Assortative Matching of Exporters and Importers

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Abstract: This paper examines the mechanism determining the 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 market induced by the end of the Multifibre Arrangement (MFA), US importers switched their Mexican partners to those making greater preshock exports whereas Mexican exporters switched their US partners to those making fewer preshock imports. To explain these facts, we present a model combining Becker-type positive assortative matching of final producers and suppliers by their capability with the standard Melitz-type model. The model indicates that the observed matching change is evidence for a new source of gains from trade associated with firm heterogeneity.

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

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1 Introduction

Over the past decade, a growing body of research has focused on heterogeneous firms and trade. A robust finding that only firms with high capability (productivity/quality) will engage in exporting and importing has spurred new theories emphasizing gains from trade associated with firm heterogeneity (Melitz, 2003; Bernard, Eaton, Jensen, and Kortum, 2003).[1] These theories consider trade liberalization as the key mechanism linking trade and industry performance because it improves aggregate industrial performance by shifting resources to more capable firms within industries (e.g., Pavcnik, 2002). These new trade theories have been applied to various issues and centered in trade research over the last decade.[2]

In contrast to our current knowledge regarding the firms that trade, we have little information regarding the exporters and importers involved in trade, i.e., the process of matching between exporters and importers in a product market. Do exporters and importers match based on their respective capabilities? Does trade liberalization change this matching process 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 wherein the matching between exporters and importers does not play an important role. Perfectly competitive models such as the Ricardian and Heckscher-Ohlin models do not predict any systematic matching pattern because exporters and importers are indifferent regarding with whom they trade in equilibrium.[3] The "love of variety" model also avoids positing any specific matching mechanism, instead predicting that all exporters will trade with all importers.

However, actual matching patterns significantly differ from those predicted by these workhorse trade models. The two graphs in Figure 1 illustrate how Mexican exporters trade with US importers in two HS6 digit textile/apparel product markets. Each small dot on the left side represents a Mexican exporter, whereas each small dot on the right side represents a US importer. Product A has slightly more firms than an average textile/apparel product that Mexico exports to the US, whereas Product B has fairly larger numbers. Each line connecting an exporter and an importer represents a "match" whereby the exporter and the importer transacted the product during June–December 2004. Both graphs clearly indicate that most firms traded with only one firm, that is, matching is approximately one-to-one. Though the graphs show some deviations from this pattern of one-to-one matching, these deviations constitute only a small share of the aggregate trade volume. Section 2 presents the trade volume by "main-to-main" matches, defined as matches where both the exporter and the importer are each other's largest main partner; this trade volume constitutes approximately 80 percent of the aggregate Mexican textile/apparel exports to

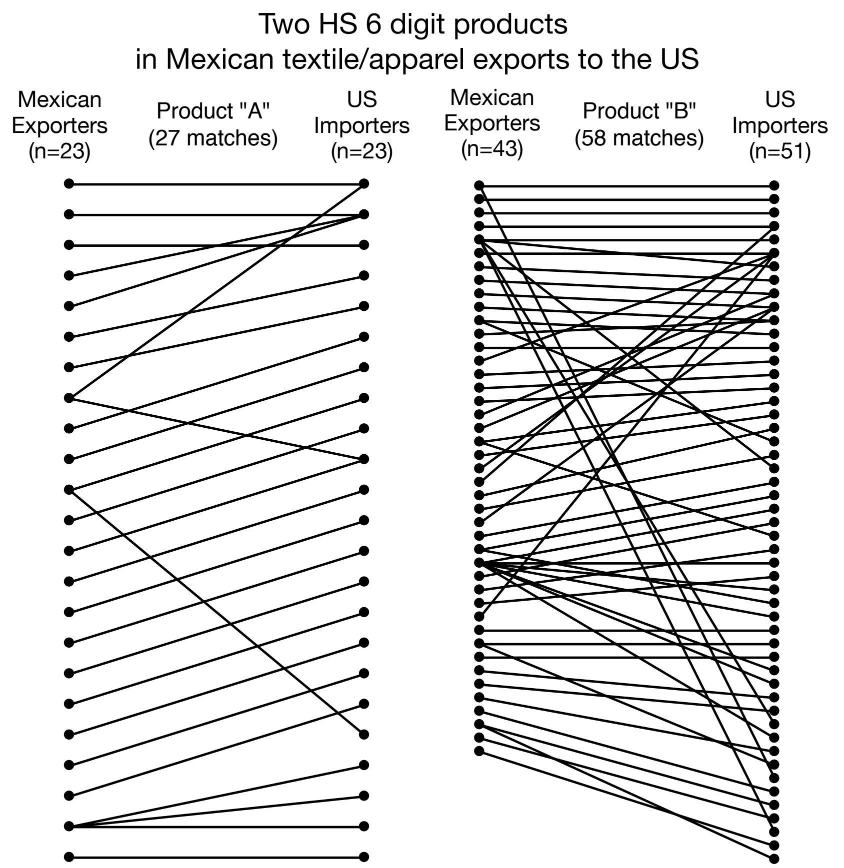
[1] See, for example, Bernard and Jensen (1995, 1999) for such findings that motivated the theories.

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

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

the US. This means that one-to-one matching between main partners is a good approximation of trade relationships in a given product market. Thus, understanding firms' choice of main partner is crucial for understanding trade at the product level.

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. Exporters and importers are ordered by trade volume with their main partners for the product.

We develop a model combining the canonical one-to-one matching model of Becker (1973) with a standard Melitz-type heterogeneous firm trade model to examine the mechanism determining importers' and exporters' choices of their main partners. The model has final producers (importers) and suppliers (exporters), both of whom are heterogeneous in capability. A final producer and a supplier form a team under perfect information. These teams compete in a monopolistically competitive market as in Melitz-type models. Since team-level capability depends on team members' capabilities, the resulting matching determines the distribution of team capability. In our benchmark case wherein members' capabilities exhibit complementarity within teams, stable matching becomes positively assortative by capability where highly capable exporters match with highly capable importers, while low capability exporters match with low capability importers.

Furthermore, we analyze trade liberalization that enables more foreign suppliers to enter the country of the final producer. The model exhibits a new adjustment mechanism undertaken by industries in response to trade liberalization. The Becker-type matching model indicates that positive assortative matching is a market outcome that depends on the capability distributions of final producers and suppliers. Trade liberalization enables foreign suppliers to enter the market, which in turn changes the capability distribution among suppliers available to final producers in the market. Existing matching becomes unstable as some final producers switch to these new foreign suppliers. This in turn induces existing firms to systematically change partners so that the resulting new matching distribution becomes positive assortative under the new capability distribution. Final producers switch to partners with higher capability, while incumbent suppliers switch to partners with lower capability. This shift in matching toward assortative matching not only leads to an efficient use of technology exhibiting complementarity but also improves the aggregate industrial performance at the world level under normal circumstances. In short, the model identifies rematching between buyers and suppliers as a new source of gains from trade liberalization associated with firm heterogeneity.

We assess this implication of Becker-type positive assortative matching by investigating how the matching behavior of US importers and Mexican exporters responds to the entry of Chinese suppliers into the US market, induced by the end of the Multifibre Arrangement (MFA) in 2005. The end of the MFA provides an ideal experiment because the US removed import quotas, followed by increases in Chinese exporters for some textile/apparel products but not others. Using firms' preshock trade volumes in 2004 as a proxy for capability, we find that for products subject to US binding quotas on imports from China, US importers more frequently switched from their Mexican main partner to one with higher capability, whereas Mexican suppliers more frequently switched from their US main partner to one with lower capability compared to switching behavior observed in other textile products not subject to binding quotas. We do not find systematic partner changes in the other direction. Furthermore, among those who switched main partners, the rank of the new partners is positively related with the capability of the old partners. These findings strongly support the existence of Becker-type positive assortative matching. In addition, we present numerous additional analyses to support the robustness of our results and to reject possible alternative explanations.

Our empirical results have several implications for trade research and policy discussions. First, our findings support the matching approach to modeling international trade pioneered by James Rauch and his coauthors. Casella and Rauch (2002), Rauch and Casella (2003), and Rauch and Trindade (2003) modeled trade as matching between exporters and importers to analyze information frictions that complicate matching. While these models consider that firms pick a match based on horizontally differentiated characteristics, we find that firms pick a match based on vertically differentiated capability (e.g., Antras, Garicano and Rossi-Hansberg, 2006; Sugita 2014).[4] Second, our findings are 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).[5] Though the current debate has mainly focused on gains from reallocation of production factors among firms (e.g., Melitz, 2003; Bernard et al. 2003), our findings suggest another type of gains from trade associated with firm heterogeneity. Third, we find that importers with high capability are "good importers" with whom all exporters prefer to trade, but only those with high capability can in fact trade with them. This finding supports policy discussions emphasizing the importance of encouraging domestic firms not only to start exporting but also to export to high capable importers. This view that all importers are not equally valuable to exporters in a non-anonymous market is also shared by a recent random network model by Chaney (2014).

Our paper is also related to the growing body of empirical literature that uses customs transaction data to examine matching between exporters and importers. 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) use the Norwegian customs data and the customs data of Costa Rica, Ecuador, and Uruguay to examine exports from one country to multiple destinations. 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 together with the number of importers for an exporter. We define matching more narrowly at the product level and identify a theoretical mechanism determining product-level matching by examining how matching behavior responds to a trade liberalization shock. Section 2 presents that our finding is compatible with the findings of aforementioned studies by replicating some of their key findings under their definition of matching. Benguria (2014) and Dragusanu (2014) find positive correlations for firm-level variables (employment, revenue, etc.) of exporters and importers for France–Colombia trade and India–US trade, respectively. However, none of these studies relates observed correlations to the Becker-type positive assortative matching. Section 4.4 presents the comparison of these correlation tests with our empirical test. Finally, regarding dynamic characteristics of matching, Eaton et al. (2012) and Machiavello (2010) conduct pioneering studies on how new exporters acquire or change buyers in Colombian exports to the US and in Chilean wine exports 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 propose Becker-type positive assortative matching. Note that our treatment–control group

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

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

comparison can identify only the existence of the Becker-type mechanism; however, it is silent about the existence of other mechanisms.

The rest of the paper is organized as follows. Section 2 explains our data set and shows statistics 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 derives predictions that will be confirmed in later sections. Section 4 explains our empirical strategies. Section 5 presents the main empirical results together with 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 used the administrative records held on every transaction (shipment) crossing the Mexican border from June 2004 to December 2011 to construct matched exporter–importer data for Mexican textile/apparel exports to the US. The Appendix explains the construction of the dataset. The dataset contains the following information for each Mexican exporter and US importer pair that trade in a HS6 product in a year: (1) exporter-ID; (2) importer-ID; (3) year of transaction; (4) the 6 digit HS product code (from HS50 to HS63); (5) value of annual shipment (in US dollars); (6) quantity and unit; and (7) an indicator of whether their trade is processing reexports (Maquiladora/IMMEX); and other information.

Some information was dropped from the dataset. First, we dropped exporters who are individuals or courier companies (e.g., FedEx, UPS, etc.) because we focus on firm to firm matching. Second, as the dataset contains information only from June to December for 2004, we dropped observations from January to May for other years to make each year's information comparable.[6] Third, we dropped one product where the number of importers unreasonably fluctuates, suggesting low data quality.[7]

Finally, we dropped transactions by exporters who do not report importer information for most transactions. For a given HS6 product and a given year, we dropped an exporter from the final data if the total value of transactions without importer information constituted more than 20 percent of the exporter's annual export value. This resulted in dropping approximately 30–40 percent of exporters and 60–70 percent of export values. Most of these dropped exporters engage in processing reexports, called Maquiladora/IMMEX exports, and Mexican customs do not mandate Maquiladora/IMMEX exporters to report importer information.[8] However, in practice and in our data, many Maquiladora/IMMEX ex-

[6] We conducted our main analysis (Tables 2 and 6) without conducting the latter two operations and obtained similar results.

[7] We dropped hs code 570210 where the number of US importers were 5 in 2004, 4 in 2005, 254 in 2006, 532 in 2007, 3 in 2008 and 123 in 2009.

[8] The Maquiladoras program is a government export promotion program, replaced by the IMMEX (Industria Manufacturera, Maquiladora y de Servicios de Exportation) program in 2006. In the Maquiladoras/IMMEX program, firms in Mexico can import materials and equipments 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

porters report importers' information, which enables 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 the matching between Mexican exporters and US importers for HS6 digit level textile/apparel products. We dropped products traded by only one exporter or only one importer in any year during 2004-07 as these products do not have a potential matching problem.[9] 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 presents that matching between exporters and importers significantly differs from the predictions derived from the conventional "love of variety" model. As this model predicts that all exporters sell to all importers, the numbers in Rows (1) and (2) can be interpreted as the "love of variety" model's predictions regarding the number of exporters selling to a typical importer and the number of importers buying from a typical exporter, respectively. Compared with these predictions, the actual numbers given in Rows (3) and (4) are extremely small. While the predicted numbers are 11–15 sellers and 15–20 buyers for the mean (6–8 sellers and 9–12 buyers for the median), more than half of exporters and importers trade with only one partner. Furthermore, though some firms trade with multiple partners, trade with one main partner is very important. Rows (5) and (6) show that even these firms transact approximately 75 percent of their trade with a single main partner. Overall, Table 1 shows that product-level matching of exporters and importers is approximately one to one.

Maquiladora/IMMEX programs, exporters must register the foreign buyers' information in advance. This registration means that exporters do not need to report foreign buyers' details for each shipment. We show in Section 2.2.2 that non-Maquiladora trade and Maquiladora trade show very similar patterns in terms of Main to Main trade shares in Table 2. Similar patterns are found for number of partners. These suggest that a sample selection problem that could potentially arise from the exclusion of data is likely to be small.

[9]These dropped products constitute 3-7% of total textile/apparel trade volume in each year.

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

HS-6 digit product level statistics (272 products)	2004	2005	2006	2007
(1) N of Exporters, mean (median)	14.7 (8)	14.1(7)	11.7 (6)	11.3 (6)
(2) N of Importers, mean (median)	19.6 (11.5)	18.7 (10)	15.5 (9)	14.9 (9)
(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)	1.5 (1)	1.4 (1)
(5) Value Share of the Main Exporters (Exporters>1)	0.77	0.77	0.76	0.77
(6) Value Share of the Main Importer (Importers>1)	0.74	0.75	0.77	0.76

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

2.2.2 Main-to-Main Shares

It is well established that exports by a few large firms constitute a large share of industrial exports. Figure 1 and Table 1 do not consider this fact. Even though more than half of firms trade with a single partner, trade by these firms may constitute only a small fraction of the aggregate trade volume.

We construct a new measure, "main to main share" to incorporate the heterogeneity in trade volumes. For each product–year combination, we identify each firm's "main partner," i.e., the partner with whom the firm trades the most. Then, we define "main-to-main trade" as trade in which the exporter is the main partner of the importer and simultaneously the importer is the main partner of the exporter. Finally, we define "main-to-main share" as the share of main-to-main trade out of the total trade volume.

The "main-to-main share" expresses the extent to which overall transactions in one product market are quantitatively close to one-to-one matching. If all exporters and importers trade with only a single partner, this share takes the maximum value, which is 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 $1/\max\{n_m, n_x\}$. Even if some large firms trade with multiple partners, the main-to-main share is still close to one when these firms concentrate their trade 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 approximately 80 percent, which is stable across years. Trade between one-to-one matches of the main partners constitutes 80% of textile/apparel trade volumes. This means that understanding the mechanism determining one-to-one matching between main partners will lead to understanding the mechanism determining 80 percent of aggregate trade volumes. In the remainder of the paper, we provide theory and evidence for the mechanism determining firms' choice of main partner.

Other columns in Table 2 investigate whether high main-to-main share is due to unique features of Mexican textile/apparel exports to the US. First, Mexican exports to the US contain a large amount of processing reexports through Maquiladora/IMMEX programs. To be eligible for Maquiladora/IMMEX, exporters must register importers in advance and these registration costs might lead firms to trade with only a small number of partners. Columns (2) and (3) report the main-to-main share for Maquiladora/IMMEX trade and other normal trade, respectively.[10] These two types of trade show very similar main-to-main shares. Thus, approximately one-to-one matching is not specific to the processing trade. Second, in our data period, some Mexican textile/apparel products in the US market experienced a drastic change in the level of trade protection. As section 4 will explain later, the US imposed import quota on some textile/apparel products until 2004 under the Multifibre arrangement. Since Mexican exports to the US are not subject to these quotas thanks to the NAFTA, they are protected from competition with other countries, notably China. Columns (4) and (5) examine whether high main-to-main share is related to high trade barriers or their removal. Column (4) reports main-to-main share for products for which Chinese exports to the US were subject to binding quotas until 2004 [see section 4.3 for the definition of quota binding], while column (5) reports for other textile/apparel products. In both columns, main-to-main share is higher than 0.76 for all years. Therefore, neither import quota nor their removal causes high main-to-main shares.

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

	Main-to-Main Share				
Year	All	Maquila Exporters	Non-Maquila Exporetrs	Quota-bound	Quota-free
	(1)	(2)	(3)	(4)	(5)
2004	0.79	0.77	0.79	0.78	0.80
2005	0.81	0.80	0.80	0.82	0.79
2006	0.81	0.81	0.82	0.81	0.82
2007	0.84	0.84	0.82	0.84	0.85

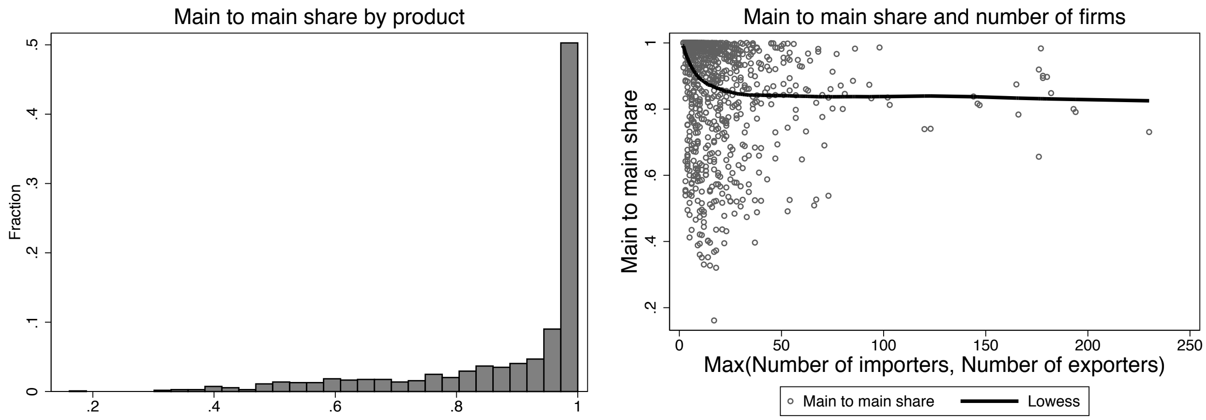
Note: Each column reports main-to-main shares in Mexico's textile/apparel exports to the US for types of transactions. "All" indicates all textile/apparel products. "Maquila" indicates Maquiladora/IMMEX transactions, whereas "Non-Maquila" indicates the other normal transactions. "Quota-bound" indicates products for which Chinese exports to the US were subject to binding quotas, while "Quota-free" indicates the other products. See section 4.3 for the definition of quota binding.

Two panels in Figure 2 draw the distribution of main-to-main share across product-year combinations

[10] Very few Mexican firms engage in both non-Maquiladora exports and Maquiladora exports.

of HS 6 digit textile/apparel products and years 2004-2007. A histogram in the left panel strikingly shows most products have higher main-to-main shares than 0.9. The median is 0.97 and 25 percentile is 0.86. As the love of variety model with symmetric firms predicts main-to-main share equals $1/\max\{n_m, n_x\}$, main-to-main shares might be related to the number of firms. To examine this, the right panel in Figure 2 plots main-to-main shares against the maximum of the number of exporters and that of importers, $\max\{n_m, n_x\}$. An estimated Lowess curve is above 0.80 and almost horizontal, which implies that main-to-main share is not related with the number of firms.

Figure 2: Main-to-Main Shares for HS 6 Digit Textile/Apparel Products



Note: Both panels draw main-to-main share across product-year combinations of HS 6 digit textile/apparel products and years 2004-2007. The left panel draws a histogram. The right panel plots main-to-main shares against the maximum of the numbers of exporters and importers.

2.2.3 Comparison with Previous Studies

Recent years have seen a rise in the literature on matching between 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) all 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 these studies that emphasize “partner margins”?

In fact, our finding is compatible with these previous studies mentioned above. First, these studies, excluding 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.[11] Specifically, in their definition, an exporter and an importer form a match in a given country if they trade a 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

[11] 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 and share of the main buyers for exporters. However, they do not analyze the number of sellers for importers.

would identify an identical set of matches. Since in reality, a number of firms trade multiple products, our definition of matching is strictly narrower than the one in these previous studies and identifies fewer partners for firms trading multiple products.

Second, if we define a match at the country level, as in these previous studies, 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 an importer buying from an exporter than the values reported by Blum et al. (2010, 2011), Bernard et al. (2013), and Carballo et al. (2013). When we calculate these numbers under these studies' definitions, the numbers increase and become similar to their findings. 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 of partners per importer. Following Table 3.2 in Blum et al. (2010) and Figure 5 in Bernard et al. (2013), we calculate the following for each Mexican exporter: (X) the number of US buyers that the exporter trades with, and (Y) the average number of Mexican partners for these US buyers. Thereafter, 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 the value of -0.13 (s.e. 0.01) for Norwegian exporters found by Bernard et al. (2013).[12] Therefore, our analysis of one-to-one matching of exporters and importers at the product-country level has no conflict with previous analyses of partner margins at the country level.

3 The Model

This section has three aims: (1) to develop a model combining a canonical Becker (1973) model of one-to-one matching with a standard Melitz-type heterogeneous firm trade model, (2) to explain the model's implications for the novel effect of trade liberalization on the aggregate industrial performance, and (3) 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 develop a matching model of global supply chains producing differentiated final goods.[13] The model includes three types of firms, namely, US final producers, Mexican suppliers, and Chinese suppliers. A US final producer matches with a supplier from either 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.

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

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

Firms' capabilities are heterogeneous. Capability reflects either productivity or quality, depending on the model's other parameters. Let x and y be the capability of final producers and suppliers, respectively. There is a fixed mass M_U of final producers in the US, M_M of suppliers in Mexico, and M_C of suppliers in China. The cumulative distribution function (c.d.f.) for the capability of US final producers is $F(x)$ with support $[x_{min}, x_{max}]$. The capability of Mexican and Chinese suppliers follows an identical distribution, and the c.d.f. is $G(y)$ with support $[y_{min}, y_{max}]$.[14] An 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 of 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, they compete in the US final good market in a monopolistically competitive fashion.

Teams' capabilities are heterogeneous. Team capability $\theta(x, y)$ is an increasing function of team members' individual 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, $p\left(\omega\right)$ is the price of ω, $q(\omega)$ is the consumption of ω, $\theta(\omega)$ is the 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 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 $\sigma \equiv 1/\left(1-\rho\right) > 1$ is the elasticity of substitution and $P \equiv \left[\int_{\omega\in\Omega}p(\omega)^{1-\sigma}\theta\left(\omega\right)^{\alpha\sigma}d\omega\right]^{1/(1-\sigma)}$ is the price index.

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

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

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

where $c \equiv c_x + c_y$ and $f \equiv f_x + f_y$. Each firm's is assumed to depend on the entire team's capability. This assumption is mainly for simplicity, but it also expresses externality within teams that makes firms' marginal costs to depend on their partner's capability and their own capability.[15]

Team capability θ may represent productivity and/or quality, depending on parameters α and β. For 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 accordingly, 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 simultaneously 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, a team 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 team capability affects joint 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 having capability $m_x(x)$ and receives the residual profit $\pi_x(x)$ after paying profits $\pi_y(m_x(x))$ to 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 the following two conditions: (i) *individual rationality*, wherein all firms earn non-negative profit, $\pi_x(x) \geq 0$ and $\pi_y(y) \geq 0$ for all x and y and (ii) *pair-wise stability*, wherein each firm is the optimal partner for the other team member[16]

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

[15]An example of a 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.

[16]Roth and Sotomayor (1990) is an excellent textbook of matching models. Parameter A is given to individual firms, but is endogenous at the market level. Therefore, stable matching considered here is an $f-$core of an economy having the widespread externality of Hammond, Kaneko, and Wooders (1989). See this paper for the existence of an $f-$core.

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

$$A\theta_2(x, m_x(x)) = \pi'_y(m_x(x)) \text{ and } A\theta_1(m_y(y), y) = \pi'_x(m_y(y)).$$

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

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

which proves 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, a cut-off level of team capability θ_L exists such that only teams with capability $\theta \geq \theta_L$ produce in the market. Simultaneously, capability cut-offs x_L and y_L exist 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) indicates that the number of suppliers in the matching market is equal to the number of final producers.

The sign of the cross derivative of a team's joint profits, which is the sign of the cross derivative θ_{12}, is known to determine 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 strictly 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 strictly submodular).[17] In Case C, we have positive assortative matching (PAM) ($m'_x(x) > 0$): high capability firms match with high capability firms whereas low capability firms match low capability firms. In Case S, we have negative assortative matching (NAM) ($m'_x(x) < 0$): high capability firms match low capability firms. In Case I, we cannot determine a matching pattern (i.e. $m_x(x)$ cannot be defined as a function) because each firm

[17] 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 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 capability firms. See e.g. Grossman and Maggi (2000) for further examples.

is indifferent about partner's capability. Therefore, we assume matching is random in Case I.[18]

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 but rejects Case I and Case S. Second, Case I is a useful benchmark because it nests traditional Melitz-type models where firm heterogeneity exists 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 the other two cases.

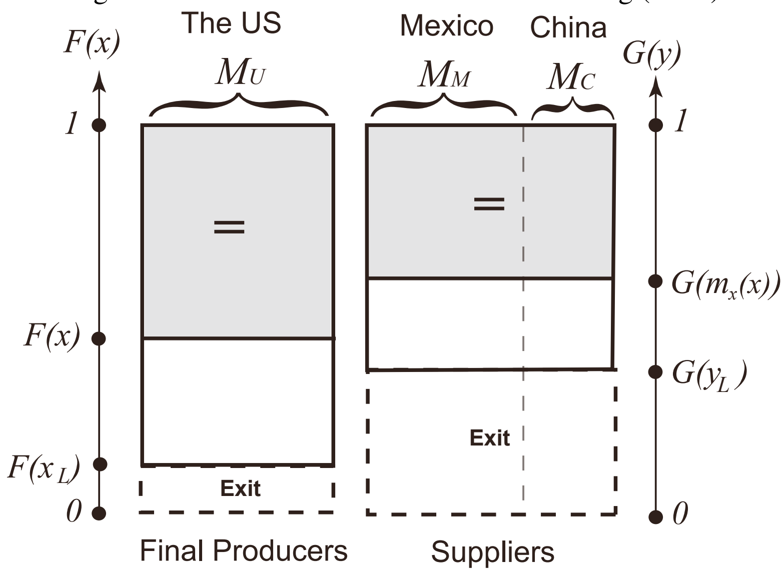
In Case C, the matching function $m_x(x)$ is determined to satisfy the following "matching market clearing" condition.

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

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, these are suppliers with higher capability than $m_x\left(x\right)$. Figure 3 describes how matching function $m_x(x)$ is determined for a given $x \geq x_L$. The width of the left rectangle equals the mass of US final producers, whereas the width of the right rectangle equals the mass of Mexican and Chinese suppliers. The left vertical axis expresses the value of $F(x)$ and the right vertical axis indicates 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 $x \geq x_L$.

[18]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' can 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 can and matches with Y (NAM). In Case I, both final producers 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'.

Figure 3: Case C: Positive Assortative Matching (PAM)



An equilibrium is obtained as follows (see Appendix for calculation). First, the matching market 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 from 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, namely x_L and y_L.[19]

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. By incorporating this property, the model emphasizes the effect of trade liberalization on the aggregate industrial performance.

To see this point more clearly, we focus on Case C, i.e. positive assortative matching. Trade liberalization enables foreign suppliers to enter the market and changes the capability distribution of suppliers available to match with final producers. Some final producers prefer to switch partners to foreign entrants

[19]Individual firm profits 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 regarding how to split the matching surplus within matches.

(this is why foreign suppliers enter the market), whereby the old matches become unstable. Firms change their partners so that the new matching becomes positively assortative at the global level 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 global level (e.g. global profits) under normal circumstances.[20]

In the remainder of the paper, we empirically test this implication of the Becker-type PAM to adjust prior matches following trade liberalization. More specifically, we consider what happens to matching between 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 Section 5.3. For simplicity, we assume positive but negligible costs for switching partners so that a firm changes its partner only if it strictly prefers the new match over 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, choosing instead to import from China. Others remain in the Mexico-US trade. We now introduce the names of these groups of firms.

Definition 1. Consider Mexican suppliers and their partner US final producers before the exogenous event of an increase in Chinese suppliers. (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; and (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 discussion, we focus on how continuing importers and exporters change their partners in response to the Chinese entry into the US market.

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

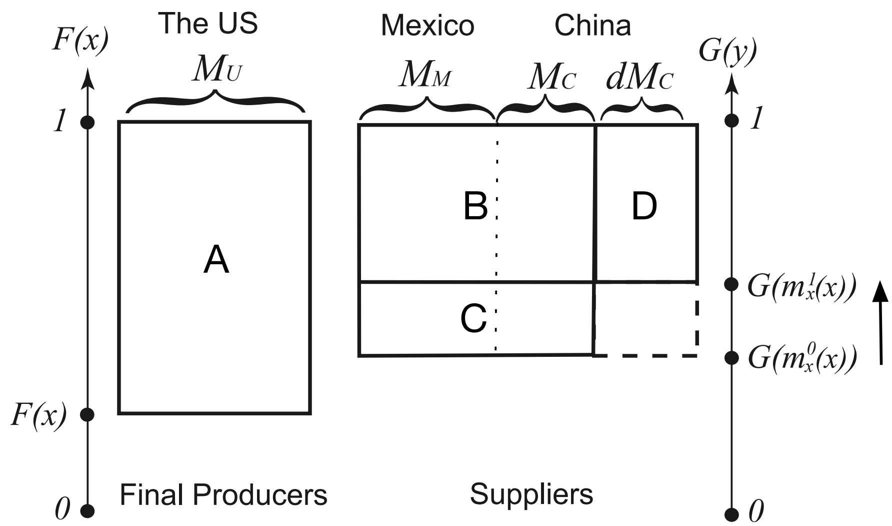
Proposition 1. *If the mass of Chinese suppliers increases in Case I, then US continuing importers and Mexican continuing exporters will not change their partners.*

In Case C, continuing importers and exporters systematically change their match of firm to satisfy the matching market clearing condition (8). Let $m_x^0(x)$ and $m_x^1(x)$ be the matching functions in an old equilibrium and a new equilibrium, respectively. Figure 4 describes how a US importer with capability x changes its partner. Area A in Figure 4 expresses US importers with capabilities higher 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 original matches become unstable because some US final producers are willing to swap

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

their partners 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 having capabilities higher than $m_x^1(x)$. The figure shows that a US final producer with a given capability x switches its main partner from the one with capability $m_x^0(x)$ to the one with the higher capability $m_x^1(x)$. We call this change "partner upgrading" by US final producers. This in turn implies "partner downgrading" by 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 prior to the entry of Chinese suppliers.

Figure 4: Case C: the Response of Matching to an Entry of Chinese Exporters ($dM_C > 0$)



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

The remainder of the paper will test Propositions 1 and 2.[21]

4 Empirical Strategies

Three types of data are needed 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 between US importers and Mexican exporters. This section explains how we obtain these data and formulate an implementable test of

[21] We have assumed identical capability distributions of Chinese and Mexican suppliers to derive Proposition 2 using the diagram. We note 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.

Propositions 1 and 2. We also explain the advantage of our test over the conventional "correlation test" of assortative matching.

4.1 End of the Multifibre Arrangement

The end of the Multifibre Arrangement (MFA) in 2005 provides a shock of exactly the required type, and that we modeled in the last section, namely a sudden increase in Chinese exporters of various capability levels entering the US textile/apparel product markets ($dM_C > 0$).

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

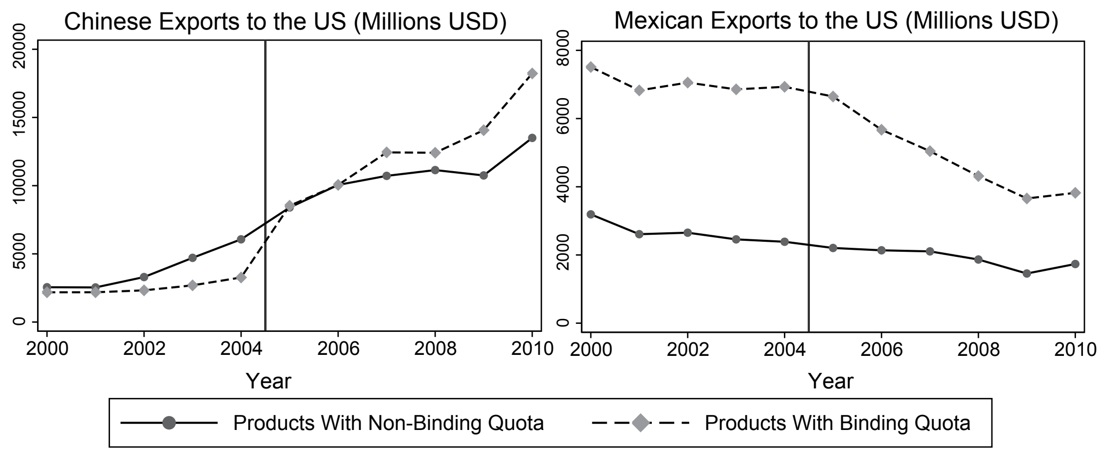
The end of the MFA in 2005 is a product-level liberalization of the US textile/apparel markets. Quotas had already been removed for a roughly half of the relevant products before 2002, while the other half underwent liberalization in 2005. Many HS2 digit chapters contain products liberalized in 2005 as well as those that had been previously liberalized and therefore did not experience any change in 2005. This situation enables us to construct a treatment group (products liberalized in 2005) and to compare it with a control group (other products) within HS2 digit chapters.

4.1.1 Surge in Chinese Exports to the US

The 2005 quota removal increased imports to the US, mostly from China. Brambilla, Khandelwal, and Schott (2010) estimate that US imports from China disproportionally increased by 271% in 2005, whereas imports from almost all other countries decreased.[22] The left panel in Figure 5 displays 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 MFA quota removal. The dashed line expresses the aggregate export volume of products upon which the US had imposed binding quotas against Chinese exports until the end of 2004 (treatment group), and the solid line indicates the export volume of other textile/apparel products (control group). After the 2005 quota removal, exports of quota-removed products (shown by the dashed line) increased much faster than those of other products (shown by the solid line).

[22] Seeing this substantial surge in import growth, the US and China had agreed to impose new quotas until 2008, but imports from China never dropped back to the pre-2005 levels. This reflects the fact that (1) new quota system covered fewer product categories than the old system (Dayaranta-Banda and Whalley, 2007), and (2) the new quotas levels were substantially greater than the MFA levels (see Table 2 in Brambilla et al., 2010).

Figure 5: 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 millions of US dollars from China to the US for the two groups of textile/apparel products from 2000 to 2010. The dashed line represents the sum of export values of all products upon which US had imposed binding quotas against China until the end of 2004, and 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.

4.1.2 Exports by New Chinese Entrants with Various Capability Levels

Khandelwal, Schott, and Wei (2013) use Chinese customs transaction data to decompose the increases in Chinese exports to US, Canada, and the EU after the quota removal into intensive and extensive margins. They find that increases in Chinese exports of quota-constrained products were mostly driven by the entry of Chinese exporters who had not previously exported these products. Furthermore, these new exporters are much more heterogeneous in capability than incumbent exporters, with many new exporters being more capable than incumbent exporters.[23] In our model, this entry of new exporters at various levels of capability corresponds to an increase in the number of Chinese suppliers $dM_C > 0$ analyzed in the last section.

4.1.3 Mexican Exports Facing Competition from China

The removal of the MFA quotas significantly impacted Mexican exports. Mexico already had tariff- and quota-free access to the US market through the North American Free Trade Agreement (NAFTA).[24] With the MFA's end, Mexico lost its advantage to third-country exporters, thus facing increased competition

[23]Khandelwal et al. (2013) offer 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 for 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 predictions of optimal quota allocation and suggest inefficient quota allocations as the cause.

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

with Chinese exporters in the US market. The right panel in Figure 4 shows Mexican exports to the US for quota-removed products for the treatment group (dashed line) and other textile/apparel products (solid line; control group) from 2000 to 2010. The figure shows that the two series had moved in parallel before 2005, whereas exports of quota-removed products significantly declined after 2005. The parallel movement of the two series before 2005 indicates the absence of underlying differential trends between Mexico–US trade in both quota-removed products and other products. This suggests that the choice of products for quota removal in 2005 was exogenous to Mexican exports to the US.

In sum, the MFA's end in 2005 provides an ideal natural experiment for testing Propositions 1 and 2. It induced a large and arguably exogenous increase in the number of Chinese exporters with various capability levels into the US market for roughly half of textile/apparel products, making the other half a natural control group. [25]

4.2 Proxy for Capability Rankings

Capability rankings for US final producers and Mexican suppliers are needed for each product to test Propositions 1 and 2. Estimating conventional capability measures such as total factor productivity (TFP) is one possibility. 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 that researchers typically use to estimate TFP. As we will explain in Section 4.4, using this method would therefore require currently unavailable data and estimation methodology. Therefore, a different approach is utilized.

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

To this end, we use a property of our model that a firm's trade volume increases in line with 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 positively assortative and matching functions are increasing, i.e. $m'_x(x) > 0$ and $m'_y(y) > 0$. Therefore, import volumes by US final producers $I(x) = T(x, m_x(x))$ increase in line with their own capabilities x as export volumes by Mexican suppliers $X(y) = T(m_y(y), y)$ increase in line with their own capability y.

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

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

We assume that the capability ranking in a fixed set of firms is stable during our sample period 2004–2007. Thereafter, we use the rank measured from 2004 data for the same firm throughout our sample period 2004–2007. We measure the capability rankings only for Mexican continuing exporters and US continuing importers that engaged in the Mexico–US trade between 2004 and 2007.

As a robustness check, we also create rankings based on total product trade volumes in 2004 aggregated across partners and rankings based on unit prices.[26]

4.3 Main Specification

Finally, we need to track partner changes between US importers and Mexican exporters, then isolate partner changes due to Chinese firm entries. Accordingly, we estimate the following four regressions:

$$\begin{aligned} Upgrading^{US}_{igs} &= \beta_1 Binding_{gs} + \lambda_s + \varepsilon^m_{igs} \\ Downgrading^{US}_{igs} &= \beta_2 Binding_{gs} + \lambda_s + u^m_{igs} \\ Upgrading^{Mex}_{igs} &= \beta_3 Binding_{gs} + \lambda_s + \varepsilon^u_{igs} \\ Downgrading^{Mex}_{igs} &= \beta_4 Binding_{gs} + \lambda_s + u^u_{igs}, \end{aligned} \tag{9}$$

where i, g, and s index a firm, a HS6 digit product, and a sector (HS2 digit chapters), respectively.

We define dummy variables $Upgrading^c_{igs}$ and $Downgrading^c_{igs}$ as follows: $Upgrading^c_{igs} = 1$ $(c = US, Mex)$ if during 2004-07, firm i in country c switched its main partner for product g to a firm with a higher capability rank; $Downgrading^c_{igs} = 1$ $(c = Mex, US)$ 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, $Upgrading^c_{igs}$ and $Downgrading^c_{igs}$ 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. The sample period of 2004-07 reflects the fact that the 2008 Lehman crisis reduced Mexican exports to the US, potentially confounding the impact of the MFA's end. $Binding_{gs}$ is a dummy variable indicating whether Chinese exports of product g to the US faced a binding quota in 2004. Brambilla et al. (2010) constructed an indicator for binding quotas on Chinese exports to the US for each HS-10 digit category.[27] Since HS product categories of Mexico and the US are the same only up to the first 6 digits, we aggregated their indicator up to the HS-6 digit level.[28] λ_s represents HS-2 digit-level sector fixed

[26] We prefer to use firms' trade volumes with their main partners rather than firm-level total product trade volumes aggregated across partners. The latter measure may not capture the ranking of profit opportunities for partners. For instance, consider two importers. One imports an overall large amount by buying small amounts from many partners. The other imports less overall but imports greater amounts from each seller. We think a typical exporter will regard trade with the latter importer as being more profitable.

[27] A quota is defined as binding if the fill rate, i.e. the realized import value over the quota value, is greater than 0.8. Our results are robust to the choice of other cut-offs.

[28] We constructed our indicator as follows. Let x^m_{g2004} be US imports of HS-10 digit product g from Mexico in 2004. Let j be a HS-6 digit product and $G(j)$ be the set of US HS-10 digit products in category j. Thereafter, we constructed a dummy

effects that control for unobservable and observable shocks during the period at the broad sector level. u_{igs}^c and ε_{ijs}^c are error terms.

When we estimate (9), some observations are dropped. First, we drop products traded by only one exporter or importer in 2004 as for these products, up/downgrading dummies are always zero by construction. Second, we drop HS 2 sectors in which there is no variation of the binding dummy.[29]

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 comparing the treatment and control groups 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 will switch their main partner to ones 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 Mexican exporters would not change their partners. In reality, other shocks inducing partner changes may exist. A virtue of our treatment-control group comparison is that we can distinguish the effect of the MFA's end from the effects of these other shocks if the latter symmetrically affected both groups. Considering this point, we reformulate the prediction for Case I: no difference should exist in the probability of partner changes in any direction between treatment and control groups. In our regressions (9), this prediction corresponds to $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$.

Proposition 2 for PAM in Case C predicts that in response to the entry of Chinese exporters, all continuing US importers upgrade whereas all continuing Mexican exporters downgrade their main partners. Though the model with frictionless matching predicts all firms will change their partners, other factors such as transaction costs are likely to exist that prevent some firms from changing partners, at least in the short run. Again, our treatment-control group comparison can control for these other factors as long as they symmetrically affect both groups. Accordingly, we reformulate the prediction for Case C: US importers' partner upgrading and Mexican exporters' partner downgrading will occur 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 PAM is a type of "correlation test" that uses cross-sectional data to determine whether the correlation of exporters' and importers' capability across matches is positive or

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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 because most of values inside the indicator function are close to either one or zero.

[29] Dropped sectors are HS 50, 51, 53, 56, 57, and 59.

negative. The correlation test has been conventionally used in labor economics for analyzing many topics such as marriage, education, worker sorting, and so on. For readers of these studies, our test examining the response of matching to the entry of new suppliers may not appear a standard approach. For the analysis of exporter–importer matching, however, our approach has several advantages over the correlation test approach.

First, our test is able to identify the mechanism behind assortative matching. The correlation test merely measures the sign of assortative matching but does not indicate the underlying mechanism. Our approach of analyzing systematic partner changes in response to the entry of new suppliers, however, enables 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 TFP at the firm-product level. In contrast to studies in labor economics where agents' abilities are reasonably observable, several difficulties arise in estimating capability for the analysis of exporter–importer matching. Such estimation would require detailed information per firm about the production outputs and inputs of each product, but information on inputs at the firm-product level is rarely available. Furthermore, no established method exists for estimating firm capability in a matching market. For instance, conventional estimation methods of TFP implicitly assume an anonymous market where matching is irrelevant. This approach enables estimation of sellers' productivity without using buyer information. We are uncertain regarding biases that might arise if these conventional methods are applied for firms in a matching market.

Third, instead of estimating capability, the correlation test could use proxy variables for measuring capability, including firm-size variables such as sales or employment. Two caveats should be noted for this approach. These firm-size variables have no variation at the firm-product level. Additionally, the correlation test based on these firm-size variables may not be at all informative about the sign for sorting true capability, and therefore may lead to an erroneous 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' and importers' employment across matches because an importer's employment increases along with volume of imported intermediate goods, which in turn increases the employment of the exporter with whom the importer trades.[30] This positive correlation arises from the complementarity of the labor inputs in the Leontief technology, not from the complementarity of capability.

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

5 Results

5.1 Baseline Regressions

Table 6 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 and probit models. Panels A and B report the results for partner changes by 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 from 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.[31] Columns (3) and (4) show that the end of the MFA's impact on partner downgrading for US importers is close to zero, which is statistically insignificant. In Panel B, Columns (5) and (6) show that the impact on partner upgrading for Mexican exporters is also close to zero, which is statistically insignificant. Columns (7) and (8) show that the removal of binding quotas from 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, partner 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; no difference exists in probabilities of partner downgrading for US importers and partner upgrading for Mexican exporters between treatment and control groups.[32] These signs of the estimates support PAM Case C and reject random matching Case I.

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

The positive estimate of β_1 also implies a previously undocumented type of trade diversion induced by NAFTA. Trade diversion is usually documented in terms of prices: with protection from third-country imports (e.g., the MFA), a preferential trade agreement (e.g., NAFTA) induces importers to buy goods from partner countries at high prices. Trade diversion thus takes a form of "mismatching" of importers and exporters. Given MFA import quotas, NAFTA forced the US firms to match with Mexican suppliers of lower capability. The end of the MFA enabled US firms to match with Mexican suppliers of higher ca-

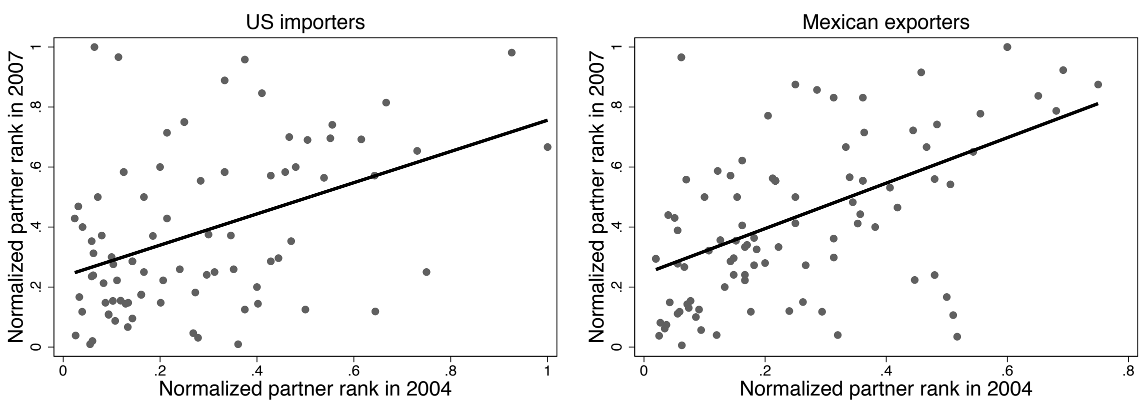
[31] This is also true for other equations in the paper. Thus, we report estimates from linear probability models in the following.

[32] Section 6.4 shows that this lack of partner changes in opposite directions supports rejection of other alternative explanations for the positive estimates of β_1 and β_4.

pability, even if they did not completely switch to Chinese exporters. This dissolution of "mismatching" is a previously undocumented type of gain from trade liberalization.

PAM among new partners The model with Case C predicts that PAM holds both before and after liberalization. Figure 6 confirms this prediction. In the left panel, the horizontal and vertical axes draw the ranks of main partners in 2004 and 2007, respectively, for those US importers who change their main partners between 2004 and 2007. Firm ranks are normalized to fall in $[0, 1]$ by dividing firm ranks by the possible maximum rank of the product (i.e. the number of firms). The right panel represets similar normalized partner ranks in 2004 and 2007 for Mexican exporters. The lines represents OLS regressions of normalized 2007 partner ranks (Y) on normalized 2004 partner ranks (X): $Y = -\underset{(0.041)}{0.24} + \underset{(0.12)}{0.52} X$ ($R^2 = 0.18$) for US importers and $Y = -\underset{(0.039)}{0.24} + \underset{(0.13)}{0.76} X$ ($R^2 = 0.26$) for Mexican exporters where standard errors in parentheses. Figure 6 and regressions show significant positive relationships. That is, firms who match with relatively high capable partners in 2004 continue to match with relatively high capable partners in 2007 as PAM predicts.[33]

Figure 6: Normalized ranks of 2004 and 2007 partners



Note: The left panel draws the normalized ranks of main partners in 2004 and 2007 for those US importers who change their main partners between 2004 and 2007. The right panel draws similar partner ranks for Mexican exporters. The lines represent OLS fits.

5.2 Robustness Checks

5.2.1 Different Time Periods

Choice of End Year Panel A in Table 4 reports estimates of β_1 and β_4 by fixing the initial year as 2004 and changing the end year to 2006, 2007, or 2008. This exercise has two aims. First, it shows that the documented higher probabilities of partner upgrading by US importers and partner downgrading by

[33]Figure combine both the treatment and control groups since the model predicts PAM for both groups. Simialr positive relationshps continue to hold if similar figures are drawn for each group separately.

Mexican exporters in the liberalized products are not sensitive to the choice of end year. All estimated coefficients on β_1 and β_4 in Table 4 are positive and statistically significant. Second, this shows a gradual adjustment between old and new equilibriums. Column (1) finds $\beta_1 = 0.036$ for 2004–06 data much smaller than the value $\beta_1 = 0.052$ found for the 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 occur gradually, probably due to certain transaction costs. Similarly, the estimate of β_4 increases from 0.056 for 2004–06 data in Column (4) to 0.127 for 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, or 2009. This exercise aims to check our crucial assumption: the markets of products previously subject to binding quotas and the markets of other products would have behaved similarly if the MFA quota were maintained. 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 end of MFA quotas. Figure 4 demonstrates the absence of differential time trends in the aggregate export volumes before the MFA quota removal in 2005. Unfortunately, this check cannot be conducted at the firm level as 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 a capability ranking based on trade volume in the new initial year and recreate the upgrading/downgrading dummies. If our positive estimates of β_1 and β_4 for 2004–2007 arise from differential time trends, these regressions with different initial years are likely to continue to 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 of 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 slightly 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 sizable difference between 2008–2011 and the other two periods is the effect of the Lehman crisis and the Great Trade Collapse of 2008-09. As exports from other countries, Mexican exports declined by a huge amount in the second half of 2008. This shock might introduce noise into the rankings. 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 6 for reference. A unique feature of the Mexico–US trade is its inclusion of a substantial amount of duty free processing trade (Maquiladora/IMMEX). If the systematic partner changes previously identified occur only in Maquiladora/IMMEX trade and not in other normal trade, our findings may be specific to the Mexico–US trade and would have limited implications 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 P1 and P4 still remain statistically significant and similar in magnitude. Furthermore, the coefficients of the interaction terms are insignificant, which means that the partner changes occur both in processing and normal trade.

We also consider the possibility that the MFA quota removals are exogenous as they were scheduled before China began expanding its exports. However, which products were liberalized in 2005 might be correlated with product or industry characteristics that vary within a HS2 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) textiles.[34] Columns (9) and (12) include Mexican state dummies of the 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

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

The first alternative ranking is 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 around their trade with their main partners. Therefore, our baseline ranking based on trade volume with the main partners and an alternative based on total product volume yield very similar results.

The second alternative ranking is based on the unit price of the product's trade with the main partner. If the exporter size is mainly explained by their quality rather than productivity, the unit price rankings

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

may agree with the true capability ranking of exporters. On the other hand, if exporter size is mainly explained by productivity, unit price rankings may become the exact reversal of exporters' true capability rankings. If Case C holds, we should observe $\beta_2 > 0$, $\beta_3 > 0$ and $\beta_1 = \beta_4 = 0$ instead.

Using unit prices poses the difficulty 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. These results suggest 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.[35] In addition to this previous finding, our results suggest that exporters need to produce high quality products to match with highly capable importers.[36]

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

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

The conditions (A1) and (B1) are unlikely to be satisfied as they contradict 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. Note that even under NAM, firms with lower capability than x_L and y_L choose to exit [see equation (7)]. Therefore, when firms are hit by a negative shock, those with the lowest capability are

[35] 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 that of Manova and Zhang (2012), who investigate positive correlations between export volumes and unit prices across exporters and products. We also find a positive correlation between them in our data.

[36] Estimates of β_1 and β_4 under the unit price ranking are smaller than those under the baseline ranking. This difference might reflect the fact that exporters being differentiated by productivity or quality is not universal across products, but heterogeneous across products (e.g., Baldwin and Ito, 2011; Mandel, 2009). Differentiating firms mainly by productivity in some products would reduce the size of β_1 and β_4 .

more likely to exit, as in standard models with heterogeneous firms. When a firm's trade volume, which is proportional to its 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 of the well-established finding that small firms are more likely to exit than large firms. Therefore, the case of NAM is unlikely to explain our findings.

5.3.2 Random Matching with Exogenous Breakups

Another alternative model that could predict $\beta_1 > 0$ and $\beta_4 > 0$ is a random matching model with exogenous breakups. In this model, matches exogenously break up at some constant rate, and firms having lost their 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 capability partners are more likely to trade with high capability partners. In other words, (1) large firms are more likely to downgrade partners in absence of the MFA shock. On the other hand, the MFA shock forced low capability firms to stop exporting. Since our sample drops exiting exporters, (2) our sample is likely to include highly 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 PAM based on complementarity.

This random matching model fails to account for the zero estimate of β_3 in Tables 6. If this hypothesis were true, Mexican exporters should upgrade more frequently in the control group, where low-capability Mexican exporters survive at a greater rate than those in the treatment group. This means that we should observe a negative and significant estimate of β_3, but this is not the case. The same argument applies 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 on a large scale and sold with low markups, while the other "custom" segment is produced on a 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.[37]

To explore the validity of this "segment-switching" hypothesis, we perform three additional regressions in Table 7 testing the following three predictions. If a firm's trade volume in 2004 indicates its segment, both small 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 by Mexican exporters should be concentrated among those who initially traded with large "standardized" US importers in 2004.

The results of our tests of these three predictions are presented in Table 7, which 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 2004 rank, 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.

No evidence supporting this alternative hypothesis were found in any of these three exercises. The interaction term 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 main partners more frequently than large "standardized" US importers in the treatment group compared to the control group. Finally, the interaction term in Column (3) suggests that main partner downgrading occurs across the entire range of Mexican exporters' initial rankings and is not concentrated among those who had large trade volumes with their 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.[38]

6 Conclusion

The heterogeneous firm trade literature successfully documented the heterogeneity of exporters and importers in terms of capability, however our knowledge about how heterogeneous importers and exporters

[37]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 PAM, 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 changed partners even in the treatment group.

[38]In addition to the evidence presented in Table 7, the segment switching hypothesis would not be consistent with our finding of Mexican exporter partner downgrading under the unit price ranking in column (12) of Table 6. This finding implies that a Mexican exporter switches from a US main importer of high price products to one of low price products. This is inconsistent with the segment switching hypothesis where exporters switch from low price "standardized" to high price "custom" products.

trade with each other has been still limited. We have identified a simple mechanism determining exporter and importer matching at the product level: Becker-type positive assortative matching by capability. We have found that when trade liberalization enables foreign suppliers to enter a market, existing firms change partners so that matching becomes positively assortative under a new environment. Our model combining Becker (1973) and Melitz (2003) interprets this rematching as evidence of a new source of gains from trade associated with firm heterogeneity.

The Becker mechanism has been applied to various topics in other fields of economics, but its application for exporter–importer matching remains limited. We believe this mechanism potentially emphasizes several questions that anonymous market models fail to address. For instance, our finding suggests that many firms are willing to trade with highly capable firms, but only highly capable firms can engage in such trade. 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 highly 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 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 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

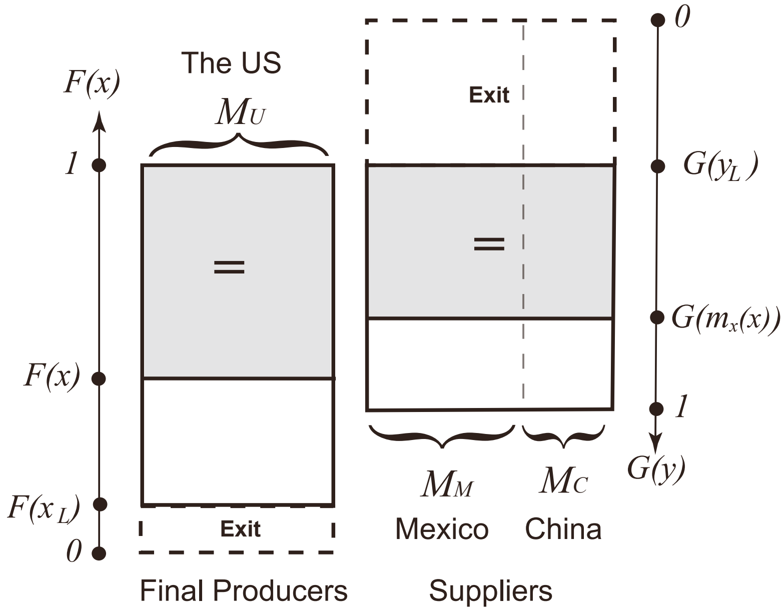
A.1 Negative Assortative Matching

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 capabilities higher than x and the right hand side is the mass of suppliers with lower capability than $m_x(x)$. Figure 7 describes the matching market clearing condition (11). The left rectangle for suppliers is described as in Figure 3. The right rectangle describes the rectangle for US final producers from Figure 3 but inverted. Therefore, a lower position in the rectangle expresses 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.

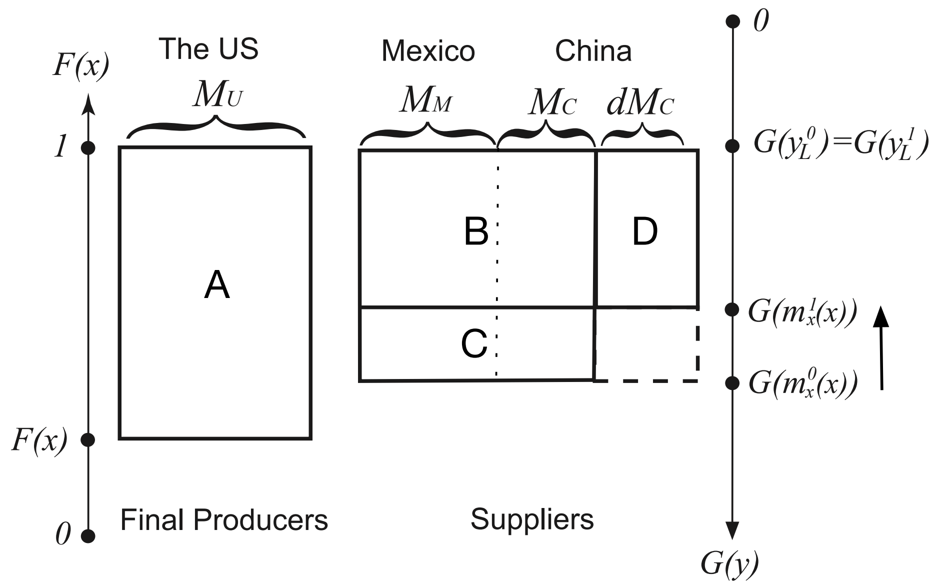
Figure 7: Case S: Negative Assortative Matching (NAM))



Suppose the mass of Chinese suppliers increases ($dM_C > 0$). In Case S, the change in matching is complex as the matching market clearing condition now 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 8 describes how importers with capability x change partner 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 4 for the case of PAM. Area A in Figure 8 expresses US importers with capabilities higher than x. These final producers initially match with suppliers with capabilities lower than $m^0_x(x)$, whose mass is expressed by areas $B + C$. After the entry of Chinese exporters, more suppliers at given capability level are available to US final producers. The original matches becomes unstable. In a new matching, final producers in area A matches with areas $B + D$, which have the same size and represent suppliers with capabilities lower than $m^1_x(x)$. The figure shows that any US final producer with given capability x downgrades its supplier from one with capability $m^0_x(x)$ to one with capability $m^1_x(x)$. In turn, consider Mexican suppliers and existing Chinese suppliers with capability $m^1(x)$. They used to match with final producers with capabilities higher than x (in the interior of area A), but downgrade partners to ones with the lower capability x. In sum, all of US final producers, Mexican suppliers, and incumbent Chinese suppliers downgrade their partners.

Figure 8: Case S: the Response of Matching to Entry of Chinese Exporters ($dM_C > 0$) if $y_L = 0$.

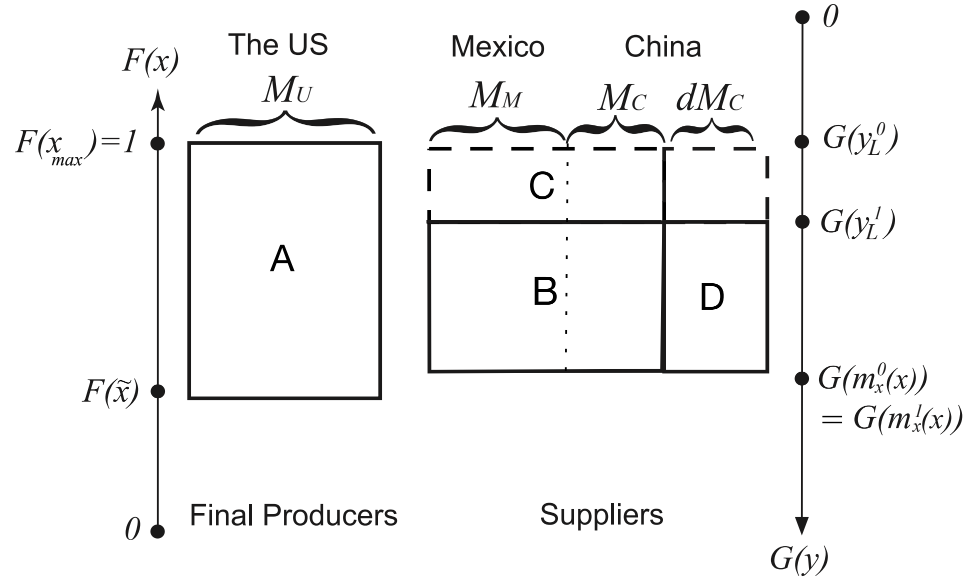


The increase in y_L adds another effect. Under NAM, final producers with maximum capability x_{max} match with suppliers with the new cut-off y^1_L. As these final producers used to match with suppliers with the old cut-off y^0_L, this indicates that final producers with the maximum capability upgrade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

Figure 9 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 $m^0_x(\tilde{x})$. 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 $B + D$. As areas C and D have the same size, we have $m^0_x(\tilde{x}) = m^1_x(\tilde{x})$. Notice that the mass of the Chinese entrants with capabilities lower 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 9: Case S: the Response of Matching to an Entry of Chinese Exporters ($dM_C > 0$).



Proposition 3. *If the mass of Chinese suppliers increases in Case C, then a threshold capability $\tilde{x}$ of final producers exists such that: (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); and (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 rankings relies on the monotonicity between firm's capability and trade volume. This monotonicity may not hold in the case of NAM. The derivatives of final producers' import volume, $I(x) = T(x, m_x(x))$, and suppliers' 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: (1) $I(x)$ is non-monotonic in x; (2) $I(x)$ is monotonically increasing in x; (3) $I(x)$ 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 have higher capability than $\tilde{x}$; (b) $\tilde{x}$ is high so that most final producers have higher capability than $\tilde{x}$; (c) $\tilde{x}$ is intermediate so that final producers are equally divided those with capability $x > \tilde{x}$ and those with $x < \tilde{x}$. Therefore, there are in total 3*3=9 cases to be considered.

Table 8 summarizes what each of the nine cases predicts on the signs of β_i in our regressions. First, if $I(x)$ is non-monotonic, then export volume $X(y)$ is also non-monotonic. In this case, we should observe, in the treatment group, 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 partners while others downgrade. Again, in this case, we should observe, in the treatment group, 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 $X'(y) = I'(m_y(y))m_y'(y) > 0$ from $m_y' < 0$. The ranking of US final producers by import volume is the 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 in the treatment group 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 in the treatment group 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 in the treatment group partner upgrading by US final producers and partner downgrading by Mexican exporters. 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 in the treatment group 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 volumes of final producers $I(x)$ are monotonically decreasing in their own capability x and (A2) the number of Mexican suppliers who stop exporting is sufficiently small [i.e. $\tilde{x}$ is high]. Case B: (B1) export volumes of Mexican suppliers $X(y)$ are monotonically decreasing in their own capability y [i.e. $I(x)$ is monotonically increasing in x] and (B2) the number of Mexican suppliers who stop exporting is sufficiently large [i.e. $\tilde{x}$ is low].

A.2 Data Construction

Customs transaction data Our primary data set is a Mexican customs transaction data set for Mexican textile/apparel exports to the US. The data set is created from the administrative records held 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) total value of shipment (in US dollars); (2) 8 digit HS product code (we use from HS50 to HS63); (3) quantity; (4) name, address, and tax identification number of the Mexican exporter; (5) name, address, and tax identification number (employment identification number, EIN) of the US importer, and other information.

Assign firm IDs We assigned identification numbers to 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, a challenge arises in 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 to 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.[39] First, as 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.", "Ltd.", etc.) and words commonly appearing in the industry (e.g., "apparel"). We removed

[39] 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 benefitted from lecture slides on "Record Linkage" by John Abowd and Lars Vilhuber.

these words from company names. Third, we standardized addresses using the software, ZP4, which received a CASS certification of address cleaning from 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 (wholesalers and retailers) due to the capacity of our workstation. For each HS2 digit industry, we matched names within customs data and names between customs data and name lists from Orbis mentioned above; we conducted similar matches for addresses and EINs. In conducting our matching, we used fuzzy matching techniques allowing small typographical errors.[40] Fifth, using matched relations and software using 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 each cluster.

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

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

[40]We used the 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 following 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 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.