response to the entry of Chinese exporters, continuing US importers and continuing Mexican exporters should not change their partners. In reality, there may exist other shocks inducing partner changes. A virtue of our treatment-control groups comparison is that we can difference out the effects of these other shocks if they symmetrically affect the treatment and control groups. Taking this point into account, we re-formulate the prediction for Case-I: there should be no difference in the probability of partner changes in any direction between the treatment group and the control group. In our regressions (9), this prediction corresponds to $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$.

Proposition 2 for positive assortative matching in Case-C predicts that in response to the entry of Chinese exporters, all continuing US importers upgrade and Mexican continuing exporters downgrade their main partners. Though the model with frictionless matching predicts all firms change their partners, there are likely to exist other factors such as transaction costs that prevent some firms from changing partners at least in the short run. Again, our treatment-control groups comparison can difference out these other factors as long as they symmetrically affect the two groups. Taking this point into account, we re-formulate the prediction for Case-C: US importers' partner upgrading and Mexican exporters' partner downgrading occurs more frequently in the treatment group than in the control group. In our regressions (9), this prediction corresponds to $\beta_1 > 0$, $\beta_2 = \beta_3 = 0$, and $\beta_4 > 0$.

4.4 Advantages over the "Correlation Test" of Assortative Matching

An alternative approach to test positive assortative matching is a type of "correlation test" that sees whether the correlation of the capability of exporters and that of importers across matches is positive or negative from cross-sectional data. The correlation test has been conventionally used in labor economics for analyzing many topics such as marriage, education, worker sorting etc. For readers of these studies,

be a HS 6 digit product and $G(j)$ be the set of US HS 10 digit products in category j. Then, we constructed a dummy variable indicating whether Chinese exports of HS 6 digit product j to the US faced binding quotas in 2004 as:

$$Binding_j = I\left\{\frac{\sum_{g\in G(j)} x^m_{g2004} I\{g \in \text{binding quota in 2004}\}}{\sum_{g\in G(j)} x^m_{g2004}} \geq 0.5\right\}, \tag{10}$$

where the indicator function $I\{X\} = 1$ if X is true and $I\{X\} = 0$ otherwise. We chose the cut-off value as 0.5 but the choice of this cut-off is unlikely to affect the results since most of values inside the indicator function are close to either one or zero.

our test examining the response of matching to the entry of suppliers may not appear as a standard approach. For the analysis of exporter-importer matching, however, our approach has several advantages over the correlation test approach .

The first advantage is that our test is able to identify the mechanism behind assortative matching. The correlation test merely measures the sign of assortative matching and is silent about the mechanism producing assortative matching. On the other hand, our approach of analyzing systematic partner changes in response to the entry of new suppliers allows us to test the key mechanism of the Becker-type positive assortative matching model.

Second, the correlation test would require us to estimate some capability measure such as total factor productivity at the firm-product level. In contrast to studies in labor economics where agent's abilities are reasonably observable, there are several difficulties in the estimation of capability for the analysis of exporter-importer matching. First, such estimation would require detailed information about the outputs and inputs for production of each product for each firm, but the information on inputs at the firm-product level is rarely available. Second, at this moment, there is no established method for estimating firm capability in a matching market. For instance, conventional estimation methods of total factor productivity implicitly assume the anonymous market where matching is irrelevant. That is why it is possible to estimate the productivity of sellers without using information of buyers. We are not sure about what kind of biases might arise if we apply these conventional methods for firms in a matching market.

Finally, instead of estimating capability, the correlation test could use proxy variables for capability. Examples of such proxy variables could be firm-size variables such as sales or employment. There are two remarks for this approach. First, these firm-size variables have no variation at the firm-product level. Second, the correlation test based on these firm-size variables may not be informative at all about the sign of sorting of true capability and therefore may lead to a wrong conclusion. For instance, in our model, all Case-i ($i = I, S, C$) including even Case-S of NAM predict a positive correlation between exporters' employment and importers' employment across matches.[26] This is simply because the employment of an importer is increasing in the amount of imported intermediate goods, which is again increasing in the employment of the exporter with whom the importer trades. This positive correlation arises from the complementarity of the labor inputs in the Leontief technology and not from the complementarity of capability.

[26]This point is more evident for our trade-volume based capability rankings. If we would take the correlation between the rank of exporters and that of their respective main partners, it would be mechanically positive. We emphasize again that this is not what we are doing in our paper.

5 Results

5.1 Baseline Regressions

Table 3 reports estimates of β_i ($i = 1, .., 4$) from our baseline regressions for partner changes during 2004-07. The table shows the estimates of each coefficient from linear probability models and probit models. Panels A and B report the results for partner changes of US importers and Mexican exporters, respectively. In Panel A, Column (1) shows that the estimate of β_1 under the linear probability model is 0.052, which means that the removal of binding quotas against Chinese exports induced US importers to upgrade their main partners more frequently by 5.2 percentage points. Column (2) shows that the probit model gives a similar estimate.[27] Columns (3) and (4) show that the impact of the end of the MFA on partner downgrading for US importers is close to zero and statistically insignificant. In Panel B, Columns (5) and (6) show that the impact on partner upgrading for Mexican exporters is also close to zero and statistically insignificant. Columns (7) and (8) show that the removal of binding quotas against Chinese exports increases the probability of partner downgrading for Mexican exporters by 12.7 to 15 percentage points.

Overall, we find that β_1 and β_4 are positive and statistically significant. That is, parer upgrading for US importers and partner downgrading for Mexican exporters occur more frequently in the treatment group than in the control group. On the other hand, β_2 and β_3 are close to and not statistically different from zero; there is no difference in the probabilities of partner downgrading for US importers and partner upgrading for Mexican exporters between the treatment group and the control group.[28] These signs of the estimates support positive assortative matching Case-C and reject random matching Case-I.

The removal of binding quotas against Chinese exports increased the probability of US importers partner upgrading by 5.2 percentage points and the probability of partner downgrading for Mexican exporters by 12.7 to 15 percentage points. The quantitative magnitude might first appear small. However, they are substantial when they are compared to the probability of partner changes in the overall sample. The probability of US importer partner upgrading in the sample is 3 percentage points and the probability of Mexican exporter partner downgrading in the sample is 15 percentage points.[29]

[27]This is also true for other equations in the paper so we report estimates from linear probability models in the following.

[28]Section 6.4 shows that this lack of partner changes in the other directions help to reject other alternative explanations for positive estimates of β_1 and β_4.

[29]The difference in the probabilities of US partner upgrading and Mexican partner downgrading comes from some departures of the actual matching from one-to-one matching. If matching of exporters and importers is exactly one-to-one, partner upgrading of US importers is equivalent to partner downgrading of Mexican exporters; there should be no difference in the probabilities of US partner upgrading and Mexican partner downgrading. However, our estimate ofβ_1 is smaller than that of β_4 because our data include the following type of partner changes for some firms. Suppose a Mexican exporter Y trades with two US importers X_1 and X_2 where X_1 is the main partner for Y, and Y is the main partner for both X_1 and X_2. Then, suppose X_1 stops importing from Y, but X_2 continues importing from Y. In this case we observe partner downgrading for Mexican exporter Y, but no partner change for US importer X_2. This type of transactions causes β_1 to be estimated smaller then β_4. If we define firm's partner change more narrowly as a switch of the main partner to the one with which the firm did not trade in 2004, then this new definition does not count Mexican exporter Y's partner change from X_1 to X_2 as partner downgrading in the above case. When we use this definition and run the same regression analysis, we find the estimates of β_1 and β_4 remain

The positive estimate of β_1 also implies a previously-undocumented type of trade diversion induced by the NAFTA. Trade diversion is usually documented in terms of prices: with protection on imports from third countries (e.g. the MFA), a preferential trade agreement (e.g. the NAFTA) induces importers to buy goods from partner countries at high prices. We find that trade diversion takes a form of "mismatching" of importers and exporters. With the MFA import quotas, the NAFTA forced the US firms to match with Mexican suppliers of lower capabilities. The end of the MFA allowed US firms to match with Mexican suppliers of higher capabilities, even if they did not switch completely to Chinese exporters. This dissolution of "mismatching" is a previously-undocumented type of gain from trade liberalization.

5.2 Robustness Checks

5.2.1 Different Time Periods

Choice of the End Year Panel A in Table 4 reports estimates of β_1 and β_4 by fixing the initial year to 2004 and changing the end year to 2006, 2007 and 2008. This exercise has two aims. The first is to show that the documented higher probabilities of partner upgrading of US importers and partner downgrading of Mexican exporters in the liberalized products are not sensitive to the choice of the end year. All estimated coefficients on β_1 and β_4 in Table 4 are positive and statistically significant. The second aim is to show that the adjustment from the old equilibrium to the new one is gradual. Column (1) finds $\beta_1 = 0.036$ of 2004-06 data much smaller than $\beta_1 = 0.052$ of 2004-07 data in Column (2). This means that the impact of liberalization on US importer's partner upgrading substantially increases from 2006 to 2007, suggesting that partner changes take place gradually probably due to some transaction costs. Similarly, the estimate of β_4 increases from $\beta_4 = 0.056$ of 2004-06 data in Column (4) to $\beta_4 = 0.127$ of 2004-07 data in Column (5).

Differential Background Trends Panel B in Table 4 reports estimates of β_1 and β_4 by fixing the end year to 2011 and changing the initial year to 2007, 2008 and 2009. This exercise aims to check our crucial assumption: the markets of the products that had binding quotas and the markets of other products would have behaved similarly in the absence of the end of MFA. If instead these two product groups had differential background time trends in partner changes, positive estimates of β_1 and β_4 may arise from these differential trends instead of the causal effect of the MFA quota removal. In Figure 4 we have already shown that there is no differential time trend in the aggregate export volumes before the MFA quota removal in 2005. Unfortunately, we are not able to do this check at the firm level since our data contain information only from June 2004. Therefore, we conduct another check.

For each period with a different initial year from 2007 to 2009, we construct the capability ranking based on trade volume in the new initial year and re-create the upgrading/downgrading dummies. If our

significant and the two estimates become closer to each other.

positive estimates of β_1 and β_4 for 2004-2007 arise from differential time trends, it is likely that these regressions with different initial years still find positive significant estimates for β_1 and β_4. On the other hand, if our positive estimates of β_1 and β_4 for 2004-2007 capture the causal effect of the MFA quota removal and if the adjustment of matching to a new equilibrium is mostly completed by 2007, we should not observe any positive and significant estimates for β_1 and β_4 for the regressions for later years.

Panel B in Table 4 shows the results. We find very small and insignificant estimates for β_1 and β_4 for 2007-2011 (Columns (7) and (10)) and 2009-2011 (Columns (9) and (12)). These results support our assumption. For the period 2008-2011 ((Columns (8) and (11)), both β_1 and β_4 have somewhat greater point estimates than other periods, though they are still much smaller than the estimates from our main regressions for 2004-2007, and β_4 becomes statistically significant. One possible reason for the big difference between 2008-2011 and the other two periods is the effect of the Lehman crisis and the Great Trade Collapse in 2008. As exports from other countries, the Mexican exports declined by a huge amount in the second half of 2008. This shock might introduce a noise in ranking. Overall, we find no evidence that potential differential trends across product groups account for our baseline results.

5.2.2 Additional Controls

Table 5 report estimates of β_1 and β_4 from regressions (9) including additional control variables. Columns (1) and (4) reproduce our baseline estimates from Table 3 for reference. A unique feature of the Mexico-US trade is that it includes a substantial amount of duty-free processing trade (Maquiladora/IMMEX). If the systematic partner changes we find happen only in Maquiladora/IMMEX trade and not in other normal trade, our findings may be specific to the Mexico-US trade and would have a limited implication for other countries. To check this point, columns (2)-(3) and (5)-(6) include the share of Maquiladora trade in the firm's trade in the product with the main partner in 2004 and its interaction with the Binding dummy. With controls on Maquiladora trade, estimates of β_1 and β_4 still remain statistically significant and similar in magnitude. Furthermore, the coefficients of the interaction terms are insignificant, which means that the partner changes happen both in processing trade and normal trade.

We consider that the MFA quota removal is exogenous since they were scheduled before China started expanding exports. However, which products were liberalized in 2005 might be correlated with product or industry characteristics that vary within a HS 2 digit chapter. The lower panel of Table 5 presents the results of our analysis that controls for the difference in transaction size, product characteristics and geography between the treatment and control groups. Columns (7) and (10) include trade volume of the product with the main partner in 2004. Columns (8) and (11) include dummies on whether products are for men, women or not specific to gender and those on whether products are made of cotton, wool or man-made (chemical) textile.[30] Columns (9) and (12) include Mexican state dummies of the

[30]These product characteristics dummies are essentially for apparel products. Since HS 2 categories for textile products are defined on differences in materials, HS 2 digit chapter fixed effects absorb these product characteristics dummies.

location of Mexican exporters. With these additional controls, estimates of β_1 and β_4 remain statistically significant and similar in magnitude.

5.2.3 Alternative Capability Measures

As measures of capability rankings we have used the rankings of exporters and importers based on trade volume with their main partners in 2004. Although this is in line with our theoretical framework, we estimate our main regressions using two alternative rankings.

The first alternative is a ranking based on the total product-level trade volume of a firm aggregated over partners. Columns labeled "Total Trade" reports estimates using this ranking. As Table 2 suggests, most firms concentrate their trade volume on their trade with their main partners. Therefore, our baseline ranking based on trade volume with the main partners and the alternative one based on the total product volume yield very similar results.

The second alternative is a ranking based on the unit price of trade of the product with the main partner. If the size of exporters are mainly explained by their quality rather than productivity, the ranking of unit prices may agree with the true capability ranking of exporters. On the other hand, if the size of exporters are mainly explained by productivity instead, the ranking of unit prices may become the exact reversal of the true capability ranking of exporters. If Case-C holds, we should observe $\beta_2 > 0$, $\beta_3 > 0$ and $\beta_1 = \beta_4 = 0$ instead.

A difficulty in using unit prices is that even within a narrowly defined product category, different firms may report their quantities in different units of measurement (square meters, kg, pieces, etc.). Since one exporter consistently uses the same unit for one product in our data, we treat transactions of one product reported in one unit and those of the same product reported in a different unit as transactions of two different products.

Columns labeled "Price" report estimates using this ranking and confirm the main results. Both β_1 and β_4 are positive and significant, while β_2 and β_3 are insignificant. The results suggests that exporters are on average ranked by product quality. This is consistent with the previous finding that high quality is an important determinant of firm exports.[31] In addition to this previous finding, our results suggest that exporters need to produce high quality products in order to match with high capable importers.[32]

[31] See e.g. Kugler and Verhoogen (2012), and Manova and Zhang (2012) for studies using firm-level data and Baldwin and Harrigan (2011), Bernard et al. (2007), Helble and Okubo (2008), and Johnson (2012) for studies using product-level data. In terms of the data, our study is close to Manova and Zhang (2012) who investigates positive correlations between export volumes and unit prices across exporters and products. We also find a positive correlation between them in our data.

[32] Estimates of β_1 and β_4 under the unit price ranking are smaller than those under the baseline ranking. One reason for this difference might be that whether exporters are differentiated by productivity or quality is not universal across products, but heterogeneous across products (e.g. Baldwin and Ito, 2011; Mandel, 2009). If firms are differentiated mainly by productivity in some products, that would reduce the size of β_1 and β_4.

5.3 Alternative Explanations

US importer partner upgrading and Mexican exporter partner downgrading might be explained by alternative hypotheses. This section discusses such alternative hypotheses and presents additional evidence to show that these alternative hypotheses do not fully explain our results.

5.3.1 Negative Assortative Matching

So far we have focused on Case-C positive assortative matching and Case-I random matching in our model. Appendix shows that Case-S negative assortative matching may predict our finding, $\beta_1 > 0$, $\beta_4 > 0$ and $\beta_2 = \beta_3 = 0$ in the following two cases. Case A: (A1) import volume of final producers $I(x)$ is monotonically decreasing in its own capability x and (A2) the number of Mexican exiting exporters is sufficiently small. Case B: (B1) export volume of Mexican suppliers $X(y)$ is monotonically decreasing in its own capability y and (B2) the number of Mexican exiting exporters is sufficiently large.

The conditions (A1) and (B1) are unlikely to be satisfied since they contradicts with a well-established fact that when an industry is hit by a negative shock (e.g. tariff cuts), small firms are more likely to exit than large firms. Notice that even under negative assortative matching, there are the capability cut-offs x_L and y_L such that firms with lower capability than the cut-off exit (see equation (7)). Therefore, when firms are hit by a negative shock, those with the lowest capability are more likely to exit as in standard models with heterogeneous firms. When a firm's trade volume, which is proportional to the scale of operation, is strictly decreasing in its capability, the model predicts that the largest traders are more likely to exit than small traders when their industry is hit by a negative shock. This is the opposite to the well-established finding that small firms are more likely to exit than large firms. Therefore, the case of negative assortative matching is unlikely to explain our findings.

5.3.2 Random Matching with Exogenous Breakups

Another alternative model that predicts $\beta_1 > 0$ and $\beta_4 > 0$ is a random matching model with exogenous breakups. In this model, matches exogenously breakup with some constant rate and firms that lost partners randomly match with each other. This combination of exogenous breakup and random matching often appears in dynamic search models. The random matching may create mean reversion: among firms who break up, firms that traded with low capable partners are more likely to trade with high capable partners. In other words, (1) large firms are more likely to downgrade the partners in absence of the MFA shock. On the other hand, the MFA shock force low capable firms to stop exporting. Since our sample drops exiting exporters, (2) our sample is likely to include high capable large exporters in the treatment group. If (1) and (2) hold, they might mechanically yield a higher probability of Mexican exporters' partner downgrading in the treatment group than in the control group. If this explains a positive estimate of β_4, we cannot interpret it as evidence of positive assortative matching based on complementarity.

This random matching model fails to account for the zero estimate of β_3 in Tables 3. If this hypothesis were true, Mexican exporters should upgrade more frequently in the control group, where low-capable Mexican exporters survive more than the treatment group. This means that we should observe a negative and significant estimate of β_3, but we do not. The same argument will apply to β_1. Therefore, we reject this hypothesis.

5.3.3 Segment Switching

Another explanation for $\beta_1 > 0$ and $\beta_4 > 0$ is a model of product segment switching inspired by Holmes and Stevens (2014). Even one HS 6 digit product category may have two different segments. One "standardized" segment is produced in large scale but sold with low markups, while the other "custom" segment is produced in small scale but sold with high markups. Suppose that large US importers produce "standardized" products, while small US importers produce "custom" products. Suppose that as Holmes and Stevens (2014) argue, Chinese exporters enter mainly in "standardized" products. If Mexican exporters switched from "standardized" to "custom" products to escape competition from China, this change might be observed as Mexican exporters' downgrading and US importers' upgrading in our regressions.[33]

To explore the validity of this "segment-switching" hypothesis, we perform three additional regressions in Table 7 testing the following three predictions. If trade volume of a firm in 2004 indicates the segment of the firm, small firms and large firms should respond to the end of the MFA in heterogeneous ways. First, small "custom" US importers should increase their trade volume more rapidly than large "standardized" US importers, as small "custom" US importers should become more attractive to Mexican exporters and able to match more capable Mexican exporters. Second, small "custom" US importers should upgrade the main partners more frequently than large "standardized" US importers. Finally, partner downgrading of Mexican exporters should be concentrated in those who initially trade with large "standardized" US importers in 2004.

To test these three predictions, in Table 7 we shows the results of regressions of each of three dependent variables, US importer's import growth (Column 1), US Importer Partner Upgrading dummy (Column 2), and Mexican Exporter Partner Downgrading dummy (Column 3) on a common set of variables: the Binding dummy, the firm's rank in 2004, and the interaction of these two, together with HS 2 digit sector fixed effects. The heterogeneous responses of small firms and large firms should appear in the coefficients of the interaction terms.

In all of the three exercises, we find no evidence supporting the hypothesis. The interaction term

[33] The existence of multiple segments within one product category does not change the interpretation of our main regressions if Mexican firms do not switch segments. In the case of the assortative matching, it still holds that Mexican exporters downgrade and US importers upgrade their main partners in the "standardized" segment, while firms do not change partners in the "custom" segment. On the other hand, the existence of multiple segments might help to explain why not all firms change their partners even in liberalized industries.

in Column (1) suggests that the growth of small “custom” US importers relative to large “standardized” US importers is not larger in the treatment group than in the control group. The interaction term in Column (2) suggests that small “custom” US importers do not upgrade the main partners more frequently than large “standardized” US importers in the treatment group than in the control group. Finally, the interaction term in Column (3) suggests that downgrading of the main partners happens in the entire range of Mexican exporters’ initial ranking and is not concentrated among those who had large trade volume with the main partners. Overall, we do not find evidence consistent with the segment-switching hypothesis, thus we conclude that this alternative hypothesis cannot explain our main results.[34]

6 Conclusion

The heterogeneous firm trade literature has successfully documented the heterogeneity of exporters and importers in their capability, however our knowledge about how heterogeneous importers and exporters trade with each other has been still limited. We have identified a simple mechanism behind matching of exporters and importers at the product level: Becker-type positive assortative matching by capability. We have found that when trade liberalization allows foreign suppliers to enter, existing firms change partners so that matching becomes positive assortative under a new environment. Our model combining Becker (1973) and Melitz (2003) interprets this re-matching as evidence for a new source of gains from trade associated with firm heterogeneity.

The Becker mechanism has been applied for various topics in other fields of economics, but the application for exporter-importer matching is still limited. We believe this mechanism potentially sheds new light on several questions that anonymous market models fail to address. For instance, our finding suggests that many firms are willing to trade with high capable firms, but only high capable firms can trade with them. This view that all importers are not equally valuable and available for all exporters seems relevant for policy discussions that often encourage domestic firms to export particularly to high capable foreign buyers.

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Table 3: Baseline Regressions

A: US Importer's Partner Changes during 2004-07

	$Upgrading^{US}(\beta_1)$		$Downgrading^{US}$ (β_2)	
	Linear Prob.	Probit	Linear Prob.	Probit
	(1)	(2)	(3)	(4)
Binding	0.052**	0.052***	-0.017	-0.017
	(0.021)	(0.020)	(0.027)	(0.024)
Sector FE (HS2)	Yes	Yes	Yes	Yes
Obs.	718	707	718	707

B: Mexican Exporter's Partner Changes during 2004-07

	$Upgrading^{Mex}(\beta_3)$		$Downgrading^{Mex}$ (β_4)	
	Linear Prob.	Probit	Linear Prob.	Probit
	(5)	(6)	(7)	(8)
Binding	-0.003	-0.003	0.127***	0.150***
	(0.020)	(0.019)	(0.035)	(0.044)
Sector FE (HS2)	Yes	Yes	Yes	Yes
Obs.	601	522	601	601

Note: The dependent variables $Upgrading^c_{igs}$and $Downgrading^c_{igs}$ are dummy variables indicating whether during 2004-07 firm i in country c switched the main partner of HS 6 digit product g in country c' to the one with a higher capability rank and to the one with a lower capability rank, respectively (c=Mexico and c'=US in Panel A; c=US and c'=Mexico in Panel B). $Binding_{gs}$ is a dummy variable indicating whether product g from China faced a binding US import quota in 2004. All regressions include HS 2 digit (sector) fixed effects. Standard errors are shown in parentheses and clustered at the HS 6 digit product level. Significance: * 10 percent, ** 5 percent, *** 1 percent.

Table 4: Partner Changes in Different Periods

A: Gradual Partner Changes

	Partner Changes in Different Periods: Linear Probability Models					
	US Importers			Mexican Exporters		
	$Upgrading^{US}(\beta_1)$			$Downgrading^{Mex}$ (β_4)		
	2004-06	2004-07	2004-08	2004-06	2004-07	2004-08
	(1)	(2)	(3)	(4)	(5)	(6)
Binding	0.036**	0.052**	0.066**	0.056*	0.127***	0.121***
	(0.015)	(0.021)	(0.027)	(0.031)	(0.035)	(0.032)
Sector FE (HS2)	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	964	718	515	767	601	442

B: Placebo Checks

	Partner Changes in Different Periods: Linear Probability Models					
	US Importers			Mexican Exporters		
	$Upgrading^{US}(\beta_1)$			$Downgrading^{Mex}$ (β_4)		
	2007-11	2008-11	2009-11	2007-11	2008-11	2009-11
	(7)	(8)	(9)	(10)	(11)	(12)
Binding	-0.001	0.027**	-0.000	-0.008	0.047	0.005
	(0.018)	(0.011)	(0.006)	(0.036)	(0.031)	(0.020)
Sector FE (HS2)	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	449	575	747	393	499	655

Note: The dependent variables $Upgrading^c_{igs}$and $Downgrading^c_{igs}$ are dummy variables indicating whether during the period indicated by each column, firm i in country c switched the main partner of HS 6 digit product g in country c' to the one with a higher capability rank and to the one with a lower capability rank, respectively (c=Mexico and c'=US in (1)-(3) and (7)-(9); c=US and c'=Mexico in (4)-(6) and (10)-(12)). $Binding_{gs}$ is a dummy variable indicating whether product g from China faceda binding US import quota in 2004. All regressions include HS 2 digit (sector) fixed effects. Standard errors are shown in parentheses and clustered at the HS 6 digit product level. Significance: * 10 percent, ** 5 percent, *** 1 percent.

Table 5: Regressions with Additional Controls

Partner Changes during 2004-07: Linear Probability Models

	US Importers			Mexican Exporters		
	$Upgrading^{US}(\beta_1)$			$Downgrading^{Mex}(\beta_4)$		
	(1)	(2)	(3)	(4)	(5)	(6)
Binding	0.052***	0.053**	0.074**	0.127**	0.127***	0.103**
	(0.020)	(0.022)	(0.029)	(0.044)	(0.035)	(0.042)
Maquila Ratio		-0.015	0.015		-0.025	-0.058*
		(0.017)	(0.019)		(0.024)	(0.031)
Maquila Ratio*Binding			-0.053			0.062
			(0.032)			(0.049)
Sector FE (HS2)	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	718	718	718	601	601	601

	US Importers			Mexican Exporters		
	$Upgrading^{US}(\beta_1)$			$Downgrading^{Mex}(\beta_4)$		
	(7)	(8)	(9)	(10)	(11)	(12)
Binding	0.049**	0.042*	0.048**	0.123***	0.130***	0.117***
	(0.022)	(0.024)	(0.022)	(0.038)	(0.037)	(0.035)
Log Volume2004	0.002			0.002		
	(0.004)			(0.007)		
Product Characteristics		Yes			Yes	
Mexican State FE			Yes			Yes
Sector FE (HS2)	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	718	718	707	601	601	588

Note: The dependent variables $Upgrading^c_{igs}$and $Downgrading^c_{igs}$ are dummy variables indicating whether during 2004-07 firm i in country c switched the main partner of HS 6 digit product g in country c' to the one with a higher capability rank and to the one with a lower capability rank, respectively (c=Mexico and c'=US in columns (1)-(3) and (7)-(9); i=US and j=Mexico in columns (4)-(6) and (10)-(12)). $Binding_{gs}$ is a dummy variable indicating whether product g from China faced a binding US import quota in 2004. $Maquila\ Ratio_{ig}$ is the share of duty free processing trade (Maquiladora) in firm $i's$ trade volume of product g with the main partner in 2004. $Volume2004_{ig}$ is firm i's trade volume in 2004. Product Characteristics are a collection of dummy variables indicating whether products are Men's, Women's, cotton, wool and man-made (chemical). All regressions include HS 2 digit (sector) fixed effects. Standard errors are shown in parentheses and clustered at the HS 6 digit product level. Significance: * 10 percent, ** 5 percent, *** 1 percent.

Table 6: Regressions Using Alternative Capability Rankings

Partner Changes during 2004-07: Linear Probability Models

	US importers					
	$Upgrading^{US}(\beta_1)$			$Downgrading^{US}$ (β_2)		
	Baseline	Total Trade	Price	Baseline	Total Trade	Price
	(1)	(2)	(3)	(4)	(5)	(6)
Binding	0.052**	0.052**	0.045**	-0.017	-0.017	-0.011
	(0.021)	(0.021)	(0.018)	(0.027)	(0.027)	(0.024)
Sector FE (HS2)	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	718	718	706	718	718	706

	Mexican Exporters					
	$Upgrading^{Mex}(\beta_3)$			$Downgrading^{Mex}$ (β_4)		
	Baseline	Total Trade	Price	Baseline	Total Trade	Price
	(7)	(8)	(9)	(10)	(11)	(12)
Binding	-0.003	0.001	0.041	0.127***	0.123***	0.067**
	(0.020)	(0.019)	(0.030)	(0.035)	(0.035)	(0.027)
Sector FE (HS2)	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	601	601	591	601	601	591

Note: The dependent variables $Upgrading^c_{igs}$and $Downgrading^c_{igs}$ are dummy variables indicating whether during 2004-07, firm i in country c switched the main partner of HS 6 digit product g in country c' to the one with a higher capability rank and to the one with a lower capability rank, respectively (c=Mexico and c'=US in (1)-(6); c=US and c'=Mexico in (7)-(12)). Columns differ in variables on which rankings of capability are based. (Baseline: firm i's trade volume of product g with the main partner in 2004; Total Trade: firm i's trade volume of product g in 2004; Price: unit prices of product g in firm's trade with the main partner). $Binding_{gs}$ is a dummy variable indicating whether product g from China faced a binding US import quota in 2004. All regressions include HS 2 digit (sector) fixed effects. Standard errors are shown in parentheses and clustered at the HS 6 digit product level. Significance: * 10 percent, ** 5 percent, *** 1 percent.

Table 7: Segment-Switching Hypothesis

	US importers		Mexican Exporters
	$\Delta \ln Imports$	$Upgrading^{US}(\beta_1)$	$Downgrading^{Mex}$ (β_4)
	OLS	Linear Prob.	Linear Prob.
	(1)	(2)	(3)
Binding	-0.061	0.62***	0.132***
	(0.292)	(0.024)	(0.038)
Rank2004	0.022***	0.002***	-0.001*
	(0.006)	(0.001)	(0.001)
Binding	-0.016**	-0.002*	0.000
*Rank2004	(0.008)	(0.001)	(0.001)
Sector FE (HS2)	Yes	Yes	Yes
R-Squared	0.018	0.060	0.034
Obs.	966	601	718

Note: The dependent variable $\Delta \ln Imports$ in Column 1 is the log difference of firm's import volume between 2004-07. The dependent variables $Upgrading^{c}_{igs}$and $Downgrading^{c}_{igs}$ are dummy variables on whether during 2004-07, firm i in country c switched the main partner of HS 6 digit product g in country c' to the one with a higher capability rank and to the one with a lower capability rank, respectively (c=US and c'=Mexico in column (2) an c=Mexico and c'=US in column (3)).$Binding_{gs}$ is a dummy variable on whether product g from China faced a binding US import quota in 2004. $Rank2004$ is firm's capability rank in 2004. All regressions include HS 2 digit p(sector) fixed effects. Standard errors are shown in parentheses and clustered at the HS 6 digit product level. Significance: * 10 percent, ** 5 percent, *** 1 percent.

Appendix

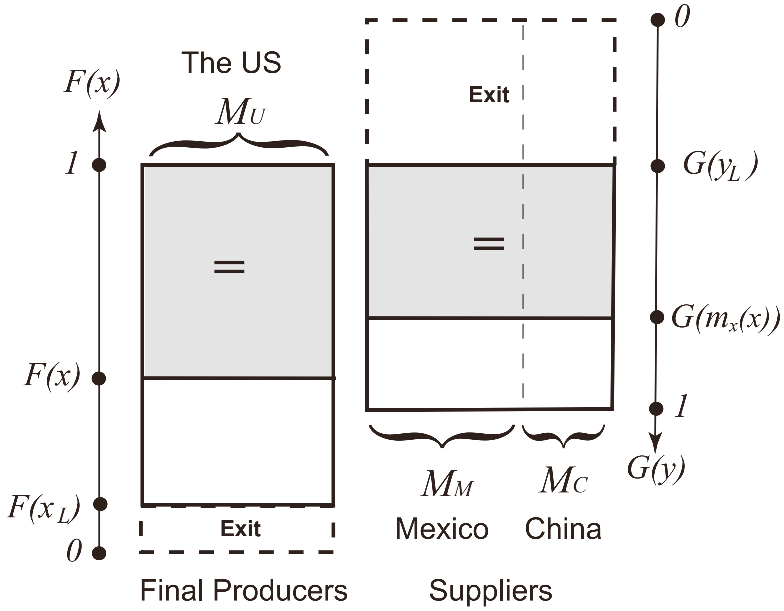
A.1 Negative Assortative Matching

In Case-S, the market clearing condition becomes

$$M_U[1-F(x)] = (M_M + M_C)\left[G\left(m_x\left(x\right)\right) - G(y_L)\right]. \tag{11}$$

The left hand side is the mass of final producers with higher capability than x and the right hand side is the mass of suppliers with lower capability than $m_x(x)$. Figure 5 describes the matching market clearing condition (11). The left rectangle for suppliers is described in the same way as in Figure 2. The right rectangle describes the rectangle for US final producers in Figure 2 turned upside down. Therefore, a lower position in the rectangle expresses a higher capability. The right gray area is equal to the mass of US final producers whose capability is between $m_x(x)$ and y_L. The matching market clearing condition (11) requires the two gray areas to have the same size for all x.

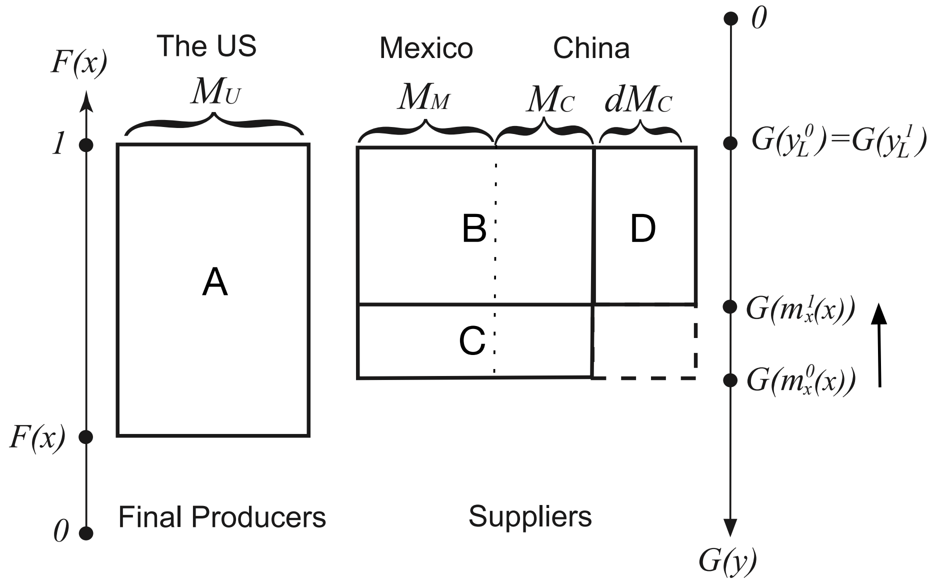
Figure 5: Case-S: Negative Assortative Matching (NAM))



Suppose the mass of Chinese suppliers increases ($dM_C > 0$). In Case-S, the change in matching is complex since the matching market clearing condition includes the cut-off of suppliers y_L. We consider a normal case in which the cut-off of suppliers increases from y_L^0 to y_L^1 due to increased competition.

Figure 6 describes how importers with capability x change their partners from $m_x^0(x)$ to $m_x^1(x)$ when y_L is fixed at the pre-liberalization level y_L^0. The figure looks similar to Figure 3 of the case of PAM. Area A in Figure 6 expresses US importers with higher x. These final producers initially match with suppliers with lower capability than $m_x^0(x)$, whose mass is expressed by Areas $B+C$. After the entry of Chinese exporters, more suppliers at given capability level are available for US final producers. Existing matching becomes unstable. In a new matching, final producers in Area A matches with Areas $B+D$ that has the same size and represents suppliers with lower capability than $m_x^1(x)$. The figure shows that any US final producer with given capability x downgrade their suppliers from those with capability $m_x^0(x)$ to the ones with capability $m_x^1(x)$. In turn, consider Mexican suppliers and existing Chinese suppliers with capability $m^1(x)$. They used to match with final producers with higher capacity than x (in the interior of Area A), but switches the main partners to the ones with lower capability x. In summary, all of US final producers, Mexican suppliers, and incumbent Chinese suppliers downgrade their partners.

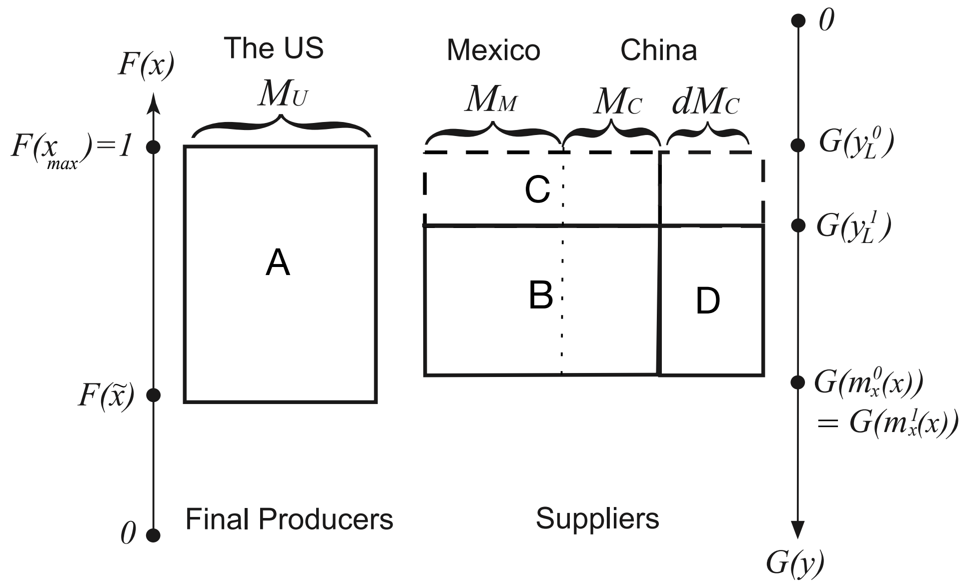
Figure 6: Case-S: the Response of Matching to Entry of Chinese Exporters ($dM_C > 0$) if $y_L = 0$.



The increase in y_L adds another effect. Under negative assortative matching, final producers with the maximum capability x_{max} match with suppliers with the new cut-off y_L^1. Since these final producers used to match with suppliers with the old cut-off y_L^0, it means that final producers with the maximum capability upgrade their partners. This in turn means that suppliers with the new cut-off y_L^1 upgrade their partners, too. These two examples show that in contrast to the case where y_L does not change, there are some final producers and suppliers that upgrade their partners when y_L increases.

Figure 7 shows a threshold cut-off level $\tilde{x}$ such that final produces with capability $\tilde{x}$ neither upgrade nor downgrade their partners. In the figure, $\tilde{x}$ is chosen so that the size of Area C, the mass of exiting suppliers, is equal to the size of Area D, the mass of Chinese entrants with lower capability than $m_x^0(\tilde{x})$. Final producers with higher capability than $\tilde{x}$ in Area A used to match with suppliers in Area $B+C$. After the Chinese entry, they match with suppliers in Area $B+D$. Since Areas C and D have the same size, we have $m_x^0(\tilde{x}) = m_x^1(\tilde{x})$. Notice that the mass of the Chinese entrants with lower capability than y is smaller than the mass of exiting suppliers (Area C) if $y < m_x^0(\tilde{x})$, while it is larger if $y > m_x^0(\tilde{x})$. Therefore, For $x > \tilde{x}$ and $y < m_x^0(\tilde{x})$, US final producers and existing suppliers both upgrade their partners. For $x < \tilde{x}$ and $y > m_x^0(\tilde{x})$, US final producers and existing suppliers both downgrade their partners. Finally, the figure also shows that the threshold $\tilde{x}$ decreases in the mass of exiting suppliers and increases in the mass of new Chinese entrants.

Figure 7: Case-S: the Response of Matching to an Entry of Chinese Exporters ($dM_C > 0$).



Proposition 3. *Suppose that the mass of Chinese suppliers increases in Case-C. There exist a threshold capability $\tilde{x}$ of final producers. (1) US final producers with $x > \tilde{x}$ and suppliers that matched with them switch their partners to those with higher capability (partner-upgrading). (2) US final producers with $x < \tilde{x}$ and suppliers that matched with them switch their partners to those with lower capability (partner-downgrading). (3) The threshold $\tilde{x}$ decreases in the mass of exiting suppliers and increases in the mass of new Chinese entrants.*

Implications for our regressions

Our strategy to proxy capability ranking by trade volume ranking relies on the monotonicity between firm's capability and trade volume. This monotonicity may not hold in the case of negative assortative matching. The derivatives of final producer's import volume, $I(x) = T(x, m_x(x))$, and supplier's export volume, $I(y) = T(m_y(y), y)$, with respect to their capabilities are

$$I'(x) = \frac{\partial T}{\partial x} + \frac{\partial T}{\partial y} m_x'(x) \text{ and } X'(y) = \frac{\partial T}{\partial x} m_y'(y) + \frac{\partial T}{\partial y}.$$

The signs of $I'(x)$ and $X'(y)$ are generally ambiguous since $\partial T/\partial x > 0$, $\partial T/\partial m_x(x) > 0$, and $m_x'(x) < 0$.

Table 8: The Prediction of Case-S on the Signs of β_i in Our Regressions

	$I(x)$		
	Non-monotonic	Decreasing	Increasing
Low $\tilde{x}$	$\beta_i > 0 (i = 1, .., 4)$	$\beta_2 > 0$,$\beta_3 > 0$,$\beta_1 = \beta_4 \simeq 0$	$\beta_1 > 0$,$\beta_4 > 0$,$\beta_2 = \beta_3 \simeq 0$
High $\tilde{x}$		$\beta_1 > 0$,$\beta_4 > 0$,$\beta_2 = \beta_3 \simeq 0$	$\beta_2 > 0$,$\beta_3 > 0$,$\beta_1 = \beta_4 \simeq 0$
Intermediate $\tilde{x}$		$\beta_i > 0\ (i = 1, .., 4)$	

Without loss of generality, we can consider three cases: (i) $I(x)$ is non-monotonic in x; (ii) $I(x)$ is monotonically increasing in x; (iii) $I(x)$ is monotonically decreasing in x. For each case, consider what we should observe in estimates of β_i from our regression. Proposition 3 shows the direction of partner changes depends on the threshold $\tilde{x}$. Therefore, we also consider three cases: (a) $\tilde{x}$ is low so that most final producers with higher capability than $\tilde{x}$; (b) $\tilde{x}$ is high so that most final producers with higher capability than $\tilde{x}$; (c) $\tilde{x}$ is intermediate so that final producers are equally divided into one group with capability $x > \tilde{x}$ and the other with $x < \tilde{x}$. Therefore, there are in total 3*3=9 cases to be considered.

Table 8 summarizes what each of the 9 cases predicts on the signs of β_i in our regressions. First of all, if $I(x)$ is non-monotonic, then export volume $X(y)$ is also non-monotonic. In this case, we should observe partner changes in both directions so that $\beta_i > 0$ for all equations $i = 1, ..., 4$. Second, if $\tilde{x}$ is intermediate, some of firms upgrade and some of firms downgrade the partners. Again in this case we should observe partner changes in both directions regardless of how we rank firms. Therefore, this case also predicts $\beta_i > 0$ for $i = 1, ..., 4$. Third, suppose $I(x)$ is decreasing. This means that $X(y) = I(m_y(y))$ is increasing since $X'(y) = I'(m_y(y))m_y'(y) > 0$. The ranking of US final producers by import volume is an exact opposite of the true capability ranking, but the ranking of Mexican exporters by export volume agrees with the true capability ranking. Proposition 3 implies that for $x > \tilde{x}$, we should observe partner downgrading by US final producers and partner upgrading by Mexican exporters for the treatment group. Therefore, if $\tilde{x}$ is low, we should observe $\beta_2 > 0$,$\beta_3 > 0$, and $\beta_1 = \beta_4 \simeq 0$. On the other hand, for $x < \tilde{x}$, we should observe partner upgrading by US final producers and partner downgrading by Mexican exporters. Therefore, if $\tilde{x}$ is high, we should observe $\beta_1 > 0$, $\beta_4 > 0$, and $\beta_2 = \beta_3 \simeq 0$. Finally, suppose $I(x)$ is increasing. This means that $X(y) = I(m_y(y))$ is decreasing since $X'(y) = I'(m_y(y))m_y'(y) < 0$. The ranking of US final producers by import volume agrees with the true capability ranking, but the ranking of Mexican exporters by export volume is the exact opposite of the true capability ranking. Proposition 3 implies that for $x > \tilde{x}$, we should observe partner upgrading by US final producers and partner downgrading by Mexican exporters for the treatment group. Therefore, if $\tilde{x}$ is low, we should observe $\beta_1 > 0$, $\beta_4 > 0$, and $\beta_2 = \beta_3 \simeq 0$. On the other hand, for $x < \tilde{x}$, we should observe partner downgrading by US final producers and partner upgrading by Mexican exporters.

Therefore, if $\tilde{x}$ is high, we should observe $\beta_2 > 0$, $\beta_3 > 0$, and $\beta_1 = \beta_4 \simeq 0$.

From Table 8, Case-S can predict our finding $\beta_1 > 0$, $\beta_4 > 0$, and $\beta_2 = \beta_3 \simeq 0$ in the following two cases. Case A: (A1) import volume of final producers $I(x)$ is monotonically decreasing in its own capability x and (A2) the number of Mexican suppliers stop exporting is sufficiently small [i.e. $\tilde{x}$ is high]. Case B: (B1) export volume of Mexican suppliers $X(y)$ is monotonically decreasing in its own capability y [i.e. $I(x)$ is monotonically increasing in x] and (B2) the number of Mexican suppliers stop exporting is sufficiently large [i.e. $\tilde{x}$ is low].

A.2 Data Construction

Customs transaction data Our primary data set is the Mexican customs transaction data set for Mexican textile/apparel exports to the US. The data set is created from the administrative records on every transaction crossing the Mexican border from June 2004 to December 2011. The Mexican customs agency requires both individuals and firms who ship goods across the border to submit a customs form (pedimento aduanal in Spanish) that must be prepared by an authorized agent. The form contains information on: (1) the total value of shipment (in US dollars); (2) the 8 digit HS product code (we use from HS50 to HS63); (3) the quantity; (4) the name, the address and the tax identification number of the Mexican exporter; (5) the name, the address and the tax identification number (employment identification number, EIN) of the US importer, and other information.

Assign firm IDs We assigned identification numbers for both Mexican exporters and US importers (exporter-ID and importer-ID) throughout the data set. It is straightforward to assign exporter-ids for Mexican exporters since the Mexican tax number uniquely identifies each Mexican firm. However, there exists a challenge for assigning importer-ids for US firms. It is known that one US firm often has multiple names, addresses, and EINs. This happens because a firm sometimes uses multiple names or changes names, owns multiple plants, and changes tax numbers. Therefore, simply matching firms by one of three linking variables (names, addresses and EINs) would wrongly assign more than one id for one US buyer and would result in overestimating the number of US buyers for each Mexican exporter.

We used a series of methods developed in the record linkage research for data cleaning to assign importer-ID.[35] First, since the focus of our study is firm-to-firm matching, we dropped transactions for which exporters were individuals and courier companies (e.g. FedEx, UPS, etc.). Second, a company name often included generic words that did not help identify a particular company such as legal terms (e.g. "Co.") and words commonly appearing in the industry (e.g. "apparel"). We removed these words from company names. Third, we standardized addresses by a software, ZP4, which received a CASS

[35] An excellent textbook for record linkage is Herzog, Scheuren, and Winkler (2007). A webpage of "Virtual RDC@Cornell" (http://www2.vrdc.cornell.edu/news/) at Cornell University is also a great source of information on data cleaning. We particularly benefit from lecture slides on "Record Linkage" by John Abowd and Lars Vilhuber.

certification of address cleaning by the United States Postal Services. Fourth, we prepared lists of fictitious names, previous names and name abbreviations, a list of addresses of company branches, and a list of EINs from data on company information, Orbis made by Bureau van Dijk, which covered 20 millions company branches, subsidiaries, and headquarters in the US. We used Orbis information for manufacturing firms and intermediary firms (wholesales and retails) due to the capacity of our workstation. For each HS 2 digit industry, we matched names within customs data and names between customs data and name lists from Orbis mentioned above; we did similar matches for address and EIN. When matching them, we used fuzzy matching techniques allowing small typographical errors.[36] Fifth, using matched relations and a software of the network theory, we created clusters of information (names, addresses, EINs) in which one cluster identifies one firm. We identified a cluster basically under a rule that each entry in a cluster fuzzy matches with some other entries in the cluster through two of three linking variables (names, addresses, EINs). Finally, we assigned importer-ids for clusters.

A3. Solving the Model

Consumer Maximization

The representative consumer maximizes the following utility function:

$$U = \frac{\delta}{\rho}\ln\left[\int_{\omega\in\Omega}\theta(\omega)^{\alpha}q(\omega)^{\rho}d\omega\right] + q_0 \text{ s.t. } \int_{\omega\in\Omega}p(\omega)q(\omega)d\omega + q_0 = I.$$

This is equivalent with maximizing

$$U = \frac{\delta}{\rho}\ln\left[\int_{\omega\in\Omega}\theta(\omega)^{\alpha}q(\omega)^{\rho}d\omega\right] - \int_{\omega\in\Omega}p(\omega)q(\omega)d\omega + I.$$

The first order conditions are

$$\frac{\delta\theta\left(\omega\right)^{\alpha}q\left(\omega\right)^{\rho-1}}{\int_{\omega'\in\Omega}\theta(\omega')^{\alpha}q(\omega')^{\rho}d\omega'} = p\left(\omega\right). \tag{12}$$

[36]We used Jaro-Winkler metric in the Record Linkage package of R and other methods, which will be explained in the next version.

For any two varieties ω and ω', we have

$$\begin{aligned}
\left(\frac{\theta\left(\omega'\right)}{\theta\left(\omega\right)}\right)^{\alpha}\left(\frac{q(\omega')}{q\left(\omega\right)}\right)^{\rho-1} &= \frac{p(\omega')}{p(\omega)} \\
\left(\frac{\theta\left(\omega'\right)}{\theta\left(\omega\right)}\right)^{\alpha\frac{\rho}{\rho-1}}\left(\frac{q(\omega')}{q\left(\omega\right)}\right)^{\rho} &= \left(\frac{p(\omega')}{p(\omega)}\right)^{\frac{\rho}{\rho-1}} \\
\left(\frac{\theta\left(\omega'\right)}{\theta\left(\omega\right)}\right)^{\alpha(1-\sigma)}\left(\frac{q(\omega')}{q\left(\omega\right)}\right)^{\rho} &= \left(\frac{p(\omega')}{p(\omega)}\right)^{1-\sigma} \\
\theta(\omega')^{\alpha}q(\omega')^{\rho} &= \left(\frac{p(\omega')}{p(\omega)}\right)^{1-\sigma}\frac{\theta\left(\omega'\right)^{\alpha\sigma}}{\theta\left(\omega\right)^{\alpha(\sigma-1)}}q(\omega)^{\rho}
\end{aligned}$$

Integrating both sides with respect to $\omega' \in \Omega$, we obtain

$$\begin{aligned}
\int_{\omega'\in\Omega}\theta(\omega')^{\alpha}q(\omega')^{\rho}d\omega' &= \frac{q(\omega)^{\rho}}{\theta(\omega)^{\alpha(\sigma-1)}p\left(\omega\right)^{1-\sigma}}\int_{\omega'\in\Omega}\theta(\omega')^{\alpha\sigma}p(\omega')^{1-\sigma}d\omega'. \\
&= \frac{q(\omega)^{\rho}}{\theta(\omega)^{\alpha(\sigma-1)}p\left(\omega\right)^{1-\sigma}}P^{1-\sigma},
\end{aligned}$$

where $P \equiv \left[\int_{\omega\in\Omega} p(\omega)^{1-\sigma}\theta\left(\omega\right)^{\alpha\sigma} d\omega\right]^{1/(1-\sigma)}$ is the price index. Substituting this into (12), we obtain the demand function:

$$\begin{aligned}
\frac{\delta\theta\left(\omega\right)^{\alpha} q\left(\omega\right)^{\rho-1}}{\int_{\omega'\in\Omega}\theta(\omega')^{\alpha}q(\omega')^{\rho}d\omega'} &= p\left(\omega\right) \\
\delta\theta\left(\omega\right)^{\alpha} q\left(\omega\right)^{\rho-1}\left(\frac{\theta(\omega)^{\alpha(\sigma-1)}p\left(\omega\right)^{1-\sigma}}{q(\omega)^{\rho}P^{1-\sigma}}\right) &= p\left(\omega\right) \\
q(\omega) &= \frac{\delta\theta\left(\omega\right)^{\alpha\sigma}}{P^{1-\sigma}}p(\omega)^{-\sigma}. \qquad (13)
\end{aligned}$$

Team's profit maximization

Facing the demand function (13), teams choose prices under monopolistic competition. Let $A \equiv \frac{\delta}{\sigma}\left(\frac{\rho P}{c}\right)^{\sigma-1}$ and $\gamma \equiv \alpha\sigma - \beta\left(\sigma-1\right)$. Since a team with capability θ has marginal costs $c\theta^{\beta}$, it chooses the optimal price $p(\theta) = \frac{c\theta^{\beta}}{\rho}$. Team's output $q(\theta)$, revenue $R(\theta)$, costs $C(\theta)$, and profits $\Pi(\theta)$ become:

$$\begin{aligned}
q(\theta) &= \delta P^{\sigma-1}\left(\frac{\rho}{c}\right)^{\sigma}\theta^{(\alpha-\beta)\sigma};\\
R(\theta) &= p(\theta)q(\theta)\\
&= \delta\left(\frac{\rho P}{c}\right)^{\sigma-1}\theta^{(\alpha-\beta)\sigma+\beta}\\
&= \sigma A\theta^{\gamma};\\
C(\theta) &= c\theta^{\beta}q(\theta) + f\\
&= \frac{\delta}{\rho}\left(\frac{\rho P}{c}\right)^{\sigma-1}\theta^{(\alpha-\beta)\sigma+\beta} + f\\
&= (\sigma-1)A\theta^{\gamma} + f;\\
\Pi(\theta) &= R(\theta) - C(\theta) = A\theta^{\gamma} - f.
\end{aligned}$$

Normalize$\gamma = 1$. From the optimal price, the price index is

$$\begin{aligned}
P &= \left[\int_{\omega\in\Omega} p(\omega)^{1-\sigma}\theta(\omega)^{\alpha\sigma}\,d\omega\right]^{1/(1-\sigma)}\\
&= \frac{c}{\rho}\left[\int_{\omega\in\Omega}\theta(\omega)^{\gamma}\,d\omega\right]^{1/(1-\sigma)}\\
&= \frac{c}{\rho}\left[\int_{\omega\in\Omega}\theta(\omega)\,d\omega\right]^{1/(1-\sigma)}.\\
&= \frac{c}{\rho}\Theta^{1/(1-\sigma)},
\end{aligned}$$

where $\Theta \equiv \int_{\omega\in\Omega}\theta(\omega)\,d\omega$ is a measure of the aggregate capability. Then, the index A becomes

$$A = \frac{\delta}{\sigma}\left(\frac{\rho P}{c}\right)^{\sigma-1} = \frac{\delta}{\sigma\Theta}.$$

From equilibrium matching, Θ is obtained as

$$\Theta = \begin{cases} M_U\int_{x_L}^{\infty}\theta(x, m_x(x))\,dF(x) & \text{for Case-C}\\ M_U\int_{x_L}^{\infty}\theta^x(x)dF(x) + (M_M + M_C)\int_{y_L}^{\infty}\theta^y(y)dG(y) & \text{for Case-I,}\end{cases}$$

where $\theta(x,y) = \theta^x(x) + \theta^y(y)$ for additive separable Case-I.