Assortative Matching of Exporters and Importers*

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Abstract

This paper presents theory and evidence that exporter–importer matching plays a major role in trade liberalization adjustments. During a liberalization period of the Mexico-US textile/apparel trade, partner switching played a dominant role in export adjustments. We develop a simple trade model where partner switching is the principal margin of adjustment, featuring Beckerian positive assortative matching of exporters and importers by capability. The model predicts that trade liberalization induces systematic partner switching to achieve efficient buyer–supplier matching and to improve consumer welfare. Partner switching patterns in data are consistent with our model, but not with anonymous market models.

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

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1 Introduction

International trade mostly takes the form of firm-to-firm transactions where firms globally seek and compete for capable buyers and suppliers. A case example is Boeing's 787 Dreamliner team. Boeing famously advertises that the team includes the most capable suppliers from all over the world. This paper studies how exporters and importers choose and match their trading partners based on capability. Trade research in the last two decades has revealed the tremendous heterogeneity of exporters and importers in terms of capability such as productivity and product quality. However, workhorse models of international trade abstract away from exporter–importer matching. Perfectly competitive models (Ricardo/Heckscher-Ohlin) assume anonymous markets where exporters and importers are indifferent about their trading partners. The love of variety model (Krugman/Melitz) predicts that all exporters will trade with all importers.

This paper presents theory and evidence that exporter–importer matching plays a major role in trade liberalization adjustments. From matched exporter-importer data during a large trade liberalization episode, we report new facts about partner switching: its large contribution to adjustment and its puzzling patterns to workhorse models featuring anonymous markets. Motivated by this, we develop a simple model, in which partner switching is the principal margin of adjustment. The model combines Becker (1973)-type positive assortative matching (PAM) of exporters and importers by capability (i.e. matching those of similar capability ranks) with a standard Melitz (2003)-type heterogeneous firm trade model. This model predicts that trade liberalization induces systematic partner switching, which achieves efficient buyer-supplier matching and improves consumer welfare. In the data, we show that partner switching patterns are consistent with Beckerian PAM but not with pure random matching or anonymous market models.

To track changes in exporter–importer matching during trade liberalization, we construct a matched exporter–importer dataset for Mexican textile/apparel exports to the US from 2004 to

2007 based on Mexico's customs administrative records. The Mexico-US textile/apparel trade is particularly suitable for our purpose. First, since Mexico and the US are large trading partners, trade between the countries include numerous heterogenous exporters and importers.[1] Second, a large-scale trade liberalization occurred in 2005, when the US removed quotas on textile/apparel imports at the end of the Multi-Fibre Arrangement (MFA). Since Mexican products already had quota-free access to the US market under the North American Free Trade Agreement (NAFTA), the liberalization effectively removed protection for Mexican products in the US market and forced them to compete with imports from third countries, principally from China. Third, the liberalization was arguably exogenous because it followed a schedule decided at the GATT Uruguay round (1986–94) when China's exports were not expected to grow. Finally, the liberalization varied substantially by product. This allows us to compare liberalized products with other textile/apparel products as treatment and control groups to identify the impact of trade liberalization on exporter–importer matching at the product level.

The end of the MFA brought substantial partner changes between Mexican exporters and US importers. First, a large number of Mexican exporters stopped exporting to US importers, which the literature calls extensive margin adjustment. Second, our new finding is that the remaining intensive margin adjustment involves substantial partner switching, i.e., simultaneous adding and dropping of partners. While changes in exports to pre-liberalization partners only accounts for less than 40% of intensive margin adjustment, more than 60% of the intensive margin involves partner switching. By simultaneously adding and dropping partners, partner switching caused a more than 200% excess reallocation of exports across US buyers beyond the intensive margin. Third, most surviving exporters and importers did not change the number of major partners. In section 2, we show that product-level matching of Mexican exporters and US importers are approximately one-to-one both before and after the end of the MFA. Finally, as a consequence, firms' switching

[1] In 2004, the US was the largest market of textile and apparel for Mexico, while Mexico was the second largest source for the US. 91.9% of Mexican exports are shipped to the US and 9.5% of US imports are from Mexico.

of their main partners plays a major role in trade liberalization, which accounts for 54% of the intensive adjustment in liberalized industries.

The dominance of partner switching in an intensive margin adjustment is at odds with the anonymous market featured in workhorse trade models. In an anonymous market where an exporter is indifferent about partners, even small costs incurred by changing partner should minimize export changes caused by partner switching. Motivated by this puzzle, we develop a simple matching model of exporters and importers where partner switching is the principal margin of adjustment.

Our model combines Sattinger (1979)'s frictionless assignment/matching model of a continuum of agents and Melitz (2003)'s standard heterogeneous firm trade model. The model consists of final producers (importers) in the US and suppliers (exporters) in Mexico and China, all of whose capabilities are heterogeneous. A final producer and a supplier form a team under perfect information. Teams compete in a final goods market under monopolistic competition. Beckerian PAM arises as a stable equilibrium from a combination of transaction costs and complementarity. Although every firm desires a match with high capability firms, matches can be made with only a limited number of partners because of transaction costs. Because exporter's and importer's capabilities exhibit complementarity, only high capability exporters can "win a bid" to match with high capability importers, while low capability exporters match with low capability importers.

As empirically documented by Kandelwal, Wei and Schott (2013), the model assumes that the MFA's end caused the entry of new Chinese suppliers at various capability level to enter the US market. The entry of Chinese suppliers changes the capability ranking of suppliers in the US market and induces partner switching among incumbent firms to achieve PAM under the new ranking. Even if the capability *level* of each Mexican supplier remains the same, its capability *rank* among suppliers in the US market falls. Therefore, to achieve PAM, Mexican exporters switch to US importers with lower capability, while US importers switch to Mexican exporters with higher capability. We call these partner switching Mexican exporters' "partner downgrading" and US importers' "partner upgrading", respectively. Allowing capable Chinese suppliers to match with capable US final producers, this re-matching achieves PAM in the global market, which improves aggregate capability and consumer welfare. In contrast, in an anonymous market where matching is random, re-matching should not occur in a systematic way or be associated with any efficiency gain.

We combine the model's predictions with the data using the following steps. We rank Mexican exporters and US importers by their 2004 pre-liberalization product trade volumes. The model predicts that under PAM and random matching, these pre-liberalization trade rankings should, on average, agree with true capability rankings. Using these rankings, we compare partner switching patterns between liberalized products (the treatment group) and other textile/apparel products (the control group) within Harmonized System (HS) 2-digit industries. We confirm five PAM predictions. First, US importers upgrade their Mexican partners more often in the treatment group than in the control group. Second, Mexican exporters downgrade their US partners more often in the treatment group than in the control group. Third, we do not find systematic partner change in other directions. Fourth, among firms that switched their main partners, the capability ranks of the new partners are positively correlated with those of the old partners. Together, these provide strong support for PAM and reject random matching. Finally, the capability cutoff for Mexican exporters increases more in the treatment group than in the control group, which is consistent with Melitz-type models, including our model. We present numerous additional analyses that support both the robustness of our results and the rejection of alternative explanations.

As far as we know, our approach to detecting Beckerian PAM by capability is novel in the context of firm-to-firm matching. In other matching contexts such as marriage, researchers typically detect Beckerian PAM by examining correlations of agents' exogenous characteristics across matches in regressions and/or structural models.[2] However, simply applying this approach for firm-to-firm matching often suffers from an endogeneity problem. In Beckerian PAM or other non-anonymous markets, most firm characteristics observable in typical production and customs data (e.g., inputs, outputs, and productivity measures) may reflect partners' unobserved capabilities as well as firm's own capabilities.[3] Our approach overcomes this endogeneity problem by using trade liberalization and the induced entry of new exporters as an exogenous shock on the capability rank of incumbent exporters. Another advantage of utilizing trade liberalization is that we can control for unobserved factors commonly affecting matching by comparing liberalized and non-liberalized products within industries. In sum, we develop a clean empirical method for detecting exporter–importer PAM that is implementable with a typical customs transaction dataset and a trade liberalization episode.

The current paper contributes to the matching approach to modeling international trade in non-anonymous markets. Pioneering studies by Rauch (1996), Casella and Rauch (2002), and Rauch and Trindade (2003) develop matching/assignment models of exporters and importers. While these models consider symmetric and horizontally differentiated firms, our model features firms whose capabilities are heterogeneous (as in Melitz, 2003). Antras, Garicano and Rossi-Hansberg (2006) analyze offshoring as PAM of managers and workers by skills across countries. Compared to workhorse trade models, these models demonstrate a distinctive mechanism of welfare gains from trade: trade liberalization induces systematic partner switching to achieve globally efficient buyer–supplier matching. Our results provide the first evidence for this matching approach from actual matching data.

This paper is part of quickly growing literature that investigates exporter–importer matching

[2] Choo and Siow (2006) is a pioneering study that structurally estimates Beckerian PAM in marriage. Graham (2011) and Chiappori and Salanie (2016) are recent surveys on the econometrics of matching.

[3] One might think of estimating firm capability such as total factor productivity or product quality from production or customs data as exogenous characteristics. However, most estimation methods about firm capability require no information about each seller's buyers. This, in effect assumes tan anonymous market, where seller's capability does not depend on its buyers.

using customs transaction data. One strand of this literature develops models to explain stylized facts on firm's export volumes and buyers' margins. Blum, Claro, and Horstmann (2010) examine the role of intermediary firms connecting small buyers and sellers. Bernard, Moxnes, and Ulltveit-Moe (2018) emphasize productivity gains and fixed costs of new matches. Carballo, Ottaviano, and Volpe Martincus (2018) incorporate the interaction of buyer's taste for ideal varieties and seller's productivity. Another strand of the literature investigates exporter's and importer's partner changes over time. Eaton, Eslava, Jinkins, Krizan, and Tybout (2014) and Eaton, Jinkins, Tybout, and Xu (2015) examine search and learning frictions in partner acquisitions. Monarch (2016) analyzes switching costs of buyers. Machiavello (2010) emphasizes exporter's reputation building. Our focus is different from these studies. First, we highlight the role of firms' competition for capable partners and capability complementarity as determinants of exporter-importer matching. Second, we investigate systematic changes of matching in trade liberalization by utilizing product-level variations in liberalization. Importantly, our finding of positive assortative matching by capability should not be confused with "negative degree assortativity" reported by Blum et al. (2010) and Bernard et al. (2018). These two patterns can be compatible with each other as we find in our dataset (see Section 2.2).

In this literature, concurrent papers by Benguria (2015) and Dragusanu (2014) are closely related to the current paper. These authors document positive correlations of size and productivity measures of exporters and importers in India–US trade and in France–Colombia trade, respectively. Benguria (2015) additionally found that at the US–Colombia free trade agreement, US exporters switch to Colombia importers with higher productivity. Our model featuring Beckerian PAM also predicts these findings. Benguria (2015) and Dragusanu (2014) develop search effort models of Stigler (1961) type that predicts exporter–importer PAM from a different mechanism: a high productivity exporter spends greater search efforts to find a high productivity importer. Their search effort models, however, do not explain our finding that Mexican exporter's partner downgrading at the end of the MFA. In their models, search costs are sunk and importers are willing to trade with all exporters that approach them. Thus, Mexican exporters should continue to trade with pre-liberalization US partners instead of switching to new importers with lower productivity, which requires additional search costs.

The rest of the paper is organized as follows. Section 2 discusses our dataset on Mexico–US textile/apparel trade and documents new facts regarding partner switching during trade liberalization. Section 3 presents our model and derives predictions. Section 4 describes our empirical strategies. Section 5 presents the main empirical results and robustness checks. Section 6 provides concluding remarks. The online Appendix provides calculations, proofs, data construction, summary statistics, and additional analyses rejecting alternative explanations for our results.

2 The Mexico–US Textile Apparel Trade

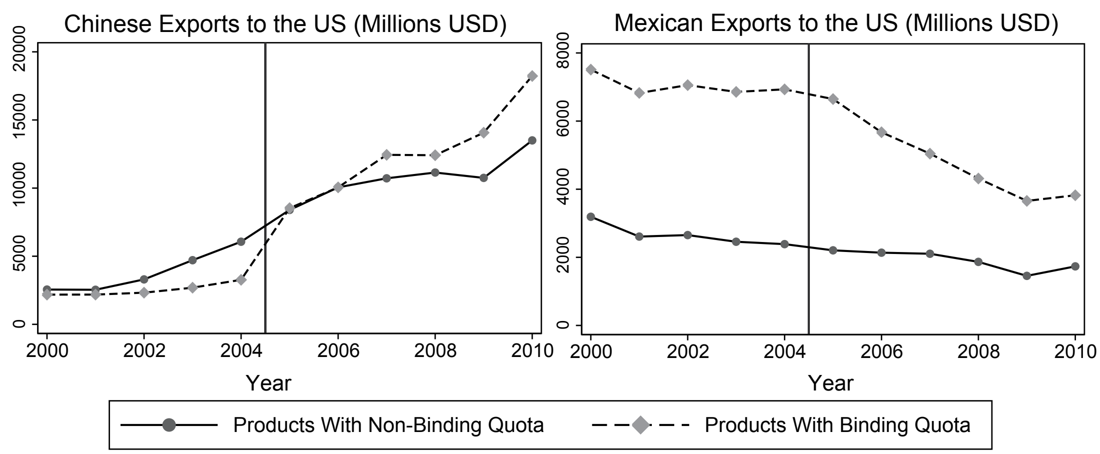
2.1 The End of the Multi-Fibre Arrangement

Mexico–US textile/apparel trade experienced large-scale liberalization in 2005 at the end of the MFA. The MFA and its successor, the Agreement on Textile and Clothing, are agreements about quota restrictions regarding textile/apparel imports among GATT/WTO member countries. At the GATT Uruguay round (1986–94), the US (together with Canada, the EU, and Norway) promised to abolish their quotas in four steps (in 1995, 1998, 2002, and 2005). The MFA's end in 2005 was the largest liberalization of the four steps, in which liberalized products constituted 49% of the imports in 1990.

Three facts (taken from previous studies) about the consequences resulting from the MFA's end motivate our analysis.

Fact 1: Surge in Chinese Exports to the US According to Brambilla, Khandelwal, and Schott (2010), US imports from China disproportionally increased by 271% in 2005, whereas imports from almost all other countries decreased. Using Brambilla et al. (2010)'s US import quota data, we classify each HS 6-digit textile/apparel product into one of two groups (see Appendix for details). The first treatment group consists of Chinese export products subject to a binding 2004 US import quota. The second control group consists of other textile/apparel products. The left panel in Figure 1 displays Chinese exports to the US from 2000 to 2010 with a dashed line for the treatment group and with a solid line for the control group. After the 2005 quota removal, Chinese exports for the treatment group increased much faster than those for the control group.[4]

Figure 1: 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 two groups of textile/apparel products from 2000 to 2010. The dashed line represents the sum of export values of all products upon which the US had imposed binding quotas against China in 2004 (the treatment group), and the solid line represents the sum of export values of other textile/apparel products (the control group). The right panel expresses the same information for exports from Mexico to the US. Data source: UN Comtrade.

Fact 2: Exports by New Chinese Entrants with Various Capability Levels Using Chinese customs transaction data, Khandelwal, Schott, and Wei (2013) decompose the increases in Chinese

[4] 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 their pre-2005 levels. This is because (1) the 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).

exports to US, Canada, and the EU after the quota removal into intensive and extensive margins. They find that increases in Chinese exports belonging to the treatment group 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.[5]

Fact 3: Mexican Exports Faced Competition from China By 2003, Mexico already had tariff- and quota-free access to the US market through NAFTA. With the MFA's end, Mexico lost its advantage over third-country exporters and faced increased competition from Chinese exporters in the US market. The right panel in Figure 1 shows Mexican exports to the US from 2000 to 2010 for the treatment group (dashed line) and the control group (solid line). While the two had moved in parallel before 2005, whereas the treatment group significantly declined after 2005. The parallel movement of the two groups before 2005 suggests that the choice of products subject to quota removal in 2005 was exogenous to Mexican exports to the US.

2.2 Partner Switching after the MFA's End

Our dataset tracks changes in product-level matching of Mexican exporters and US importers in response to the end of the MFA.

Data From Mexico's customs records, we construct a matched exporter–importer dataset from June 2004 to December 2011 for Mexican textile/apparel exports (covering HS50 to HS63) to the US. For each match of a Mexican exporter and a US importer, the dataset contains the following information: exporter-ID; importer-ID; 6-digit HS product code; annual shipment value (USD);

[5] Khandelwal et al. (2013) report that incumbent exporters are mainly state-owned firms, whereas new exporters include private and foreign firms, which are typically more productive than state-owned firms. In addition, the distribution of unit prices set by new entrants has a lower mean but greater support than that by incumbent exporters.

quantity and unit; an indicator of a duty free processing reexport program (Maquiladora/IMMEX); and other information. Appendix explains the dataset construction.

Data cleaning drops some observations. First, since the dataset covers only observations from June to December for the year 2004, we drop observations from January to May for other years to make each year's information comparable. We obtain similar results when January–May observations are included. Second, while importer information is reported for most normal trade transactions, it is sometimes missing for processing trade transactions under the Maquiladora/IMMEX program where exporters do not have to report an importer for each shipment.[6] We drop exporters who do not report importer information for most transactions. To address potential selection issues caused by this action, we distinguish normal trade and processing trade in the analyses below and conduct weighted regressions in the Appendix as a robustness check.

Approximately One-to-One Matching at Product Level Our first finding is that matching of Mexican exporters and US importers at product level is approximately one-to-one. Table 1 reports mean and median statistics about product-level matching. While Rows (1) and (2) show that an average product has 11–15 exporters and 15–20 importers, Rows (3) and (4) show that the majority of firms trade with only one partner. Rows (5) and (6) show that even firms who trade with multiple partners concentrate more than 70% of their trade volume with their single main partners. In sum, most firms conduct most of their trade with only one partner in a given year.

[6]The Maquiladoras program started in 1986 and was replaced by the IMMEX (Industria Manufacturera, Maquiladora y de Servicios de Exportation) program in 2006. In the Maquiladoras/IMMEX programs, firms in Mexico can import materials and equipment duty free used for products exported. Exporters must register importer's information in advance but do not need to report it for each shipment.

Table 1: Summary Statics for Product-Level Matching

HS 6-digit level statistics, mean (median)	2004	2005	2006	2007
(1) Number of Exporters	14.7 (8)	14.1(7)	11.7 (6)	11.3 (6)
(2) Number of Importers	19.6 (11.5)	18.7 (10)	15.5 (9)	14.9 (9)
(3) Number of Exporters Selling to an Importer	1.1 (1)	1.1 (1)	1.1 (1)	1.1 (1)
(4) Number of Importers Buying from an Exporter	1.5 (1)	1.5 (1)	1.5 (1)	1.4 (1)
(5) Value Share of the Main Exporter (Number of Exporters > 1)	0.77	0.77	0.76	0.77
(6) Value Share of the Main Importer (Number of Importers > 1)	0.74	0.75	0.77	0.76

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

A potential concern for Table 1's statistics is that they might over-represent small firms that only minimally impact aggregate trade volumes. To check this point, we develop a new measure "main-to-main share," which expresses the extent to which overall transactions in one product market are quantitatively close to one-to-one matching. We first define a "main-to-main match" as a product-level match in which the exporter is the importer's main partner for the product, while simultaneously, the importer is the exporter's main partner. We then calculate "main-to-main share" as the share of trade volume conducted by main-to-main matches out of the total aggregate trade volume. If all matching is one-to-one, main-to-main share takes on a maximum value of one. Even when matching is many-to-many, the share can be close to one when trade with non-main partners is in small amount.

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

Year	Main-to-Main Share				
	All	Quota-bound	Quota-free	Processing	Normal
	(1)	(2)	(3)	(4)	(5)
2004	0.79	0.78	0.80	0.79	0.80
2005	0.81	0.82	0.79	0.82	0.81
2006	0.81	0.81	0.82	0.83	0.83
2007	0.84	0.84	0.85	0.85	0.84

Note: Each column reports main-to-main shares in Mexico's textile/apparel exports to the US for several types of transactions. Column (1) is about all textile/apparel products. Column (2) is about products for which Chinese exports to the US were subject to binding quotas (the treatment group), while column (3) is about the other textile/apparel products (the control group). Column (4) is about processing trade, while column (5) is about other normal trade.

Column (1) in Table 2 reports that the main-to-main share for Mexico's overall textile/apparel exports to the US is approximately 80% and stable across years.[7] Column (2) show the main-to-main share for liberalized products at the MFA's end (quota-bound) while Column (3) shows other products (quota-free). The share remains stable whether or not products are liberalized by the MFA's end. Columns (4) and (5) show the main-to-main share separately for Maquiladora/IMMEX processing trade and other normal trade. These stable and high main-to-main shares suggest that one-to-one matching is a fair approximation of product-level matching in Mexico–US textile/apparel trade.[8]

One might be concerned that our finding is specific to our dataset. To address this concern, we check whether our dataset can replicate previous studies' findings from datasets for other countries. First, in our dataset, numbers in Rows (1) to (4) in Table 1 are smaller than those in Blum et al. (2010), Bernard et al. (2018), and Carballo et al. (2018), respectively. These differences are largely caused by difference in the definition of matching. When matches are defined at the

[7] Appendix investigates main-to-main shares at product-year level. The median main-to-main share is 0.97 and the 25th percentile is 0.86. Furthermore, high main-to-main share is not associated with the number of firms in each product.

[8] One reason for one-to-one matching may be exclusive dealing. A firm might not allow a partner to trade with others to prevent information leakage or to raise rival's costs through vertical foreclosure. Another reason may be quality control. Final producers might avoid quality variance of intermediate goods caused by purchasing from multiple suppliers.

country level as in these studies, the numbers in our dataset become close to those in these studies. Second, our dataset also replicates the "negative degree assortativity" in Blum et al. (2010) and Bernard et al. (2018), where the number of exporter's partners negatively correlates with the number of importer's partners across matches, if as in these studies, matches are re-defined at the country level.[9] Thus, our finding about the quantitative importance of main-to-main trade is compatible with negative degree assortativity. The fact that our dataset can replicate findings from other datasets suggests that our findings are not necessarily specific to our dataset.

Partner Switching after the MFA's end The fact that main-to-main shares are stable during trade liberalization does not necessarily imply that partner relationships are also stable. Exporters and importers actively switch partners during liberalization. Table 3 reports changes in Mexican textile/apparel exports to the US from 2004 to 2007 by incumbent exporters who export in 2004. These changes are reported separately for liberalized products at the MFA's end (quota-bound) and other products (quota-free). The changes in total exports in Column (1) are decomposed into two traditional margins, "extensive margin" adjustments in Column (2) by exiters who stop exporting in 2007 and "intensive margin" adjustments in Column (3) by survivors who continue to export in 2007. Consistent with standard heterogeneous exporter models (e.g., Melitz, 2003; Chaney, 2008), extensive margin plays a large role in liberalized industries.

[9]Following Figure 1 in Bernard et al. (2018), we re-define a match at firm level and 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, -0.12 (s.e. 0.018), for 2004, which is very similar to the slope of -0.13 (s.e. 0.01) for Norwegian exporters in Bernard et al. (2018).

Table 3: Changes in Mexican Textile/Apparel Incumbent Exports to the US from 2004 to 2007 (Million USD)

	Total	Traditional margins		Partner margins			Export
		Extensive	Intensive	Stay	Add	Drop	Reallocation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Quota-bound	-950.6	-887.4	-63.4	-25.1	83.5	-121.9	205.4
% of (3)			100%	39.5%	-131.7%	192.2%	323.9%
Switcher share					(0.95)	(0.82)	
Quota-free	-223.0	-179.6	-43.4	-24.0	37.5	-56.9	103.5
% of (3)			100%	55.4%	-86.5%	131.1%	217.6%
Switcher share					(0.79)	(0.87)	

Note: Each column reports changes in Mexican textile/apparel exports to the US between 2004 and 2007 by incumbent exporters in 2004, for quota-bound products, for which Chinese exports to the US were subject to binding quotas in 2004, and other quota-free products. Changes in total exports in (1) are decomposed to extensive margin by exiters in (2) and intensive margin by survivors in (3). The intensive margin in (3) is decomposed to: (4) exports to continuing partners; (5) exports to new partners; (6) exports to dropped buyers. Column (7) is the absolute sum of (5) and (6).

Our new finding is that export changes previously treated as "intensive margin" in Column (3) actually involve substantial partner changes. We decompose Column (3) based on patterns of partner changes. "Partner staying" in Column (4) reports changes in exports to continuing partners both in 2004 and in 2007. "Partner adding" in Column (5) reports changes in exports to new partners who import from the exporter in 2007 but not in 2004. "Partner dropping" in Column (6) report changes in exports to dropped partners who import from the exporter in 2004 but not in 2007. For liberalized products, more than 60% of the intensive margin adjustment is associated with partner changes, i.e. partner adding and dropping in Columns (5) and (6). Parentheses in Column (5) and (6) report the share of export changes by "partner switchers" who simultaneously add and drop partners. Its large share (more than 80%) suggests that most partner changes are in fact "switches" rather than the adding or dropping of partners.

Partner switching causes substantial reallocation of exports across buyers. In labor economics, to capture the extent of labor market churning, the absolute sum of hired workers and fired workers is often calculated as "job reallocation"(e.g., Davis, Haltiwanger and Schuh, 1996). Following this literature, Column (7) reports export reallocation, the absolute sum of Columns(5) and (6), which examines the extent of buyer-supplier churning. In liberalized products, export reallocation is more than 300% of the intensive margin, which is at odds with anonymous market models. In such models where partners are indifferent, partner changes should be minimized to save costs caused by partner changes. Thus, export reallocation in Column (7) must be equal to the intensive margin in Column (3). However, Column (7) shows more than 200% of excess reallocation occurs beyond the intensive margin. This large churning has been masked in typical exporter data, without matching information being provided.

Table 4: Intensive Margin Changes in Mexican Textile/Apparel Incumbent Exports to the US from 2004 to 2007 (Million USD)

	Intensive Margin	Main Partner		Non-Main Partner
		Same	Switch	
	(1)	(2)	(3)	(4)
Quota-bound	-63.4	-13.7	-34.5	-15.2
% of (1)	100%	21.6%	54.4%	24.0%
Quota-free	-43.4	-10.9	-18.3	-14.2
% of (1)	100%	25.1%	42.1%	32.7%

Note: Each column reports main-to-main shares in Mexico's textile/apparel exports to the US for several types of transactions: All: all textile/apparel products; Quota-bound (treatment group): products for which Chinese exports to the US were subject to binding quotas; Quota-free (control group): the other textile/apparel products; Maquila: Maquiladora/IMMEX transactions; and Non-Maquila: other normal transactions.

Although partner switching causes quantitatively large adjustments, matching remains approximately one-to-one. As these two facts suggest, Table 4 shows that the switching of main partners plays a major role in intensive margin adjustments. The intensive margin adjustment from 2004 to 2007 in Column (1) is decomposed into three types: (1) changes in exports to the same main partners in Column (2), where the main partners are the same both in 2004 and 2007; (2) changes in exports to switched main partners in Column (3), where the main partners in 2004 and 2007 are different; (3) changes in exports to non-main partners in Column (4). In liberalized industries, switching of main partners is associated with more than 50% of the intensive margin adjustment.

The dominance of partner switching in intensive margin adjustments is puzzling in anonymous market models. Thus, we need to move beyond these types of models to understand the active churning of buyer-supplier relationships during trade liberalization. In the next section, we develop a matching model of exporters and importers where partner switching is the principal margin of adjustment.

3 The Model

3.1 Matching Model of Exporters and Importers

The model includes three types of continuum of firms, namely, US final producers, Mexican suppliers, and Chinese suppliers.[10] A US final producer matches with a supplier from either Mexico or China to form a team that produces one variety of differentiated final goods.[11] Once teams are formed, suppliers tailor intermediate goods for their teams; therefore, firms transact intermediate goods only within their team. Each firm joins only one team. The model has two stages. In Stage 1, teams are formed under perfect information. This frictionless matching model is the simplest model predicting assortative matching. Introducing one-sided or two-sided search friction does not change qualitative predictions that we will bring to data.[12] In Stage 2, teams compete in the US final-good market in a monopolistically competitive fashion.

Firms' capabilities are heterogeneous. Capability reflects productivity and/or quality. Let x and y be the capability of final producers and suppliers, respectively. There exist 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 continuous support $[x_{min}, x_{max}]$. The capability of Mexican and Chinese suppliers follows an

[10] Our model is a partial equilibrium version of Sugita (2015), a two-country general equilibrium model with endogenous firm entry.

[11] US final producers need not conduct physical production. They could be retailers or wholesalers.

[12] There is a theoretical literature on matching models with search frictions. Smith (2011) is an excellent survey. The general conclusion of the literature is that as long as complementarity within matches is sufficiently large, matching becomes positive assortative as in a frictionless matching model that we consider.

identical distribution, and the c.d.f. is $G(y)$ with continuous support $[y_{min}, y_{max}]$.[13] For simplicity, a Chinese supplier is a perfect substitute for a Mexican supplier of the same capability.

Teams' capabilities are heterogeneous. Team capability $\theta(x, y)$ increases in members' 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 θ.

The US representative consumer maximizes the following utility function:

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

where Ω is a set of available differentiated final goods, ω is a variety of differentiated final goods, $p(\omega)$ is the price of ω, $q(\omega)$ is the consumption of ω, $\theta(\omega)$ is the capability of a team producing ω, q_0 is the consumption of a numeraire good, I is an exogenously given income. $\alpha \geq 0$ and $\delta > 0$ are given parameters. Consumer demand for a variety with price p and capability θ is derived as $q(p, \theta) = \delta\theta^{\alpha\sigma}P^{\sigma-1}p^{-\sigma}$, where $\sigma \equiv 1/(1-\rho) > 1$ is the elasticity of substitution and $P \equiv \left[\int_{\omega\in\Omega}p(\omega)^{1-\sigma}\theta(\omega)^{\alpha\sigma}d\omega\right]^{1/(1-\sigma)}$ is the ideal price index.

Production technology is of Leontief type. When a team with capability θ 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, the final producer assembles these intermediate goods into final goods with costs $c_x\theta^{\beta}q + f_x$, where c_i and f_i are positive constants ($i = x, y$). Team's total costs are $c(\theta, q) = c\theta^{\beta}q + f$, where $c \equiv c_x + c_y$ and $f \equiv f_x + f_y$. Externalities within teams make firms' marginal costs dependent on both their partner's capability and their own capability.[14] For simplicity, we assume firm's marginal costs depend on the team's capability.

[13] An identical capability distribution of Chinese and Mexican suppliers is assumed for graphical exposition and is not essential for the main predictions.

[14] 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, each member's marginal cost may depend on the entire team's capability.

Team capability θ may represent productivity and/or quality, depending on α and β. For instance, when $\alpha = 0$ and $\beta < 0$, teams face symmetric demand and team's marginal costs decrease in θ. In this case, θ represents productivity (e.g., Melitz, 2003). When $\alpha > 0$ and $\beta > 0$, a high value of θ implies a large demand at a given price and high marginal costs. In this case, θ may be called quality (e.g., Baldwin and Harrigan, 2011; Johnson, 2012; Verhoogen, 2008).

Backward induction obtains an equilibrium (see Appendix for calculations).

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

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

where $A \equiv \frac{\delta}{\sigma}\left(\frac{\rho P}{c}\right)^{\sigma-1}$ summarizes factors that (infinitesimal) individual teams take as given. We assume $\gamma \equiv \alpha\sigma - \beta(\sigma - 1) > 0$ so that team profits are increasing in team capability. Furthermore, we normalize $\gamma = 1$ by choosing the unit of θ as comparative statics on α, β, and σ is not our main interest. Let M and $H(\theta)$ be the mass and capability distribution of active teams. The price index $P = c/\left(\rho\Theta^{1/(\sigma-1)}\right)$ turns out to be decreasing in aggregate team capability $\Theta \equiv M\int \theta dH(\theta)$.

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 $m_x(m_y(y)) = y$.

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; (ii) *pair-wise stability*, wherein each firm is the optimal partner for the other team member:[15]

$$\pi_x(x) = [A\theta(x, m_x(x)) - f] - \pi_y(m_x(x)) = \max_y A\theta(x, y) - \pi_y(y) - f;$$
$$\pi_y(y) = [A\theta(m_y(y), y) - f] - \pi_x(m_y(y)) = \max_x A\theta(x, y) - \pi_x(x) - f. \tag{2}$$

The envelop theorem using the first order conditions leads to

$$\pi'_x(x) = A\theta_1(x, m_x(x)) > 0 \text{ and } \pi'_y(y) = A\theta_2(m_y(x), y) > 0 \tag{3}$$

which proves that profit schedules are increasing in capability. Thus, capability cut-offs x_L and y_L exist such that only final producers with $x \geq x_L$ and suppliers with $y \geq y_L$ engage in international trade. These cut-offs satisfy

$$\pi_x(x_L) = \pi_y(y_L) = 0 \text{ and } M_U[1 - F(x_L)] = (M_M + M_C)[1 - G(y_L)]. \tag{4}$$

The second condition in (4) indicates that the number of suppliers in the matching market is equal to the number of final producers.

Differentiating (3) by x, we obtain

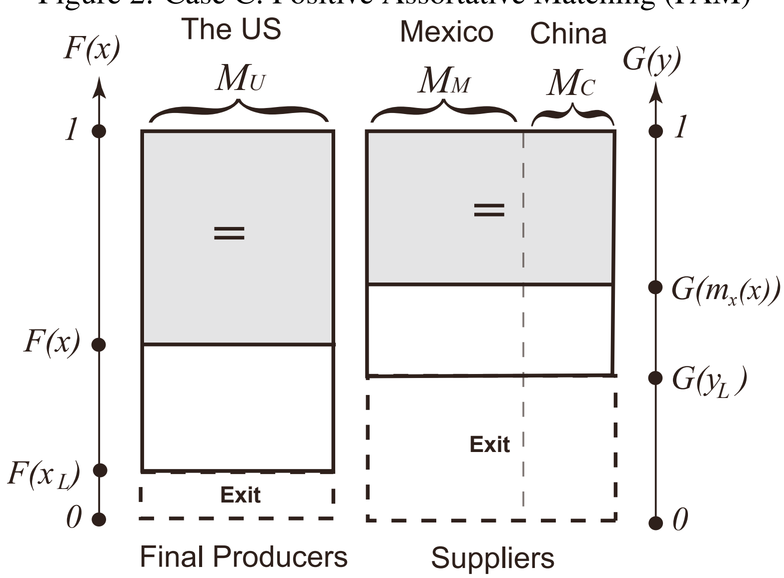
$$m'_x(x) = \frac{A\theta_{12}}{\pi''_x - A\theta_{11}}, \text{ where } \theta_{12} \equiv \frac{\partial^2\theta}{\partial x \partial y} \text{ and } \theta_{11} \equiv \frac{\partial^2\theta}{\partial x^2}. \tag{5}$$

Since the denominator in (5) is positive from the second order condition, the sign of cross derivatives θ_{12} is the same as the sign of $m'_x(x)$, i.e. 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 for all x and y: (1)

[15]Roth and Sotomayor (1990) and Browning, Chiappori and Weiss (2014) provide excellent backgrounds on matching models.

Case C (Complement) $\theta_{12} > 0$; (2) Case I (Independent) $\theta_{12} = 0$; (3) Case S (Substitute) $\theta_{12} < 0$.[16] 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 is indifferent about partner capability. Therefore, we assume matching is random in Case I. Case I is a useful benchmark because it nests traditional models where firm heterogeneity exists only for one side of the market, i.e., either among exporters ($\theta_1 = \theta_{12} = 0$) or among importers ($\theta_2 = \theta_{12} = 0$). We focus on Case C and Case I in the main text of the paper and examine Case S in the Appendix.

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



[16]In Case C and Case S, θ is also called strict supermodular and strict submodular, respectively. An example for Case C is the complementarity of quality of tasks in a production process (e.g., Kremer, 1993). 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 on Case C and Case S.

In Case C, $m_x(x)$ satisfies the "matching market clearing" condition:

$$M_U\left[1-F(x)\right]=\left(M_M+M_C\right)\left[1-G\left(m_x(x)\right)\right] \text{ for all } x \geq x_L. \tag{6}$$

The left hand side of (6) is the mass of final producers with higher capability than x and the right hand side is the mass of suppliers who match with them, i.e., suppliers with higher capability than $m_x\left(x\right)$. Figure 2 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 the mass of final producers with higher capability than x, while the right gray area is the mass of suppliers with higher capability than $m_x(x)$. Matching function $m_x(x)$ is determined so that the two areas are the same size for all $x \geq x_L$.

In both Case C and Case I, the team with the capability cutoff θ_L comprises a final producer with x_L and a supplier with y_L. In Case C, matching function $m_x(x)$ determines the aggregate capability $\Theta\left(x_L\right)=M_U\int_{x_L}^{\infty}\theta\left(x,m_x(x)\right)dF(x)$ and the capability cutoff $\theta_L\left(x_L\right)=\theta\left(x,m_x(x_L)\right)$ as functions of x_L. In Case I, Condition (4) determines $y_L(x_L)$ as a function of x_L. Let $\theta(x,y)\equiv\theta^x(x)+\theta^y(y)$. Then, $\Theta\left(x_L\right)=M_U\int_{x_L}^{\infty}\theta^x\left(x\right)dF(x)+\left(M_M+M_C\right)\int_{y_L(x_L)}^{\infty}\theta^y(y)dG(y)$ and $\theta_L(x_L)=\theta^x\left(x_L\right)+\theta^y\left(y_L(x_L)\right)$ become functions of x_L. From (1), (4) and $A=\delta/\sigma\Theta$, the team with the capability cutoff earns zero profits:

$$\Pi\left(\theta_L\right)=\frac{\delta\theta(x_L)}{\sigma\Theta\left(x_L\right)}-f=0. \tag{7}$$

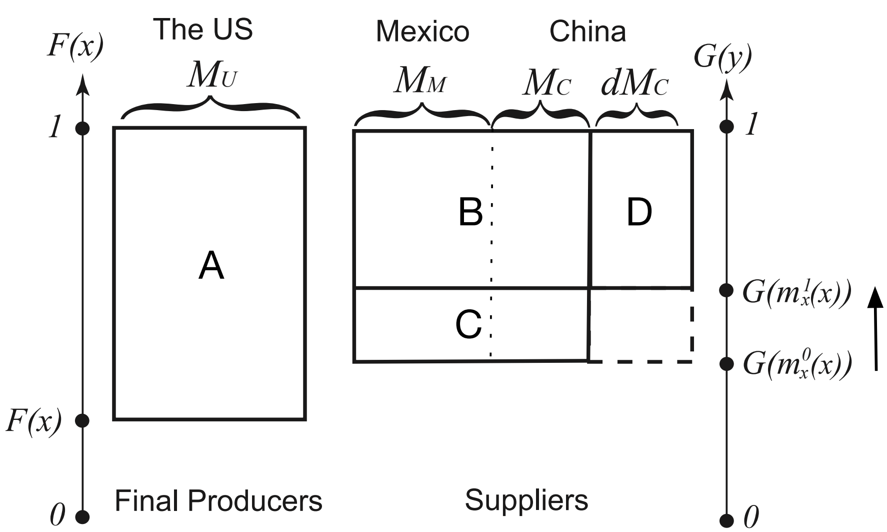
Notice that in both Case C and Case I, equation (7) determines a unique x_L since $\Theta\left(x_L\right)$ is decreasing and $\theta_L(x_L)$ is increasing in x_L. Finally, we formally define a stable matching equilibrium as follows.

Definition 1. In Case C with $\theta_{12} > 0$, a stable matching equilibrium consists of a matching function $m_x(x)$, profit schedules $\{\pi_x(x), \pi_y(y)\}$ and capability cutoffs $\{x_L, y_L\}$ that satisfy (3), (4), (6) and (7). In Case I with $\theta_{12} = 0$, a stable matching equilibrium consists of $\{\pi_x(x), \pi_y(y), x_L, y_L\}$ that satisfy (3), (4) and (7).

3.2 Consequences of Chinese Firm Entry at the End of the MFA

We analyze the impact of Chinese firm entries at the end of the MFA on matching between US importers and Mexican exporters. As discussed in Section 2, new entrants are heterogeneous in capability. Thus, we model this event as an exogenous increase in the mass of Chinese suppliers ($dM_C > 0$) in the US market. 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.

Figure 3: Case C: Response of Matching to the MFA's End



Case C Figure 3 shows how matching functions change from $m_x^0(x)$ to $m_x^1(x)$ for given capability x. Area A expresses US importers with capabilities higher than x. They initially match with suppliers in areas $B + C$ who have higher capability than $m_x^0(x)$. When new Chinese exporters enter the market, the original matches become unstable because they are not PAM in the new environment. Some US importers are willing to switch their partners to the new entrants. In the new matching, final producers in area A match with suppliers in areas $B+D$ who have higher capability than $m_x^1(x)$. A US final producer with a capability x switches main partner from 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. Mexican suppliers with capability $m_x^1(x)$ matched with final producers with strictly higher capability than x prior to the entry of Chinese suppliers. However, not all Mexican suppliers can match with new US partners. Mexican suppliers with low capability must exit the US market, which is formally proved in the Appendix.

Our data on Mexico–US trade only record rematching by firms engaging in Mexico–US trade both before and after the MFA's end. We call these firms *US continuing importers* and *Mexican continuing exporters*. Then, we obtain three predictions for Case C as follows.

C1: US continuing importers switch their Mexican partners to those with higher capability (partner upgrading), while Mexican continuing exporters switch their US partners to those with lower capability (partner downgrading).

C2: PAM holds both before and after the MFA's end.

C3: The capability cutoff for Mexican exporters rises.

Case I Entry of Chinese suppliers also raises the capability cutoff y_L for suppliers so that low capability suppliers exit, which is proved in the Appendix. US importers who matched with these exiting suppliers switch to new Chinese suppliers. Other firms continue to match with their old partners, though they change price and quantity of goods traded. This is because firms are indifferent about their partners as long as they have higher capability than the cutoffs. Thus, we obtain three predictions.

I1: US continuing importers do not change their Mexican partners, while Mexican continuing exporters do not change their US partners.

I2: Matching is random before and after the MFA's end.

I3: The capability cutoff for Mexican exporters rises.

Rematching Gain from Trade The end of the MFA causes two adjustments. First, new Chinese suppliers with high capability replace Mexican suppliers with low capability (replacement effect), which exists in both Cases C and I. Second, continuing firms re-match (rematching effect), which exists in Case C but not in Case I. We show both adjustments lower the price index and benefits the consumer.

To see each adjustment, we consider a hypothetical "no-rematching" equilibrium where no rematching occurs and where firms switch partners only if their current partner exits the market. Denote variables in this no-rematching equilibrium by "NR," variables before the MFA's end by "B," and variables after the MFA's end by "A." Then, the change in the price index $P^B - P^A$ is decomposed into the replacement effect $P^B - P^{NR}$ and the rematching effect $P^{NR} - P^A$. The following lemma establishes these two effects (the proof is in the Appendix).

Lemma 1. *In Case C, $P^A < P^{NR} < P^B$, while in Case I, $P^A = P^{NR} < P^B$.*

In Case C, the rematching effect is positive, i.e., the rematching creates an additional consumer gain. From $P = c/\left(\rho\Theta^{1/(\sigma-1)}\right)$, this gain comes from increases in the aggregate capability, $\Theta^A > \Theta^{NR} > \Theta^B$, which arises from a classic theorem in the matching theory that a stable matching maximizes aggregate payoffs, $A\Theta - Mf$, for given A (Koopmans and Beckmann, 1957; Shapley and Shubik, 1972; Gretsky, Ostroy and Zame, 1992).[17] In Case I, the rematching effect is zero

[17] In the case of finite agents, the intuition of the theorem follows from the definition of supermodularity of θ such that for any $x > x'$ and $y > y'$, $\theta(x, y) + \theta(x', y') > \theta(x', y) + \theta(x, y')$. In the case of continuums of agents, the theorem needs additional technical assumptions shown by Gretsky et al. (1992).

because matching is irrelevant. If data observe rematching consistent with Case C, the model interprets it as a process of improving global buyer–supplier matching and consumer welfare.[18]

4 Empirical Strategies

4.1 Proxy for Capability Rankings

Testing predictions C1-C3 and I1-I3 requires data on firm capability. We use firm trade volumes as a proxy for firm capability, using properties of the model.

For Case C, let $I(x)$ be the import volume by an US importer with capability x and let $X(y)$ be the export volume by a Mexican exporter with capability y. For Case I, let $\bar{I}(x)$ be the expected import volume by a US importer with capability x and let $\bar{X}(y)$ be the expected export volume by a Mexican exporters with capability y. Then, using the fact that within team trade $T(x, y)$ is increasing in x and y, we obtain the following lemma for the monotonic relationship between firm capability and trade volume (the proof is in Appendix).

Lemma 2. *In Case C, $I(x)$ and $X(y)$ are strictly increasing functions. In Case I, $\bar{I}(x)$ and $\bar{X}(y)$ are strictly increasing functions.*

For each product, we create a ranking of US continuing importers by the amount of their imports from their main partner in 2004 before the MFA's end. Similarly, for each product, we rank Mexican continuing exporters by the amount of their exports to their main partner in 2004. From Lemma 2, these rankings should agree with the rankings of true capability in Case C and on average so in Case I. We assume that the capability ranking is stable in a short run and thus use the

[18] This re-matching gains from trade indicates inefficieny of "matching diversion" caused by the preferential trade agreement: high capability US final producers are diverted to match with low capability Mexican suppliers instead of high caiability Chinese suppliers. Ornelas, Turner, and Bickwit (2019) theoretically analyze "matching diversion" by the preferential trade agreement in a model of one-sided heterogeneity.

rank measured from 2004 data for the same firm throughout our sample period.[19]

Using these rankings, we first create three variables: (1) firm i's own rank in product g in country c, $OwnRank^c_{ig}$; (2) rank of the firm's main partner of product g in 2004 before the MFA's end, $OldPartnerRank^c_{ig}$; and (3) rank of the firm's main partner of product g in 2007 after the MFA's end, $NewPartnerRank^c_{ig}$.[20] Note that $OldPartnerRank^c_{ig}$ differs from $NewPartnerRank^c_{ig}$ if and only if the firm switches the main partner during 2004–07. These ranks are standardized using the number of firms so as to fall in [0,1]. Smaller ranks indicate higher capability. Finally, we create variables of partner changes as follows. Partner upgrading dummy Up^c_{igs} equals one if $NewPartnerRank_{igs} < OldPartnerRank_{igs}$. Partner downgrading dummy $Down^c_{igs}$ equals one if $NewPartnerRank_{igs} > OldPartnerRank_{igs}$.

4.2 Specifications

Partner Changes (C1 and I1) We estimate the following regressions to test predictions C1 and I1 on partner changes:

$$\begin{aligned} Up^c_{igs} &= \beta^c_U Binding_{gs} + \lambda_s + \varepsilon^c_{Uigs} \\ Down^c_{igs} &= \beta^c_D Binding_{gs} + \lambda_s + \varepsilon^c_{Digs}, \end{aligned} \tag{8}$$

where c, i, g, and s represent a country (US and Mexico), firm, HS 6-digit product, and sector (HS 2-digit level), respectively. Dummy variable $Binding_{gs}$ equals one if Chinese exports of product g to the US faced a binding quota in 2004, which is constructed from Brambilla et al. (2010). λ_s represents HS 2-digit level fixed effects.[21] ε^c_{Uigs} and ε^c_{Dijs} are error terms. Appendix explains the

[19]Trade volume ranks in 2004 and 2007 are highly correlated, which confirms our assumption. All correlation coefficients are above 0.85 and similar between the treatment and control groups.

[20]We choose the period of 2004-07 because the 2008 Lehman crisis, which greatly reduced Mexican exports to the US, potentially confounds the impact of the MFA end.

[21]We include HS 2 digit level fixed effects instead of HS 4 digit level fixed effects because of their collinearity with the binding dummy. When the binding dummy is regressed on only HS 4 digit level fixed effects, R^2 is 0.86 in both

construction of the binding dummy and other variables. The sample for the regressions is beyond main-to-main matches and includes all firms that engage in Mexico-US trade relationships both in 2004 and in 2007 to avoid a potential sample selection problem.

The coefficients of interest in (8) are β_U^c and β_D^c. With HS 2-digit product fixed effects, these coefficients are identified by comparing treatment and control groups within the same HS 2-digit sectors. The treatment is the removal of binding quotas on Chinese exports to the US. The coefficients β_U^c and β_D^c estimate its impact on the probability that firms will switch from their initial main partner to one with higher and lower capabilities, respectively.

Prediction I1 for random matching states that in response to the MFA's end, continuing US importers and Mexican exporters would not change their partners at all. In reality, other shocks that could induce partner changes may exist. Considering this point, we reformulate Prediction I1: no difference should exist in the probability of partner changes in any direction between treatment and control groups. This prediction corresponds to $\beta_U^{US} = \beta_D^{US} = \beta_U^{Mex} = \beta_D^{Mex} = 0$ in (8).

Prediction C1 for PAM states that in response to the MFA's end, all continuing US importers upgrade whereas all continuing Mexican exporters downgrade their main partners. Though the frictionless matching model predicts all firms will change their partners, in reality, other factors such as transaction costs are likely to prevent some firms from making such a change, at least in the short run. Accordingly, we reformulate Prediction C1 as follows: US importers' partner upgrading and Mexican exporters' partner downgrading will occur more frequently in the treatment group than in the control group, which corresponds to $\beta_U^{US} > 0$, $\beta_D^{US} = \beta_U^{Mex} = 0$, and $\beta_D^{Mex} > 0$ in (8).

Our regression (8) does not suffer from the endogeneity problem that existed in the conventional correlation approach of regressing exporter's characteristics on importer's. For instance, a cross-sectional regression of exporter's ranks on importer's ranks across matches provides a me-

US and Mexico samples, which means only 14% of the variations of the binding dummy can be used for the estimation of β_U^C and β_D^C in (8). On the other hand, when the binding dummy is regressed on only HS 2 digit level fixed effects, R^2 is 0.48 (the US sample) and 0.50 (the Mexican sample), which leave sufficient variations. We also drop HS 2-digit sectors (HS 50, 51, 53, 56, 57, and 59) in which no variation of the binding dummy at HS 2-digit level occurs.

chanical positive correlation regardless of the sign of sorting.[22] We use firm characteristics (trade volume) only to construct the outcome variables in the left hand side, not any variable in the right hand side. Any discrepancy between the true capability ranking and the trade volume ranking should appear in error terms ε^c_{Uigs} and ε^c_{Digs}, which might reflect own capability, partner's capability and other unobservable firm and product characteristics. However, as long as the binding dummy is uncorrelated with these unobservable characteristics, β^c_U and β^c_D are consistently estimated.[23] Furthermore, the outcome variables are changes in partner ranks, which is equivalent with controlling for all time invariant firm-specific determinants of the level of partner ranks.

Old and New Partner Ranks (C2 and I2) To test predictions C2 and I2, we estimate the following regression for firms who switched partners during 2004-07:

$$NewPartnerRank^c_{ig} = \alpha^c + \gamma^c OldPartnerRank^c_{ig} + \varepsilon^c_{ig} \tag{9}$$

$$\text{for firm } i \text{with } NewPartnerRank^c_{ig} \neq OldPartnerRank^c_{ig}.$$

Prediction C2 states that PAM holds both before and after the MFA's end. New partner ranks should be positively correlated with old partner ranks, i.e., $\gamma^c > 0$. Predictions I2 states that matching is random before and after the MFA's end. Thus, there should be no correlation among them, i.e., $\gamma^c = 0$.

Two additional points need to be mentioned. First, if we run (9) only for firms that do not change partners, then γ^c equals to one by construction. To avoid this mechanical correlation, we estimate (9) only for firms who change partners. Second, the regression (9) combines both the

[22]To see this point, consider the following example. Suppose importers are homogeneous in capability (i.e., $\theta_1 = 0$), such as simple warehouses. This is a special case of Case I and there is no sorting. All variations in measured importers' ranks are driven by unobserved exporter's capability, which yields a positive mechanical correlation of exporters' ranks and importers' ranks.

[23]In our data, some firms export or import multiple products. If a pair of US and Mexican firms traded in multiple products with each other in 2004 and if they switched to new main partners regarding all products (maybe to save transaction costs), then it might cause biases in our estimates. However, this is unlikely since such pairs account for only 8% of Mexican exporters who switched partners.

treatment and control groups since PAM should hold for both groups in Case C.[24]

Capability Cutoff Changes (C3 and I3) Finally, we test predictions C3 and I3 that the capability cutoff for Mexican exporters rises in the treatment group. While the MFA's end is the only shock occurring in the model, other shocks might occur that induce firm exit from the market. Indeed, it is observed in many datasets that entry and exit of exporting simultaneously occur even without trade liberalization (e.g., Eaton et. al., 2014). To address this possibility, we consider a simple threshold model of exit behavior. In each period r, Mexican supplier i receives a random i.i.d. shock ε_{ir} to its profits, which captures idiosyncratic factors inducing firm exit in absence of trade liberalization. The firm chooses to exit if ε_{ir} is below a threshold $\bar{\varepsilon}_{ir}(y)$, that is, firm i's exit probability is $\Pr[\varepsilon < \bar{\varepsilon}_{ir}(y)]$. Case C and Case I have two predictions: (i) threshold $\bar{\varepsilon}_{ir}(y)$ is a decreasing function in the firm's capability y; and (ii) the MFA's end increases threshold $\bar{\varepsilon}_{ir}(y)$ for a given capability y.

To control for intrinsic differences between treatment and control groups, we conduct a difference-in-difference comparison of firm exit rates between groups for two periods, namely pre-liberalization (2001–04) and post-liberalization (2004–07). Since Mexican customs data before 2004 have no (digitized) record on importers, we use Mexican exporter's total product export volumes as a proxy for capability, which is highly correlated with exports with the main partners in the 2004–07 data. Then, we estimate the following regression for Mexican firm i who exports product g to the US in the initial year of period $r \in \{2001-04,\, 2004-07\}$:

$$\begin{aligned} Exit_{igsr} = {} & \delta_1 Binding_g + \delta_2 Binding_g * After_r + \delta_3 After_r + \delta_4 \ln Exports_{igr} \\ & + \delta_5 After_r * \ln Exports_{igr} + \lambda_s + u_{igsr}. \end{aligned} \tag{10}$$

[24]For instance, if an industry-wide shock induces Mexican exporter's partner to downgrade in both treatment and control groups, the model with PAM should predict $\gamma^c > 0$ for both groups.

Dummy variable $Exit_{igsr}$ equals one if the firm stops exporting during period r. Dummy variable $After_r$ equals one if period r is 2004–07. $\ln Exports_{igr}$ is the log of the firm's total export volume of product g in the initial year of period r, which proxies firm capability.[25] λ_s represents HS 2-digit level fixed effects and u^c_{igs} are error terms.

Based on positive correlations between firm's capability and trade volume, the above mentioned predictions (i) and (ii) are expressed as follows: (i) $\delta_4 < 0$ and $\delta_4 + \delta_5 < 0$, i.e., small low capability firms are more likely to exit; (ii) $\delta_2 > 0$, i.e., the end of the MFA increased exit probability for a given capability level.[26]

5 Results

5.1 Partner Changes

Table 5 reports regressions for partner changes during 2004–07 using linear probability models.[27] Columns with odd numbers report estimates of β^c_d ($c = US, Mex$ and $d = U, D$) from baseline regressions (8). We find that β^{US}_U in Column (1) and β^{Mex}_D in Column (7) are positive and statistically significant, while β^{US}_D in Column (3) and β^{Mex}_U in Column (5) are close to and not statistically different from zero. These signs on β^c_d support Case C and reject Case I. The removal of binding quotas from Chinese exports increased the probability that US importers upgrade partners by 5.2 percentage points and the probability that Mexican exporters downgrade partners by 12.7 percent-

[25]Regression (10) includes (the log of) export volumes instead of the rank of export volumes used in regressions (8) and (9). This is because in the model, the level of capability determines firm's exit, while the rank of capability determines matching.

[26]One might think of introducing the triple interaction $Binding_g * After_r * \ln Exports_{igr}$ to see that the treatment effect on exit probability monotonically decreases in firm's initial export volume. However, this alternative specification will not be an appropriate test of C3 and I3. As observed in other customs data (e.g., Eaton et. al., 2014), the exit probability of small volume exporters is very high even without trade liberalization. Therefore, the treatment effect on exit probability is naturally estimated small for these small exporters, but it does not necessarily contradict with C3 and I3.

[27]Probit regressions provide very similar results for all regressions.

age points.[28] These effects are quantitatively large when compared with the sample averages of Up^{US}_{igs} and $Down^{Mex}_{igs}$, which are 3 percentage points and 15 percentage points, respectively.[29]

Table 5: Partner Change during 2004–07

	Liner Probability Models							
	Up^{US}		$Down^{US}$		Up^{Mex}		$Down^{Mex}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Binding	0.052**	0.041*	-0.017	0.004	-0.003	-0.000	0.127***	0.130***
	(0.021)	(0.023)	(0.027)	(0.042)	(0.020)	(0.018)	(0.035)	(0.049)
OwnRank		-0.001		-0.074*		0.004		-0.087
		(0.024)		(0.042)		(0.014)		(0.054)
Binding*		0.034		-0.070		-0.007		-0.018
OwnRank		(0.049)		(0.074)		(0.026)		(0.087)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	718	718	718	718	601	601	601	601

Note: Dependent variables Up^{c}_{igs} and $Down^{c}_{igs}$ are dummy variables indicating whether during 2004-07 firm i in country c switched its main partner of HS 6-digit product g in country c' to one with a higher capability rank or lower capability rank, respectively. $Binding_{gs}$ is a dummy variable indicating whether product g from China faced a binding US import quota in 2004. $OwnRank_{igs}$ is the normalized rank of firm i in 2004. All regressions include HS 2 digit (sector) fixed effects. Standard errors are in parentheses and clustered at the HS 6-digit product level. Significance: * 10 percent, ** 5 percent, *** 1 percent.

In Table 5, columns with even numbers report regressions adding the firm's own rank and its interaction with the binding dummy. The coefficients on the interaction terms are estimated to be small and statistically insignificant, while the coefficients on the binding dummy remain similar to the baseline estimates. This means that both large and small firms switch their partners as in the

[28]The finding that β^{Mex}_{D} is estimated larger than β^{US}_{U} comes from that the actual matching is not exactly one-to-one and includes the following type of partner changes. Suppose a Mexican exporter Y trades with two US importers X_1 and X_2 where X_1 is the main partner for Y; Y is the main partner for both X_1 and X_2. Then, suppose X_1 switch from Y to a Chinese exporter, but X_2 continues importing from Y and becomes the main partner of Y. In this case we observe partner downgrading for Mexican exporter Y, but no partner change for US importer X_2 (and US importer X_1 disappears from our data). This type of transactions causes β^{Mex}_{D} estimated larger than β^{US}_{U} . If we define firm's partner change more narrowly as a switch of the main partner to the one with which the firm did not trade in 2004, we find the estimates of β^{US}_{U} and β^{Mex}_{D} remain significant and they become closer to each other.

[29]These numbers *do not* mean that 97% of US importers and 85% of Mexican exporters traded with the same main partner both in 2004 and 2007. In the data, only 12% of US importers and 12% of Mexican exporters traded with the same main partner both in 2004 and 2007. Note that the sample averages of Up^{US}_{igs} and $Down^{Mex}_{igs}$ are likely to underestimate the true probabilities of partner changes in the population. In our data partner upgrading/downgrading are observed only if the firm, new partner, and old partner are all continuing firms. Partner switching to firms in other countries and to firms that did not exist in 2004 are not included.

model.

Panel A in Table 6 reports estimates of β_U^{US} and β_D^{Mex} after changing the end year to 2006, 2007, or 2008. First, β_D^{US} and β_U^{Mex} remain positive and statistically significant, showing that our findings are not sensitive to our choice of end year. Second, estimates of β_U^{US} and β_D^{Mex} in later periods such as 2004–07 and 2004–08 are larger than those in the early period 2004–06. This suggests that partner changes occur gradually over time, probably due to certain partner switching costs.

Panel B in Table 6 examines partner changes in later periods of 2007–11 and 2009–11 in order to check our assumption that both treatment and control groups exhibit similar partner change patterns if the treatment was absent.[30] For each period, we re-construct capability rankings based on trade volume in the new initial years and re-create the upgrading/downgrading dummies. If the transition from old to new equilibrium was largely completed by 2007, we should not observe any difference in partner changes between the two groups. Panel B in Table 6 reports very small and insignificant estimates for β_U^{US} and β_D^{Mex} in 2007–11 [Columns (7) and (10)] and 2009–11 [Columns (9) and (12)]. These results support our assumption.[31]

[30]Comparing partner changes between the two groups before 2004 is one way to check this assumption, but not feasible since our data contain information only from June 2004 onwards. At the aggregate level, Figure 1 demonstrates the absence of differential time trends in the aggregate export volumes before MFA quota removal in 2005.

[31]The period 2008–11 [Columns (8) and (11)] shows a very different pattern from other two periods. One possible reason is the effect of the Lehman crisis and the Great Trade Collapse of 2008. 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.

Table 6: Partner Change in Different Periods

A: Gradual Partner Changes

	Partner Change in Different Periods: Linear Probability Models					
	Up^{US}			$Down^{Mex}$		
	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)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	964	718	515	767	601	442

B: Placebo Checks

	Partner Change in Different Periods: Linear Probability Models					
	Up^{US}			$Down^{Mex}$		
	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)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	449	575	747	393	499	655

Note: Dependent variables Up^c_{igs} and $Down^c_{igs}$ are dummy variables indicating whether during the period indicated by each column, firm i in country c switched its main partner of HS 6-digit product g in country c' to one with a higher capability rank or lower capability rank, respectively. $Binding_{gs}$ 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 controls for product and firm characteristics in 2004. In the Appendix, we choose several characteristics that might affect partner changes and examine whether they significantly differ between the treatment and control groups. Table 7 includes characteristics that are statistically different between the two groups within HS 2-digit product categories.[32] Even with additional

[32]Panel A includes product-level characteristics: number of exporters and importers ($\#Exporters$ and $\#Importers$, respectively), log of product level trade volume ($lnTotalTrade$), and product type dummies on whether products are for men, women, or not specific to gender and those on whether products are made of cotton, wool, or synthetic (man-made) textiles. Panel B includes firm-product level characteristics: log of firm's product trade volume with the main partner($lnTrade$), share of Maquladora/IMMEX trade in firm's product trade ($Maquiladora$), number of partners ($\#Partners$), and dummy of whether a US importer is an intermediary firm such as wholesalers and retailers ($US\ Intermediary$). The results are also robust when controlling for main-to-main share, the ratio of numbers of exporters and importers, and location of Mexican exporters, all of which do not statistically differ between the two groups within HS 2-digit products (see Appendix).

controls, estimates of β_U^{US} and β_D^{Mex} remain statistically significant and similar in magnitude.

Table 7: Partner Change during 2004–07 with Additional Controls

	A: HS 6-digit Product Level Controls: Linear Probability Models							
	Up^{US}				$Down^{Mex}$			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Binding	0.043**	0.44*	0.049**	0.042*	0.122***	0.125***	0.123***	0.130***
	(0.022)	(0.022)	(0.022)	(0.024)	(0.035)	(0.037)	(0.038)	(0.037)
#Exporters	0.001***				0.000			
	(0.000)				(0.000)			
#Importers		0.0003**				0.000		
		(0.0001)				(0.000)		
LnTotalTrade			0.002				0.002	
			(0.004)				(0.007)	
Product type				Yes				Yes
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	718	718	718	718	601	601	601	601

	B: Firm-Product Level Controls: Linear Probability Models							
	Up^{US}				$Down^{Mex}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Binding	0.049**	0.053**	0.051**	0.049**	0.123***	0.127***	0.103***	0.104***
	(0.022)	(0.022)	(0.021)	(0.019)	(0.038)	(0.035)	(0.037)	(0.034)
LnTrade	0.002				0.002			
	(0.004)				(0.007)			
Maquiladora		-0.015				-0.025		
		(0.017)				(0.024)		
#Partners			0.007***				0.036***	
			(0.002)				(0.009)	
US Intermediary				0.011				0.034
				(0.013)				(0.031)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	718	718	718	629	601	601	601	489

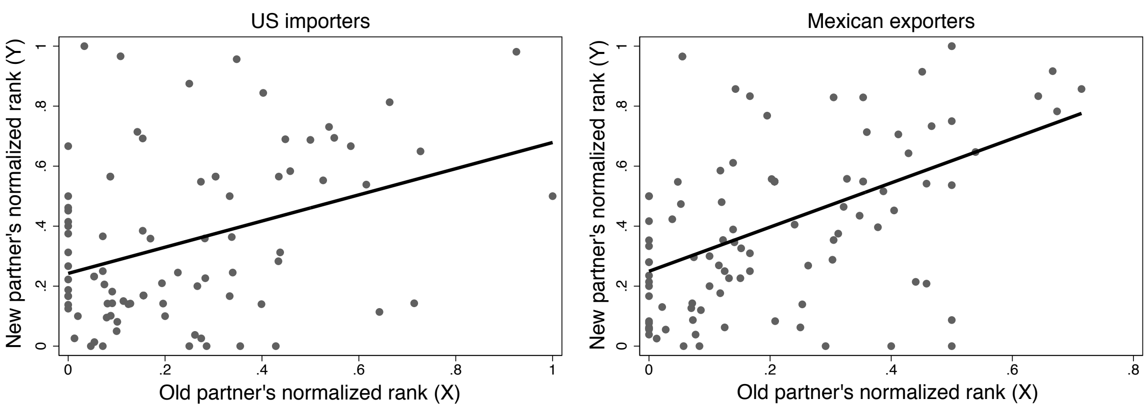
Note: Dependent variables Up^c_{igs} and $Down^c_{igs}$ are dummy variables indicating whether during 2004-07 firm i in country c switched its main partner of HS 6-digit product g in country c' to one with a higher capability rank or lower capability rank, respectively. $Binding_{gs}$ is a dummy variable indicating whether product g from China faced a binding US import quota in 2004. $\#Exporters_g$ and $\#Importers_g$ are numbers of exporters and importers of product g in 2004, respectively. $LnTotalTrade_g$ is the log of trade volume for product g in 2004. Product Types are a collection of dummy variables indicating whether products are men's, women's, cotton, wool, or synthetic (man-made). $LnTrade_{ig}$ is the log of firm i's trade volume of product g in 2004. $Maquiladora_{ig}$ is the share of Maquiladora/IMMEX trade in firm i's trade of product g in 2004. $\#Partners_{ig}$ is the number of firm i's partner in product g in 2004. $US\,Intermediary_{ig}$ is a dummy variable indicating whether US firm i or firm i's US main partner is an intermediary firm. 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.

Finally, to address missing observations for processing trade, we conduct weighted regressions in the Appendix and obtain similar results.

5.2 New and Old Partners Ranks

Figure 4 reports regression (9) testing predictions C2 and I2 with corresponding scatter plots. For those US importers who change their main partners between 2004 and 2007, the left panel displays the ranks of old partners in the horizontal axis and those of new partners in the vertical axis. The right panel draws a similar plot for Mexican exporters. The lines represent OLS regression (9). Figure 4 and regressions show significant positive relationships. Firms who match with relatively high capability partners in 2004 switch to relatively high capability partners in 2007. This result again supports Case C PAM and rejects Case I random matching.

Figure 4: Old and New Partner Ranks



$Y = 0.24 + 0.44\,X,\ R^2 = 0.13,\ Obs. = 88.$
(s.e. 0.048) (0.12)

$Y = 0.25 + 0.74\,X,\ R^2 = 0.24,\ Obs. = 104$
(s.e. 0.036) (0.13)

Note: The left panel plots the rank of new main partners in 2007 against the rank of old main partners in 2004 for 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.

5.3 Capability Cutoff Changes

Table 8 reports the results of using regressions (10) to test predictions C3 and I3. Columns (1), (3), and (5) report baseline regressions using three different lengths of the two periods, respectively. Columns (2), (4), and (6) include additional control variables of product and firm characteristics in the initial year of each period and their interactions with the After dummy. We choose the same control variables as used in Table 7 when they are available.[33]

Table 8: Mexican Exporter's Exit from the US market

	Linear Probability Models					
	$Exit_{igsr}$					
Period 1	2001–04		2002–04		2000–04	
Period 2	2004–07		2004–06		2004–08	
	(1)	(2)	(3)	(4)	(5)	(6)
Binding	-0.040***	-0.035***	-0.037**	-0.019	-0.019	-0.017
(δ_1)	(0.014)	(0.013)	(0.015)	(0.015)	(0.013)	(0.013)
Binding	0.076***	0.099***	0.044**	0.064***	0.032**	0.054***
*After (δ_2)	(0.016)	(0.020)	(0.018)	(0.021)	(0.014)	(0.02)
After	-0.361***	-0.331***	-0.454***	-0.427***	-0.262***	-0.184***
(δ_3)	(0.042)	(0.069)	(0.049)	(0.081)	(0.030)	(0.068)
$\ln Export$	-0.058***	-0.059***	-0.078***	-0.076***	-0.045***	-0.046***
(δ_4)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\ln Export$*	0.020***	0.026***	0.031***	0.036***	0.012***	0.017***
After (δ_5)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)
Controls		Yes		Yes		Yes
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	22625	22624	20655	20655	24474	24474

Note: Dependent variable $Exit_{igsr}$ is a dummy variables indicating whether Mexican firm i stops exporting product g to the US in period r. $Binding_{gs}$ is a dummy variable indicating whether product g from China faced a binding US import quota in 2004. $After_r$ is a dummy variable indicating whether period r is after 2004. $lnExport_{igr}$ is the log of firm i's export of product g in the initial year of period r. Columns (2), (4) and (6) include the following control variables of the initial year and their interactions with $After_r$: share of Maquiladora/IMMEX trade in firm i's trade of product g in the initial year; log of trade volume for product g; number of exporters of product g; a collection of dummy variables indicating products types: whether products are men's, women's, cotton, wool, or synthetic (man-made). 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.

Estimated coefficients confirm C3 and I3. First, estimates of δ_4 and $\delta_4 + \delta_5$ are both negative and statistically significant, which means that small exporters are more likely to exit. Second, δ_2 are estimated positive and statistically significant. Thus, the MFA's end increased the capability cutoff for Mexican exporters and their exit probability for a given capability level. These patterns are stable across different periods and robust to inclusions of control variables.

[33]Variables requiring importer information such as $\#Importers$, $\#Partners$ and $US\,Intermediary$ are not included.

5.4 Alternative Capability Rankings

We create two alternative rankings using firm's total product trade volume in 2004 and firm's unit price of the product's trade with the main partners in 2004, respectively. Then, we estimate partner change regression (8) and new and old partner ranks regression (9) using these two rankings.[34] We use the total trade ranking as a robustness check and the price ranking for investigating the source of exporter's capability. If exporter's capability mainly reflects quality rather than productivity, the unit price ranking may agree with the true capability ranking. On the other hand, if capability mainly reflects productivity, the unit price ranking may become the exact reversal of the true capability ranking.

Table 9 reports partner change regressions in Panel A and regressions of new and old partner ranks in Panel B. Columns labeled "Baseline", "Total Trade", and "Price" report estimates using our baseline rankings, total volume rankings, and price rankings, respectively. All three rankings support the main results. The results from price rankings also imply that exporter's capability mainly reflects its quality. Previous studies on export data find that quality is an important determinant of firm's export participation.[35] Table 9 shows one further aspect: quality also determines a firm's export partner.[36]

5.5 Alternative Explanations

Our empirical tests have confirmed all of PAM's predictions C1, C2, and C3. Pure random matching and matching based on idiosyncratic match-specific shocks, both of which predict I1, I2, and I3, alone cannot explain these patterns. Of course, such randomness in matching could also play

[34]The baseline exit regression (10) already uses firm's total product trade volume as capability. Since price data before 2004 are very noisy, we do not estimate the exit regression using price data.

[35]See e.g., Kugler and Verhoogen (2012) and Manova and Zhang (2012) for studies using firm-level data and Baldwin and Harrigan (2011) and Johnson (2012) for studies using product-level data.

[36]Regressions using price rankings report smaller coefficients than those using baseline rankings. This difference might reflect that exporters being differentiated by productivity in some products (e.g., Baldwin and Ito, 2011; Mandel, 2009).

Table 9: Alternative Capability Rankings

A: Partner Changes during 2004–07: Linear Probability Models

	Up^{US}			$Down^{US}$		
	Baseline	Total Trade	Price	Baseline	Total Trade	Price
	(1)	(2)	(3)	(4)	(5)	(6)
Binding	0.052**	0.052**	0.047**	-0.017	-0.017	0.006
	(0.021)	(0.021)	(0.018)	(0.027)	(0.027)	(0.023)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	718	718	672	718	718	672

	Up^{Mex}			$Down^{Mex}$		
	Baseline	Total Trade	Price	Baseline	Total Trade	Price
	(7)	(8)	(9)	(10)	(11)	(12)
Binding	-0.003	0.001	0.037	0.127***	0.123***	0.069**
	(0.020)	(0.019)	(0.031)	(0.035)	(0.035)	(0.028)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	601	601	559	601	601	559

B: Old and New Partners 2004–07: OLS

	New Partner Rank					
	US Importers			Mexican Exporters		
	Baseline	Total Trade	Price	Baseline	Total Trade	Price
	(13)	(14)	(15)	(16)	(17)	(18)
Old Partner	0.44***	0.44***	0.17*	0.74***	0.68***	0.47***
Rank	(0.12)	(0.13)	(0.10)	(0.13)	(0.13)	(0.12)
Constant	0.24***	0.24***	-0.44***	0.25***	0.25***	0.30***
	(0.05)	(0.04)	(0.06)	(0.04)	(0.04)	(0.07)
R^2	0.13	0.15	0.04	0.24	0.21	0.14
Obs.	88	88	80	104	104	98

Note: Rankings are based on firm's product trade with the main partner in 2004 in "Baseline", firm's product total trade in 2004 in "Total Trade", and firm's unit price of product in 2004 in "Price". Significance: * 10 percent, ** 5 percent, *** 1 percent. (Panel A) Dependent variables Up^c_{igs} and $Down^c_{igs}$ are dummy variables indicating whether during 2004–07 firm i in country c switched its main partner of HS 6-digit product g in country c' to one with a higher capability rank or lower capability rank, respectively. $Binding_{gs}$ 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. (Panel B) Regressions are run for firm i in country c who switched their main partners of product g during 2004-07. The dependent variable $NewPartnerRank^c_{ig}$ is the normalized rank of firm i's new main partner of product g in 2007. $OldPartnerRank^c_{ig}$ is the normalized rank of firm i's old main partner of product g in 2004.

some roles because the goodness of fit of PAM's predictions is not perfect.

In the Appendix, we discuss three alternative hypotheses for our findings. The first hypothesis is negative assortative matching where trade volume rankings may not agree with true capability rankings. The second "segment switching" hypothesis is that Mexican exporter's switch a product segment from large scale production with small markups to small scale production with large markups. The final "production capacity" hypothesis is that US importer's partner switch from small to large suppliers to seek for large production capacity. For these hypothesis, we conduct additional analyses and show that these do not fully explain our results.

5.6 Extensions for Many-to-Many Matching

We have developed an exporter–importer matching model featuring Beckerian PAM by capability and provided evidence for its five main predictions. Our analysis has focused on one-to-one matching of main partners because product-level matching is approximately one-to-one in our dataset. However, it is possible that product-level main-to-main share might be small in other datasets, making many-to-many matching a better approximation. In this section, we briefly discuss when and how our analysis can be extended to a many-to-many matching setting.

We first note that our theory defines matches for a narrowly defined intermediate good. For example, suppose that a car producer buys tires from one tire company and airbags from one airbag company. In our theory, this defines one-to-one matching in two product markets (tire and airbag) rather than one-to-two matching. However, if trade statistics combine tires and airbags into one "car parts" category, we might observe it as one-to-two matching in data. If many-to-many matching is observed because of this kind of statistical artifact, all the major insights of our analysis are valid. Facing the entry of new foreign suppliers with trade liberalization, existing suppliers downgrade all partners and existing final producers upgrade all partners. The model also predicts similar efficiency gains from re-matching, as in Lemma 1.

Our analysis can be extended to a many-to-many setting if the maximum number of partners for each firm stays the same before and after trade liberalization. Suppose a supplier i can trade with at most $n(i)$ buyers, and a final producer j can trade with at most $m(j)$ suppliers both before and after liberalization. Integers $n(i)$ and $m(j)$ can vary across firms, possibly depending on their capabilities. If each match of a supplier and a final producer generates a joint profit similar to a super-modular function of their capabilities as in (2), then stable equilibrium matching is still PAM. When new foreign suppliers enter, the existing suppliers downgrade all major partners and the existing final producers upgrade all partners.[37] That is, Predictions C1–C3 are applied for all major partners instead of for single main partners. The model also predicts aggregate efficiency gains from re-matching, as in Lemma 1. Thus, all the major insights of our analysis can be extended for a many-to-many matching.

6 Concluding Remarks

During the last tow decades, trade research has flourished by incorporating for individual firm's entry/exit into international trade, permitting, in other words, both extensive and intensive margin adjustments to trade liberalization. This paper presents new stylized facts about partner switching in intensive margin adjustments. As a mechanism behind partner switching, we have identified a simple mechanism of exporter–importer matching at the product level: Beckerian PAM by capability.

Beckerian PAM offers several new insights on buyer–supplier relationships in international trade. For instance, as our model has shown, re-matching in trade liberalization brings two new gain-accruing channels. On the one hand, at industrial or aggregate levels, trade liberalization im-

[37] Furthermore, one could introduce a idiosyncratic match-specific component in capability. This modification generates variations of trade volume across partners and allows the number of partners to change in response to the entry of new foreign suppliers. Existing suppliers may stop exporting to buyers instead of partner downgrading, while existing final producers may start trading with new sellers instead of partner upgrading.

proves industrial efficiency by re-matching buyers and suppliers, which complement gains from reallocation of production factors within industries (e.g., Pavcnik, 2002; Trefler, 2004). Quantifying these matching-induced gains from trade is an important topic for future research. On the other hand, at the individual level, firms see improved performance when they upgrade their partners. As confirmed by recent empirical evidence, this echoes trade promotion policies that aim to improve local firm's performance through trading with high capability foreign firms.[38] Furthermore, Beckerian PAM has two implications that can be brought to data in future studies. First, benefits to local firms increase in the capability of foreign partners. Second, only local firms with high capability can maintain stable relationships with high capability foreign firms. The latter suggests the importance of capability development policies to complement trade promotion policies.

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[38] See e.g., De Loecker (2007) and Atkin, Khandelwal and Osman (2017) for learning technologies; Machiavello (2010) and Machiavello and Morjaria (2015) for reputation building; Takana (2018) for improving management practices; Verhoogen (2008) for quality upgrading. The same rationale is also discussed when promoting FDI (see e.g., Javorcik (2004) for vertical FDI spillovers).

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Online Appendix for "Assortative Matching of Exporters and Importers" (Not for Publication)

A1. Solving the Model

Consumer Maximization

The consumer maximization problem is equivalent to 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

$$\frac{\delta\theta\left(\omega\right)^{\alpha}q\left(\omega\right)^{\rho-1}}{\int_{\omega'\in\Omega}\theta(\omega')^{\alpha}q(\omega')^{\rho}d\omega'} = p\left(\omega\right) \text{ for all } \omega\in\Omega. \tag{11}$$

The first order conditions for two varieties $\omega, \omega' \in \Omega$, imply that

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

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

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

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 (11), we obtain the demand function:

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

Stage 2: Team profit maximization

Facing the demand function (12), 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 $p(\theta) = \frac{c\theta^{\beta}}{\rho}$. The team's output $q\left(\theta\right)$, revenue $R(\theta)$, costs $C(\theta)$, and profits $\Pi(\theta)$ thus 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 the aggregate capability. Then, the index A becomes

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

Stage 1

The mass of active final producers equals that of active suppliers:

$$M_U[1 - F(x_L)] = (M_M + M_C)\,[1 - G(y_L)]$$

This equation determine $y_L(x_L)$ as an increasing function of x_L.

In Case C and Case I, a team with the lowest capability θ_L consists of a final producer with x_L and a supplier with y_L. This implies two properties. First, the lowest capability $\theta_L(x_L) = \theta\,(x_L, y_L(x_L))$ becomes an increasing fiction of x_L. Second, this team's profit is zero [$\Pi(\theta_L) = \pi_x(x_L) + \pi_y(y_L) = 0$], which implies the team cutoff condition:

$$A\theta_L = f.$$

In Case C, the matching market clearing condition,

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

determines matching function $m_x(x)$. Then, Θ is obtained as a function of x_L:

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

where $\theta\,(x, y) = \theta^x\,(x) + \theta^y\,(y)$ for additive separable Case I. Note that $\Theta\,(x_L)$ is a decreasing function of x_L.

In Case C and Case I, the team with the cutoff team capability is determined by

$$A\theta_L = \frac{\delta\theta_L(x_L)}{\sigma\Theta(x_L)} = f$$

Since $\theta_L(x_L)$ is increasing and $\Theta(x_L)$ is decreasing in x_L, the above equation uniquely determine x_L.

Proof for Lemma 2

Trade volume within a match $T(x, y)$ is equal to supplier's costs plus supplier's profit:

$$\begin{aligned} T(x, y) &= [c_x q(\theta(x, y)) + f_x] + \pi_y(y) \\ &= \left[\frac{c_y}{c}\{C(\theta(x, y)) - f\} + f_y\right] + \pi_y(y \end{aligned}$$

From $C'(\theta) > 0$ from (1), both $\partial T(x, y)/\partial x$ and $\partial T(x, y)/\partial y$ are positive. In Case C, from $m'_x(x) > 0$ and $m'_y(y) > 0$, both import volumes by US importers $I(x) = T(x, m_x(x))$ and export volumes by Mexican suppliers $X(y) = T(m_y(y), y)$ increase in their own capabilities, respectively. In Case I, both expected import volumes by US importers, $\bar{I}(x) = [1 - G(y_L)]^{-1} \int_{y_L}^{y_{max}} T(x, y)dG(y)$, and expected export volumes by Mexican exporters, $\bar{X}(y) = [1 - G(x_L)]^{-1} \int_{x_L}^{x_{max}} T(x, y)\, dF(x)$, increase in their own capabilities.

A.2 Proof for Lemma 1 and Predictions C3/I3

This section proves Lemma 1 and predictions C3/I3 that the supplier capability cutoff y_L rises after the MFA end. Both results are derived from a classic theorem from the matching theory with transferable payoffs.

Theorem 1. *Among feasible matching, stable matching maximizes the aggregate payoffs of participants in a frictionless matching market.*

Theorem 1 was developed by Koopmans and Beckmann (1957) and Shapley and Shubik (1972) for the case with finite agents and by Gretsky, Ostroy and Zame (1992) for the case with a continuum of agents. In the case of finite agents, the intuition of the theorem directly follows from the definition of supermodularity of θ such that for any $x > x'$ and $y > y'$, $\theta(x, y) + \theta(x', y') > \theta(x', y) + \theta(x, y')$. In the case of continuums of agents, the theorem needs additional technical assumptions. See Gretsky et al. (1992) for a formal proof.

We compare equilibria of two different environments I and J (e.g. before and after the end of the MFA). Label variables in the corresponding equilibria by "I" and "J", respectively. In the current model, the aggregate payoff of firms is $A\Theta - Mf$ and individual firms take A as given. Thus, Theorem 1 implies the following corollary:

Corollary 1. *If equilibrium matching of environment J is feasible in environment I, then $A^I\Theta^I - M^I f \geq A^I\Theta^J - M^J f$. The inequality is strict when equilibrium matching of environment J is not stable in environment I.*

Using this corollary, we establish the following lemma.

Lemma 3. *(i) Suppose equilibrium matching of environment J is feasible in environment I. If $M^I > M^J$, then $\Theta^I > \Theta^J$. (ii) Suppose equilibrium matching of environment J is feasible and not stable in environment I. If $M^I \geq M^J$, then $\Theta^I > \Theta^J$.*

Proof. (i) Since equilibrium matching of environment J is feasible in environment I,

$$A^I\Theta^I - M^I f \geq A^I\Theta^J - M^J f \Leftrightarrow A^I \left(\Theta^I - \Theta^J\right) \geq \left(M^I - M^J\right) f$$

from Corollary 1. Since $M^I > M^J$, the above inequality implies $\Theta^I > \Theta^J$. (ii) Since equilibrium matching of environment J is feasible and not stable in environment I,

$$A^I\Theta^I - M^I f > A^I\Theta^J - M^J f \Leftrightarrow A^I \left(\Theta^I - \Theta^J\right) > \left(M^I - M^J\right) f$$

from Corollary 1. Since $M^I \geq M^J$, this implies $\Theta^I > \Theta^J$ $\square$

Proof for $dy_L > 0$ for Case C and Case I

Denote the environment after the MFA's end as *A-environment* (After) and the environment before the MFA's end as *B-environment* (Before). Label equilibrium variables of A-environment by "A" and those of B-environment by "B".

Lemma 4. *$y_L^A > y_L^B$ in Case C and Case I.*

Proof. Suppose $y_L^A \leq y_L^B$. Thus, more Mexican firms export in A-environment, which means the mass of produced varieties and active final producers increase: $M^A > M^B$ and $x_L^A < x_L^B$. Since equilibrium matching of B-environment is feasible in A-environment, Lemma 3 implies $\Theta^A > \Theta^B$. In Case C and Case I, $\theta_L = \theta(x_L, y_L)$, $x_L^A < x_L^B$ and $y_L^A \leq y_L^B$ imply $\theta_L^A < \theta_L^B$. From $\theta_L = \frac{\sigma f}{\delta}\Theta$ in (7), we have $\Theta^A < \Theta^B$. This contradiction implies $y_L^A > y_L^B$. $\square$

Proof for Lemma 1

Denote the environment after the MFA's end *A-environment,* the environment of the no-rematching equilibrium as *NR-environment*, and the environment before the MFA's end as *B-environment*.

Claim 1. $\Theta^A = \Theta^{NR}$ in Case I.

Proof. An equilibrium in the NR-environment agrees with an equilibrium in the A-environment because no rematching occurs after the MFA's end in Case I. $\square$

Claim 2. $y_L^A > y_L^{NR} > y_L^B$ in Case C.

Proof. Suppose $y_L^{NR} \leq y_L^B$. This means $x_L^{NR} < x_L^B$ and $M^{NR} > M^B$. Since $\theta_L = \theta(x_L, y_L)$ holds in Case C and Case I, $y_L^{NR} < y_L^B$ and $x_L^{NR} < x_L^B$ imply that $\theta_L^{NR} < \theta_L^B$. From $\theta_L = \frac{\sigma f}{\delta}\Theta$ in (7), this means $\Theta^{NR} < \Theta^B$. Since equilibrium matching in the B-environment is feasible in the

NR-environment, Lemma 3 and $M^{NR} > M^B$ imply that $\Theta^{NR} > \Theta^B$. This contradiction implies $y_L^{NR} > y_L^B$.

Suppose $y_L^A \leq y_L^{NR}$. By an argument similar to that above, we have $x_L^A \leq x_L^{NR}$ and $M^A \geq M^{NR}$ so that $\theta_L^A \leq \theta_L^{NR}$, which implies $\Theta^A \leq \Theta^{NR}$. Since equilibrium matching of the NR-environment is feasible and not stable in the A-environment, Lemma 3 and $M^A \geq M^{NR}$ imply $\Theta^A > \Theta^{NR}$. This contradiction implies $y_L^A > y_L^{NR}$. □

Claim 3. $\Theta^A > \Theta^{NR} > \Theta^B$ in Case C and $\Theta^{NR} > \Theta^B$ in Case I.

Proof. Suppose $\Theta^{NR} \leq \Theta^B$, which implies that $\theta^{NR} \leq \theta^B$ from (7). Since equilibrium matching in the B-environment is feasible and not stable in the NR-environment, Lemma 3 implies $M^{NR} < M^B$. From $M = M_U[1 - F(x_L)]$, this means $x_L^{NR} > x_L^B$. In Case C and Case I, $\theta_L = \theta(x_L, y_L)$, $y_L^{NR} > y_L^B$ from Claim 2, and $\theta_L^{NR} \leq \theta_L^B$ imply $x_L^{NR} < x_L^B$. This contradiction implies $\Theta^{NR} > \Theta^B$.

Consider Case C and suppose $\Theta^A \leq \Theta^{NR}$, which implies $\theta^A \leq \theta^{NR}$ from (7). Since equilibrium matching in the NR-environment is feasible and not stable in the A-environment in Case C, Lemma 3 implies $M^A < M^{NR}$. From $M = M_U[1 - F(x_L)]$, this means $x_L^A > x_L^{NR}$. In Case C, $\theta_L = \theta(x_L, y_L)$, $y_L^A > y_L^{NR}$ from Claim 3, and $\theta_L^A \leq \theta_L^{NR}$ imply $x_L^A < x_L^{NR}$. This contradiction implies $\Theta^A > \Theta^{NR}$. □

From $P = c/\left(\rho\Theta^{1/(\sigma-1)}\right)$, Claims 1–3 prove Lemma 1.

A.3 Negative Assortative Matching

Solving the Model

In Case S, the market clearing condition becomes

$$M_U[1 - F(x)] = (M_M + M_C)\left[G\left(m_x\left(x\right)\right) - G(y_L)\right] \text{ for all } x \geq x_L. \tag{13}$$

The left hand side is the mass of final producers with higher capability than x and the right hand side is the mass of suppliers with lower capability than $m_x(x)$.

An equilibrium is obtained as follows. The condition (13) determines $m_x(x)$ for all $x \geq x_L$. Then, Θ is obtained as a decreasing function of x_L:

$$\Theta(x_L) = M_U \int_{x_L}^{x_{max}} \theta\left(x, m_x(x)\right) dF(x).$$

A supplier with y_{max} matches with a final producer with x_L and receives whole team profits because $\pi_x(x_L) = 0$:

$$\pi_y(y_{max}) = \Pi(\theta(x_L, y_{max})) = A\theta\left(x_L, y_{max}\right) - f.$$

The profit of supplier with y_{max} is obtained by integrating the first order condition:

$$\pi_y(y_{max}) = \int_{y_L}^{y_{max}} \pi_y'(y)dy = A\int_{y_L}^{y_{max}} \theta_2(m_y(t), t)dt.$$

From $A = \frac{\delta}{\sigma\Theta}$ and $y_L = m_x(x_{max})$, the above two equations imply

$$\begin{aligned} A\theta\left(x_L, y_{max}\right) - f = A\int_{m_x(x_{max})}^{y_{max}} \theta_2(m_y(t), t)dt \\ \frac{\delta}{\sigma\Theta(x_L)}\left[\theta\left(x_L, y_{max}\right) - \int_{m_x(x_{max})}^{y_{max}} \theta_2(m_y(t), t)dt\right] = f. \end{aligned} \tag{14}$$

The above equation uniquely determines x_L since the left hand side is monotonically increasing in x_L. Formally, an equilibrium is defined as follows.

Definition 2. In Case S with $\theta_{12} < 0$, a stable matching equilibrium consists of a matching function $m_x(x)$, profit schedules $\{\pi_x(x), \pi_y(y)\}$ and capability cutoffs $\{x_L, y_L\}$ that satisfy (3), (4), (13) and (14).

Supplier Exit after the MFA's End

Following section A.2, denote the environment after the MFA's end as *A-environment* and the environment before the MFA's end as *B-environment*. Label equilibrium variables of the A-environment by "A" and those of the B-environment by "B". Then, we establish the following lemma.

Lemma 5. *$y_L^A > y_L^B$ in Case S.*

Proof. Suppose $y_L^A \leq y_L^B$. This means that the mass of produced varieties and active final producers increase: $M^A > M^B$ and $x_L^A < x_L^B$. Since equilibrium matching in the B-environment is feasible in the A-environment, Lemma 3 implies $\Theta^A > \Theta^B$.

From $y_L = m_x(x_{max})$, equation (14) implies

$$\begin{aligned}&\frac{\delta}{\sigma\Theta^A}\left[\theta\left(x_L^A, y_{max}\right) - \int_{y_L^A}^{y_{max}} \theta_2(m_y^A(t), t)dt\right]\\ =&\frac{\delta}{\sigma\Theta^B}\left[\theta\left(x_L^B, y_{max}\right) - \int_{y_L^B}^{y_{max}} \theta_2(m_y^B(t), t)dt\right] = f.\end{aligned}$$

Since $\Theta^A > \Theta^B$ and $\theta\left(x_L^A, y_{max}\right) < \theta\left(x_L^B, y_{max}\right)$ from $x_L^A < x_L^B$, it must hold that

$$\int_{y_L^B}^{y_{max}} \theta_2(m_y^B(t), t)dt > \int_{y_L^A}^{y_{max}} \theta_2(m_y^A(t), t)dt.$$

Since $y_L^A \leq y_L^B$, this implies

$$\begin{aligned}
\int_{y_L^B}^{y_{max}} \int_{m_y^A(t)}^{m_y^B(t)} \theta_{12}(z,t) dz dt &= \int_{y_L^B}^{y_{max}} \left[\theta_2(m_y^B(t),t) - \theta_2(m_y^A(t),t)\right] dt \\
&= \int_{y_L^B}^{y_{max}} \theta_2(m_y^B(t),t) dt - \int_{y_L^B}^{y_{max}} \theta_2(m_y^A(t),t) dt \\
&\geq \int_{y_L^B}^{y_{max}} \theta_2(m_y^B(t),t) dt - \int_{y_L^A}^{y_{max}} \theta_2(m_y^A(t),t) dt \\
&> 0. \qquad (15)
\end{aligned}$$

On the other hands, the matching market clearing condition implies for all $y \geq y_L^B$, it must hold that

$$\begin{aligned}
M_U \left[1 - G(m_y^A(y))\right] &= \left(M_M + M_C^A\right) \left[G(y) - G(y_L^A)\right], \\
M_U \left[1 - G(m_y^B(y))\right] &= \left(M_M + M_C^B\right) \left[G(y) - G(y_L^B)\right].
\end{aligned}$$

Taking the difference of both sides, we obtain for all $y \geq y_L^B$,

$$\begin{aligned}
M_U \left[G(m_y^B(y)) - G(m_y^A(y))\right] &= \left(M_M + M_C^A\right) \left[G(y) - G(y_L^A)\right] \\
&\quad - \left(M_M + M_C^B\right) \left[G(y) - G(y_L^B)\right] > 0
\end{aligned}$$

since $M_C^A > M_C^B$ and $G(y_L^A) \leq G(y_L^B)$ from $y_L^A \leq y_L^B$. Thus, we have $m_y^B(y) > m_y^A(y)$ for all $y \geq y_L^B$. From $\theta_{12} < 0$, this implies

$$\int_{y_L^B}^{y_{max}} \int_{m_y^A(t)}^{m_y^B(t)} \theta_{12}(z,t) dz dt < 0,$$

which contradicts with (15). □

Partner Changes after the MFA's End

Assumption 1. *If the mass of Chinese suppliers M_C increases, then the total mass of suppliers in the US $(M_C + M_M)[1 - G(y_L)]$ increases.*

Under this assumption, the capability cutoff for importing x_L falls. The following lemma shows the direction of US importers' partner changes is heterogeneous.

Lemma 6. *Under Assumption 1, there exists a threshold capability $\tilde{x} \in (x_L, x_{max})$ such that when the mass of Chinese suppliers increase, continuing US final producers with $x > \tilde{x}$ switch Mexican partner to one with higher capability (partner upgrading), while continuing US final producers with $x < \tilde{x}$ switch Mexican partner to one with lower capability (partner downgrading).*

Proof. Totally differentiating (13), we obtain the partner change of importers with capability x:

$$dm_x(x) = \frac{\Gamma(x)}{g(m_x(x))}, \Gamma(x) \equiv g(y_L)dy_L - \frac{G(m_x(x)) - G(y_L)}{(M_M + M_C)} dM_C. \tag{16}$$

Since $dy_L > 0$, $dM_C > 0$, and $m_x'(x) < 0$, $\Gamma(x)$ is increasing in x and $\Gamma(x_{max}) = g(y_L)dy_L > 0$ since $y_L = m_x(x_{max})$. Since Assumption 1 implies

$$d(M_C + M_M)[1 - G(y_L)] = [1 - G(y_L)]dM_C - (M_C + M_M)g(y_L)dy_L > 0,$$

$\Gamma(x_L) \equiv g(y_L)dy_L - \frac{1-G(y_L)}{(M_M+M_C)} dM_C < 0$. Since $\Gamma(x)$ is continuous, there exists $\tilde{x} \in (x_L, x_{max})$ such that $\Gamma(x) > 0$ for $x > \tilde{x}$ and $\Gamma(x) < 0$ for $x < \tilde{x}$. $\square$

To understand the intuition for this lemma, it is useful to consider how firms with maximum capabilities change partners. Suppose x_L falls from x_L^B to x_L^A and y_L rises from y_L^B to y_L^A. Since final producers with maximum capability x_{max} always match with suppliers who have the cutoff capability y_L, they upgrade partner suppliers with y_L^B to y_L^A. On the other hand, since suppliers with maximum capability y_{max} always match with final producers with the cutoff capability x_L, they downgrade final producers from x_L^B to x_L^A. This in turn means that final producers with x_L^B downgrade partner suppliers. Since a matching function is continuous, there is a threshold $\hat{x}$ of the lemma.

A.4 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 Mexico–US 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) date of clearing customs; (2) total value of shipment (in US dollars); (3) 8-digit HS product code (we use from HS50 to HS63); (4) quantity and unit; (5) name, address, and tax identification number of the Mexican exporter; (6) name, address, and tax identification number (employment identification number, EIN) of the US importer; (7) an indicator of a duty free processing reexport program (the Maquiladora/IMMEX program); 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/establishments, or 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 therefore used a series of methods developed in record-linkage research 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, we standardized the format of addresses using a software, ZP4 by Semaphore Corporation, which received a quality certification of address cleaning (CASS certification) from the United States Postal Services. Third, we remove generic words in company names that did not help identify a particular company such as legal terms (e.g., Co., Ltd., etc.). 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, using Orbis by Bureau van Dijk, which covers 20 millions company branches, subsidiaries, and headquarters in the US.[40] Fifth, for each HS 2-digit industry, we matched names within customs data and names between customs data and name lists from Orbis mentioned above.

Using these data, we conduct matching by EINs, names, and addresses. EIN matching is simple exact matching, after dropping EINs that do not follow the regular format. In matching of names and addresses, we used fuzzy matching techniques allowing small typographical errors and abbreviations. The two names compared are "fuzzy matched" if one of the followings is satisfied: (1) they are close to each other in terms of the Jaro-Winkler distance metric JW where the criterion is $JW \geq 0.9$)[41]; (2) they agree on the number of the first n letters ($n = 15$); (3) $JW \geq 0.85$, the

[39] An excellent textbook for record linkage is Herzog, Scheuren, and Winkler (2007). In addition, a webpage of "Virtual RDC@Cornell" (http://www2.vrdc.cornell.edu/news/) by 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.

[40] The primary source of US company information in Orbis (2012 version) is Dun&Bradstreet. We used Orbis information for manufacturing firms and intermediary firms (wholesalers and retailers) due to the capacity of our workstation.

[41] The Jaro-Winkler distance metric function is available in the Record Linkage package of R. We find the Jaro-Winkler metric performs better in our data than the Levenshtein distance metric.

length of the shorter name l satisfies $l \geq 7$, and the longer of the two names includes the shorter one. We choose this criterion through trials and errors using subsamples. To increase the accuracy of fuzzy matching, we removed words commonly appearing in the industry (e.g., "apparel") from the two names compared if the word appears in both names. Also we do not apply fuzzy matching techniques to very short names with less than 5 letters. When matching addresses, we also use fuzzy matching techniques for street and city name matching. The criterion is $JW \geq 0.9$ both for street names and for city names.

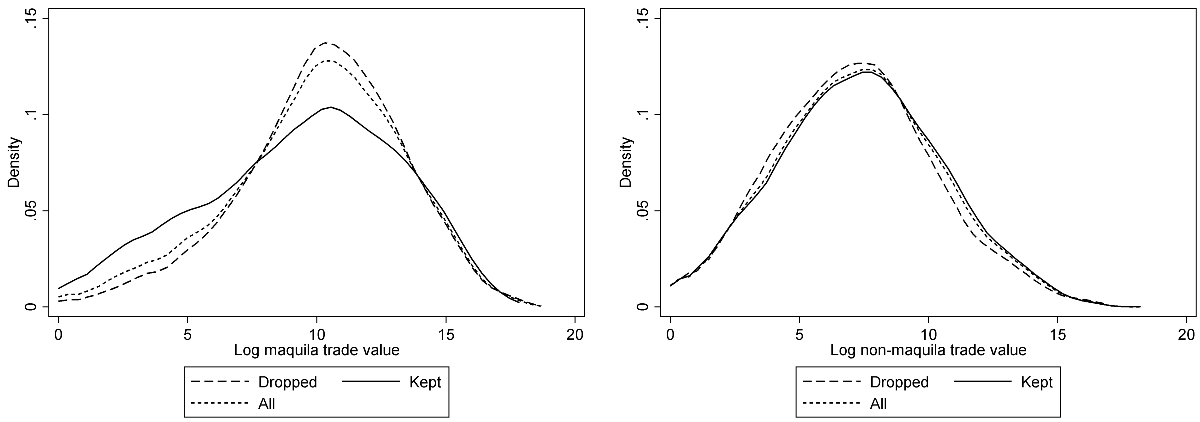
From these operations, we obtain matched pairs of names, addresses and EINs. Then, using these matched relations and the network theory software (the igraph package of R), we created clusters of information (names, addresses, and EINs) in which one cluster identifies one firm. We identified a cluster utilizing the following general rule. Each entry a in a cluster C matches with some other entries $b, c \in C$ in the cluster by at least one of the following ways (b and c can be the same): (1) a matches b by EINs; (2) a matches b by names and c by addresses; (3) a matches b strongly by names ($JW \geq 0.97$) and c by city-names. This clustering criterion loosely connects entries, allowing two entries to disagree on more than one linking variable. This loose connection follows a conventional technique in record linkage research. Since the probability that randomly chosen two entries match is very low, it is much easier to loosely match entries and to manually separate entries that should not be matched than the other way. Then, we manually checked every cluster that includes unmatched names by looking for their relationships in search engines and the firms' websites. Finally, we assigned importer-IDs to each cluster.

Data Cleaning 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. We conducted our main analysis (Tables 2 and 5) without conducting these two operations and still obtained similar results. Third, we dropped one product (HS570210) where the number of importers unreasonably fluctuates, suggesting low data quality.[42] Finally, we dropped transactions by exporters who do not report importer information for most transactions. For a given HS 6-digit 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% of the exporter's annual export value. This resulted in dropping approximately 30–40% of exporters and 60–70% of export values. These dropped exporters are mostly Maquiladora/IMMEX exporters as 82% of other normal exporters remain in the final sample.

Figure 5 examines sample selection due to the data cleaning. The left panel draws the distributions of log HS 6-digit product trade volume in 2004 by Maquiladora/IMMEX exporters, while the right panel does those by other normal exporters. Each panel presents estimated trade volume densities for exporters in the pre-cleaned original sample ("All"), those dropped from the final sample ("Dropped"), and those kept in the final sample ("Kept"). The original and final samples of normal exporters show very similar distributions, those of Maquiladora/IMMEX exporters show some differences. Though the final sample well represents large exporters, it under-represents medium size exporters and over-represents small exporters

[42]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.

Figure 5: Sample Selection



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 presents a histogram. The right panel plots main-to-main shares against the maximum of the numbers of exporters and importers.

Weighted Regression To address potential biases due to sample selection, we run a weighted regression, following Solon, Haider, and Wooldridge (2015). We first estimate the selection probability of remaining in the final sample by its locally weighted regression on log HS 6-digit product trade volume in 2004, separately for Maquiladora/IMMEX exporters and for other normal exporters.[43] Then, we run weighted least squares of the main specification in Table 5, using the inverse of estimated selection probability as weight. The results shown in Table 10 are very similar to those in Table 5. Thus, our results are not driven by sample selection due to the data cleaning.

A5. Variable Construction

Product-Level Variables Dummy variable $Binding_{gs}$ equals one if Chinese exports of product g to the US faced a binding quota in 2004, which we construct from Brambilla et al. (2010), who constructed an indicator for binding quotas on Chinese exports to the US for each HS 10-digit category. Since HS product categories for Mexico and the US are the same only up to the first 6

[43]For an exporter conducting both Maquiladora/IMMEX exports and normal exports, its sample selection probability is obtained as a trade volume weighted average of estimated sample selection probabilities of Maquiladora/IMMEX exporters and normal exporters. We also estimate sample selction probability separately for each HS 2 digit product and obtain very similar results.

Table 10: Weighted Regression: Partner Change during 2004–07

	Liner Probability Models Weighted by Inverse Selection Probability							
	Up^{US}		$Down^{US}$		Up^{Mex}		$Down^{Mex}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Binding	0.040**	0.036*	-0.022	0.005	-0.001	-0.002	0.118***	0.141***
	(0.017)	(0.020)	(0.035)	(0.053)	(0.028)	(0.022)	(0.035)	(0.048)
OwnRank		0.004		-0.063		0.014		-0.025
		(0.030)		(0.062)		(0.013)		(0.059)
Binding*		0.014		-0.063		-0.008		-0.081
OwnRank		(0.045)		(0.099)		(0.036)		(0.082)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	718	718	718	718	601	601	601	601

Note: Dependent variables Up^{c}_{igs} and $Down^{c}_{igs}$ are dummy variables indicating whether during 2004-07 firm i in country c switched its main partner of HS 6-digit product g in country c' to one with a higher capability rank or lower capability rank, respectively. $Binding_{gs}$ is a dummy variable indicating whether product g from China faced a binding US import quota in 2004. $OwnRank_{igs}$ is the normalized rank of firm i in 2004. All regressions include HS 2 digit (sector) fixed effects. Standard errors are in parentheses and clustered at the HS 6-digit product level. Significance: * 10 percent, ** 5 percent, *** 1 percent.

digits, we aggregated their indicator up to the HS 6-digit level. A quota is defined as binding if the fill rate, i.e., realized import value over the quota value, is greater than 0.8. Our results are robust to choice of other cut-offs. We constructed our indicator as follows. Let x^{m}_{j2004} be US imports of HS 10-digit product j from Mexico in 2004. Let g be a HS 6-digit product and $J(g)$ be the set of US HS 10-digit products in category g. Thereafter, we constructed a dummy variable indicating whether Chinese exports of HS 6-digit product g to the US faced binding quotas in 2004 as:

$$Binding_g = I\left\{\frac{\sum_{j\in J(g)} x^{m}_{j2004} I\{\text{quota on } j \text{ was binding in 2004}\}}{\sum_{j\in J(g)} x^{m}_{j2004}} \geq 0.5\right\}, \qquad (17)$$

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.

Product type dummies "Men", "Women", "Wool", "Cotton", and "Manmade" equal one if the description of the HS 6 product classification includes the words "men", "women", "wool", "cotton", or "manmade", respectively. $\#Exporters_{gs}$ is the number of exporters of product g in 2004, $\#Importers_{gs}$ is the number of importers of product g in 2004, and $TotalTrade_{gs}$ is the total trade volume of product g in 2004 .

Firm-Level and Firm-Product-Level Characteristics $OwnRank_{igs}$ is firm's normalized rank in terms of trade volume in product g that falls in $[0,1]$. For exporter i, define $ExRank_{igs}$ as firm i's rank based on its trade volume of product g with the main partner in 2004 among exporters of product g in 2004 (small $ExRank_{igs}$ means large export volume). Similarly, define $ImRank_{igs}$ for importers. Then, the exporter's normalized rank is $OwnRank_{igs} = (ExRank_{igs} - 1) / (\#Exporters_{gs} - 1)$ so that $OwnRank_{igs}$ falls in $[0,1]$. $OwnRank_{igs}$ becomes zero for the highest ranked (largest) exporter becomes and one for the lowest ranked (smallest) exporter. Similarly, for the importers, $OwnRank_{igs} = (ImRank_{igs} - 1) / (\#Importers_{gs} - 1)$.

Dummy variable $NorthernState_{igs}$ equals one if exporter i of product g is located in one of the northern states of Mexico: Baja California, Sonora, Chihuahua, Coahuila, Nuevo Leon and Tamaulipas. $Maquiladora_{igs}$ is the ratio of firm i's Maquiladora trade volume of product g over the firm's total trade volume of product g in 2004. $\ln TotalTrade_{gs}$ is the log of total trade volume for product g in 2004.

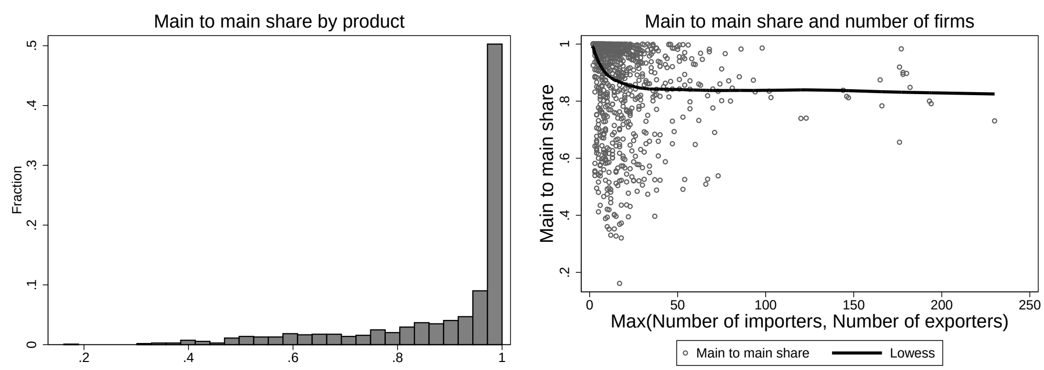
Dummy variable $US\,Intermediary_{igs}$ equals one either if firm i is a US intermediary firm or if firm i is a Mexican exporter and its US main partner is an intermediary firm. US intermediary firms are identified as follows. One US importer is typically matched with several records of US firms in Orbis data since Orbis data record branches and subsidiaries as distinct records. The US importer is identified as an intermediary firm if one of matched records report retail or wholesaling as its main industry and if none of matched records report manufacturing as its main industry.

Other firm-level characteristics include the following. $\#Partners_{igs}$ is the number of partners with whom firm i trade in product g in 2004. $Main\ Partner\ Share_{igs}$ is the ratio of firm i's trade volume of product g with the main partner over firm i's total trade volume of product g in 2004. $\ln Trade_{igs}$ is the log of firm i's total trade volume of product g in 2004.

A6. Main-to-Main Share at Product Level

Two panels in Figure 6 draw the distribution of main-to-main shares across product-year combinations. A histogram in the left panel strikingly shows that main-to-main shares exceed 0.9 for most combinations with the median 0.97 and 25th percentile 0.86. The right panel in Figure 6 plots main-to-main shares against the maximum of the number of importers (n_m) and exporters (n_x), $\max\{n_m, n_x\}$. This exercise is motivated by the love of variety model with symmetric firms that predicts main-to-main share will equal $1/\max\{n_m, n_x\}$. An estimated Lowess curve is above 0.80 and almost horizontal, which implies that main-to-main share is not related with the total number of firms. Figure 6 remains very similar when the horizontal axis expresses either n_m or n_x.

Figure 6: 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 presents a histogram. The right panel plots main-to-main shares against the maximum of the numbers of exporters and importers.

A8. Summary Statistics and Treatment Control Group Comparison of Product and Firm Characteristics

Table 11 provides summary statics of product-level characteristics. Column (1) reports means and standard deviations of each product level characteristics for the control group, with the number of observations in Column (2). Columns (3) and (4) report the difference in each characteristic between treatment and control groups. We regress each characteristic of product g on the treatment dummy $Binding_{gs}$ and report the OLS coefficient b of the dummy in Column (3). Column (4) reports the OLS coefficient b of the dummy from a similar regression with HS 2-digit fixed effects, which captures the difference between the two groups within the same HS 2-digit sector. Column (5) reports the number of observations for the regressions for Columns (3) and (4). Though a simple comparison in Column (3) shows that the two groups differ in many characteristics, with HS 2-digit fixed effects the difference becomes smaller and even insignificant for many characteristics, as shown in Column (4).

By the nature of the MFA's end, the control group consists of products that were already liberalized before 2002. Thus, the treatment group, which was protected in 2004, show more exporters and importers and greater trade volume then the control group.

Table 12 reports similar summary statistics for importer-product level characteristics. Even with HS 2-digit fixed effects, the treatment group shows more trade volume and a higher share of processing trade (Maquiladora/IMMEX).

Table 13 reports similar summary statistics for exporter-product level characteristics. Even with HS 2-digit fixed effects, Mexican exporters in the treatment group export more with more partners, have a higher share of processing trade (Maquiladora/IMMEX) and are less likely to trade with intermediary firms.

Table 11: Product-Level Characteristics in 2004

Product-Level Characteristics in 2004					
	Control group		Treatment-Control Difference		
	Means	Obs.	b	b (w. HS2 FE)	Obs.
	(1)	(2)	(3)	(4)	(5)
#Exporters	7.89	230	8.065***	6.028***	375
[s.d.](s.e.)	[15.11]		(2.110)	(1.687)	
#Importers	10.47	230	9.986***	8.742***	375
	[15.11]		(2.789)	(2.395)	
#Importers/	1.49	230	-0.195*	0.105	375
#Exporters	[1.27]		(0.104)	(0.103)	
LnTotalTrade	11.84	230	1.334***	1.254***	375
	[2.58]		(0.291)	(0.312)	
Main-to-Main Share	0.89	230	0.006	-0.015	375
	[0,18]		(0.017)	(0.018)	
Men	0.07	230	0.172***	0.054	375
	[0.25]		(0.039)	(0.040)	
Woman	0.11	230	0.273***	0.080*	375
	[0.32]		(0.046)	(0.046)	
Wool	0.03	230	0.013	-0.030	375
	[0.18]		(0.022)	(0.027)	
Cotton	0.18	230	0.160***	0.066*	375
	[0.38]		(0.047)	(0.039)	
Man-Made	0.33	230	0.046	0.136***	375
	[0.47]		(0.051)	(0.041)	

Note: For each characteristic, the followings are reported: Column (1): mean and standard deviation for the control group of products for which imports from China did not face binding US quota in 2004; Column (2): number of products in the control group; Column (3): coefficient of a treatment group dummy in a regression of the characteristics on the dummy; Column (4): coefficient of a treatment group dummy in a regression of the characteristics on the dummy and HS 2-digit fixed effects; Column (5) number of observations in regressions for Columns (3) and (4). Significance: * 10 percent, ** 5 percent, *** 1 percent. Definitions of the characteristics: $\#Exporters_g$ and $\#Importers_g$ are the numbers of exporters and importers of product g in 2004, respectively. $LnTotalTrade_g$ is the log of trade volume of product g in 2004. Main-to-main share is the main to main share of the product in 2004. Men, Women, Wool, Cotton, and Man-Made are dummy variables indicating whether products are Men's, Women's, cotton, wool and man-made (chemical).

Table 12: Importer-Product Level Characteristics in 2004

Importer-Product Level Characteristics in 2004					
Own Characteristics					
	Control group		Treatment-Control Difference		
	means	Obs.	b	b (w. HS2 FE)	Obs.
	(1)	(2)	(3)	(4)	(5)
US Intermediary	0.33	1570	-0.002	-0.033	3429
[s.d.](s.e.)	[0.47]		(0.016)	(0.022)	
LnTrade	7.86	2408	0.785***	0.571***	5374
	[3.24]		(0.093)	(0.119)	
N of Partners	1.12	2408	0.013	0.012	5374
	[1.32]		(0.027)	(0.034)	
Maquiladora	0.25	2408	0.198***	0.130***	5374
	[0.42]		(0.013)	(0.016)	
Main Partner Share	0.76	124	0.012	-0.011	396
	[0.21]		(0.020)	(0.027)	
Main Partner's Characteristics					
	Control group		Treatment-Control Difference		
	Mean	Obs.	b	b (w. HS2 FE)	Obs.
Northern State	0.15	2408	-0.027***	0.002	5374
[s.d.](s.e.)	[0.36]		(0.010)	(0.012)	

Note: For each characteristic, the followings are reported: Column (1): mean and standard deviation for the control group of products for which imports from China did not face binding US quota in 2004; Column (2): number of products in the control group; Column (3): coefficient of a treatment group dummy in a regression of the characteristics on the dummy; Column (4): coefficient of a treatment group dummy in a regression of the characteristics on the dummy and HS 2-digit fixed effects; Column (5): number of observations in regressions for Columns (3) and (4). Significance: * 10 percent, ** 5 percent, *** 1 percent. Definitions of the characteristics: $LnTrade_{ig}$ is the log of firm i's trade volume of product g in 2004. $Maquiladora_{ig}$ is the share of Maquiladora/IMMEX trade in firm i's trade of product g in 2004. $\#Partners_{ig}$ is the number of firm i's partner in product g in 2004. $US\,Intermediary_i$ is a dummy variable indicating whether US importer or US main partner is an intermediary firm. $NorthernState_{ig}$ is a dummy indicating whether firm i's Mexican main partner of product g is located in a northern state in Mexico.

Table 13: Exporter-Product Level Characteristics in 2004

Exporter-Product Level Characteristics in 2004

Own Characteristics					
	Control group		Treatment-Control Difference		
	Mean	Obs.	*b*	*b* (w. HS2 FE)	Obs.
	(1)	(2)	(3)	(4)	(5)
Maquiladora	0.33	1818	0.122***	0.093***	4131
[s.d.](s.e.)	[0.46]		(0.015)	(0.019)	
Northern State	0.24	1818	-0.103***	0.002	4131
Dummies	[0.43]		(0.012)	(0.015)	
LnTrade	7.60	1818	1.562***	0.963***	4131
	[3.52]		(0.109)	(0.139)	
N of Partners	1.5	1818	-0.036	0.213***	4131
	[2.01]		(0.056)	(0.072)	
Main Partner Share	0.73	296	0.018	-0.014	724
	[0.21]		(0.016)	(0.022)	
Main Partner's Characteristics					
	Control group		Treatment-Control Difference		
	Mean	Obs.	*b*	*b* (w. HS2 FE)	Obs.
US Intermediary	0.31	1219	0.020	-0.053**	2833
[s.d.](s.e.)	[0.46]		(0.018)	(-0.024)	

Note: For each characteristic, the followings are reported: Column (1): mean and standard deviation for the control group of products for which imports from China did not face binding US quota in 2004; Column (2): number of products in the control group; Column (3): coefficient of a treatment group dummy in a regression of the characteristics on the dummy; Column (4): coefficient of a treatment group dummy in a regression of the characteristics on the dummy and HS 2-digit fixed effects; Column (5): number of observations in regressions for Columns (3) and (4). Significance: * 10 percent, ** 5 percent, *** 1 percent. Definitions of the characteristics: $LnTrade_{ig}$ is the log of firm i's trade volume of product g in 2004. $Maquiladora_{ig}$ is the share of Maquiladora/IMMEX trade in firm i's trade of product g in 2004. $\#Partners_{ig}$ is the number of firm i's partner in product g in 2004. $US\,Intermediary_{ig}$ is a dummy variable indicating whether firm i's US main partner of product g is an intermediary firm. $NorthernState_i$ is a dummy indicating whether firm i is located in a northern state in Mexico.

A.9. Alternative Explanations

This section discusses alternative hypotheses for our findings and presents additional evidence showing these do not fully explain our results.

Negative Assortative Matching (NAM) Appendix A.3 shows that Case S is different from Case C and Case I in two aspects. First, firm's trade volume may not be monotonically increasing in capability. The import volume of US importers with capability x, $I(x)$, and export volume of Mexican exporters with capability y, $X(y)$, satisfy $X(m_x(x)) = I(x)$. Since $X'(m_x(x))m'_x(x) = I'(x)$ and $m'_x(x) < 0$, then $I'(x)$ and $X'(y = m_x(x))$ must have the opposite signs. Thus, it is impossible that the trade ranking agrees with true capability ranking both for exporters and importers. Second, the MFA's end is likely to increase the mass of total suppliers in the US. In this case, the direction of partner change depends on the firm's capability. A threshold capability $\tilde{x}$ exists such that US importers with $x > \tilde{x}$ upgrade their partners, while those with $x < \tilde{x}$ downgrade their partners. With these two complications, it is theoretically possible yet unlikely that NAM explains the observed systematic relationships between rematching and trade ranking.

Segment Switching Another explanation for partner changes is the "segment switching" theory inspired by Holmes and Stevens (2014). Even one HS 6-digit product category may have two different segments. One, a "standardized" segment, is produced on a large scale and sold with low markups, while the other, a "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. Further suppose that Chinese exporters enter mainly in "standardized" products and that Mexican exporters switched from "standardized" to "custom" products to escape competition. This change might be observed as Mexican exporters' partner downgrading and US importers' partner upgrading.

If this hypothesis mainly explains our findings, small firms and large firms should respond to the end of the MFA in heterogeneous ways. As small "custom" US importers should become more attractive to Mexican exporters and able to match to more capable Mexican exporters, small US importers should upgrade partners more frequently than large US importers. However, Table 5 shows that both small and large US importers upgrade partners in a similar way.

Furthermore, Table 14 examines whether imports by initially small "custom" US importers show higher growth rates than those by large "standardized" US importers. The hypothesis predicts predicts such heterogeneous growth should be stronger in the treatment group than in the control group. To test this hypothesis, Column (1) regresses US importer's import growth on the binding dummy and the firm's own rank and Column (2) adds the interaction of the firm's own rank with the binding dummy. Note that a small OwnRank indicates a large size. A positive coefficient on Own Rank in Row (1) shows small-sized US importers grow more than large US importers. However, a small and insignificant interaction term in Column (2) shows this heterogeneous effect is almost the same between the treatment and control groups, which is inconsistent with the segment-switching hypothesis.

Production Capacity Another hypothesis posits that firm's trade volume mainly reflects the size of Mexican supplier's production capacity instead of productivity and quality. Since production capacity can be regarded as an element of firm's capability, this hypothesis is still consistent with PAM by capability.

Furthermore, the mere demand for production capacity is unlikely to be the main reason for the observed partner upgrading. Columns (3) and (4) in Table 14 tests the production capacity hypothesis. If US importers in the treatment group switch to Mexican exporters with greater preshock exports mainly to seek greater production capacity, we should see the following two patterns. First, US importers in the treatment group should show greater import growth than those in the control group. Second, the difference should be driven by US importers in the treatment group who actually upgrade partners. To test these two predictions, Column (3) regresses US importer's import growth on the binding dummy and Column (4) adds the partner upgrading dummy and its interaction with the binding dummy. Columns (3) and (4) show that the import growth of US importers is not correlated with whether firms belong to the treatment group or whether the firms actually upgraded partners. Thus, the demand for production capacity alone is unlikely to explain the observed partner upgrading.

Table 14: Import Growth of US Importers during 2004-2007

	$\Delta \ln Import_{igs}$			
	(1)	(2)	(3)	(4)
Binding	-0.034	-0.019	-0.127	-0.140
	(0.222)	(0.289)	(0.256)	(0.259)
OwnRank	3.069***	3.088***		
	(0.367)	(0.382)		
OwnRank*Binding		-0.042		
		(0.782)		
Up^{US}_{igs}				-0.191
				(1.062)
Up^{US}_{igs}*Binding				0.374
				(1.238)
Constant	-2.035***	-2.042***	-0.547	-0.551
	(0.750)	(0.737)	(0.782)	(0.792)
HS2 FE	Yes	Yes	Yes	Yes
R^2	0.144	0.144	0.014	0.014
Obs.	718	718	718	718

Note: Dependent variable $\Delta \ln Import_{igs}$ is the log difference of US firm i's import volume of product g during 2004–07. $Binding_{gs}$ is a dummy variable indicating whether product g from China faced a binding US import quota in 2004. $OwnRank_i$ is the normalized rank of firm i in 2004. Up^{US}_{igs} is a dummy variable indicating whether during 2004–07 US firm i switched its main partner of HS 6-digit product g in Mexico to one with a higher capability rank. All regressions include HS 2-digit product fixed effects. Standard errors are in parentheses and clustered at the HS 6-digit product level. Significance: * 10 percent, ** 5 percent, *** 1 percent.

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