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 these new facts, 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, partner switching patterns are consistent with Beckerian PAM but not with independent 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, the remaining intensive margin adjustment involves substantial partner switching, i.e., simultaneous adding and dropping of partners. Partner switching account for more than 60% of the intensive margin and caused a more than 250% 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 of their main partners causes a significant role in trade liberalization.

The dominance of partner switching in the trade liberalization adjustment is at odds with the

[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.

anonymous market models. In such models where an exporter is indifferent about partners, even small costs incurred by changing partner should minimize export changes involving 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 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 independent of capability, 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. The model predicts that under PAM and random matching, these pre-liberalization trade rankings should, on average, agree with true capability rankings. Using these pre-liberalization 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.

Data 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 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 addressing an endogeneity problem that exists in firm-to-firm matching based on unobservable apabilities. 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.

[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.

Furthermore, there is no established method of estimating unobserved capability in a matching market from typical production and customs data.[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 utilize industry fixed effects to control for unobserved factors commonly affecting matching 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 with heterogenous capabilities (as in Melitz, 2003). Antras, Garicano and Rossi-Hansberg (2006) analyze offshoring as PAM of managers and workers by skills across countries. These matching 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 the mechanism from actual matching data.

This paper is part of quickly growing literature that investigates exporter–importer matching using customs transaction data. One strand of this literature develops models to explain stylized facts on firm's exports 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

[3] Most estimation methods about firm capability require no information about each seller's buyers. This, in effect assumes an anonymous market, where seller's capability does not depend on its buyers.

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 those prior studies that mainly analyzed exporter–importer matching at firm-level. We investigate systematic changes of product-level matching in trade liberalization by utilizing product-level variations in liberalization. Importantly, our finding of product-level PAM by capability should not be confused with firm-level "negative degree assortativity" reported by Blum et al. (2010) and Bernard et al. (2018). These two concepts can be compatible with each other both theoretically and empirically. In section 5.6, we present a unified model and evidence that reconciles product-level PAM and firm-level negative degree assortativity. Therefore, our finding of product-level PAM should not be interpreted as any criticism against those models developed to analyze firm-level matching.

In this literature, concurrent papers by Benguria (2015) and Dragusanu (2014) also document positive correlations of size and productivity measures of exporters and importers in France–Colombia trade and in India–US trade, respectively. 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 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 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, extended models, robustness checks and additional analyses rejecting alternative explanations for our results.

2 The Mexico–US Textile/Apparel Trade

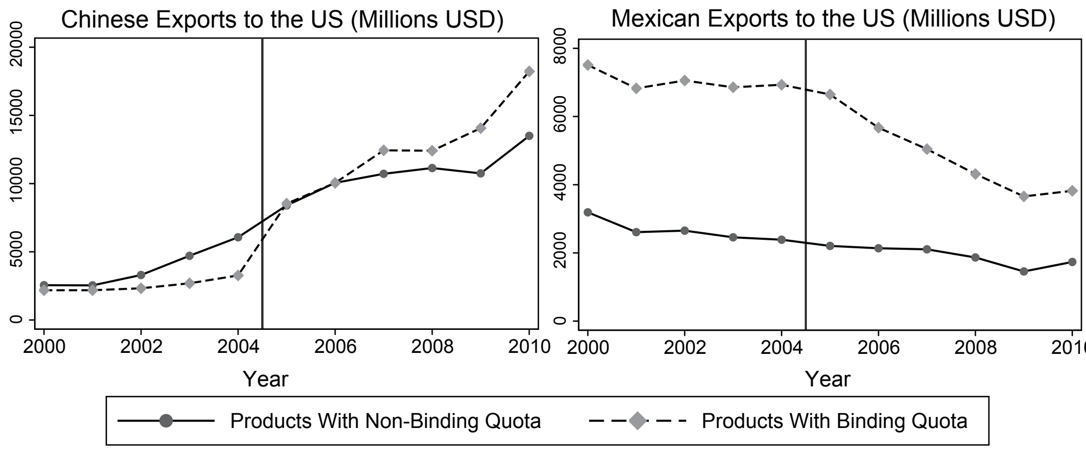
2.1 The End of the Multi-Fibre Arrangement

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 import quota on textile/apparel products 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, 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 Online Appendix C.5 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 From Chinese customs transaction data, Khandelwal, Schott, and Wei (2013) decompose the increases in Chinese exports to US in the liberalized products after the quota removal into intensive and extensive margins. Increases in Chinese exports were mostly driven by the entry of new exporters who had not previously exported the products. These new exporters are much more heterogeneous in capability than incumbent exporters, with many new exporters being more capable than incumbents.[5]

Fact 3: Mexican Exports Faced Competition with 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

[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).

[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.

advantage over third-country exporters and faced increased competition from Chinese exporters in the US market.[6] 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.

2.2 Partner Switching after the MFA's End

Data From Mexico's customs administrative 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 Harmonized System (HS) product code; annual shipment value (USD); quantity and unit; an indicator of a duty free processing reexport program (Maquiladora/IMMEX); and other information.

We have assigned exporter-ID and importer-ID throughout the dataset. The assignment of exporter ID uses the tax number uniquely identifying each firm in Mexico. Assigning importer IDs for US firms was challenging. Although the customs records report a name, an address and an employment identification number (EIN) of US importer for each transaction, it is known that none of them can uniquely identify a firm because a firm sometimes uses multiple names or changes names, owns multiple plants/establishments, or changes tax numbers. Furthermore, firm's name and address may be written in multiple ways and suffer from typographical errors. Therefore, simply counting combinations of names, addresses, and EINs would wrongly assign more than one ID to one US importer and overestimate the number of US buyers for each Mexican exporter.

We, therefore, assigned importer ID by applying a series of record linkage techniques.[7] First,

[6] In theory, Mexican firms may import materials from China, produce textile/apparel products and export them to the US, but it is only negligible because NAFTA sets restrictive rules of origin. The basic rule is informally called "yarn-forward" (US CBO, 2014). For textile and apparel products to be qualified as NAFTA products, the yarn must be made in Mexico from fibers possibly imported from China. However, Mexico's import in fibers from China is 7 million USD in 2004, only 0.08% of Mexico's textile/apparel exports to the US.

[7] An excellent reference for record linkage is Herzog, Scheuren, and Winkler (2007). In addition, we benefitted

we prepared a list of name variations such as fictitious names, previous names and name abbreviations, a list of addresses of company branches/subsidiaries, and a list of EINs from Orbis by Bureau van Dijk, which covers 20 millions company branches, subsidiaries, and headquarters in the US. These lists are used as dictionaries to which customs records are matched. Second, the format of address is standardized by a software certified by the US Postal Office. Third, we match the lists from Orbis and each of linking variables (name, address, EIN) in customs data by fuzzy matching. Two types of errors may occur in fuzzy matching: "false matching" (matching records that should not be matched) and "false unmatching" (not matching records that should be matched). The criteria for fuzzy matching is chosen to minimize false unmatching because false matching is easier to identify by manual checks than false unmatching. Six, binary matched records are aggregated into their clusters so that each record match some record in the cluster. A resulting cluster represents a firm. Seventh, we manually checked each cluster and removed false matched records. Finally, we assign importer ID for each cluster. Online Appendix C.2 explains the process in detail.

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.[8] We drop exporters that 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 Online Appendix C.4.

from lecture slides on "Record Linkage" by John Abowd and Lars Vilhuber.

[8]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.

Approximately One-to-One Matching at Product Level Our first finding is that product-level matching of Mexican exporters and US importers is approximately one-to-one.[9] A product-level match is defined if an importer and an exporter trade in a particular product, while a firm-level match is defined if an importer and an exporter trade in some product. Columns (a) and (b) in Table 1 reports mean and median statistics about product-level matching.[10] The first four rows show that 11–15 exporters and 15–20 importers exist in an average product market, but the majority of firms trade with only one partner.[11] Rows (5) and (6) show that even firms who trade with multiple partners concentrate more than 70% of their trade with their single main partners. Columns (c) and (d) show the same statistics for firm-level matching. The pattern is robust: most firms concentrate their trade with their single main partners.

Table 1: Summary Statics for Product-Level Matching and Firm-Level Matching in Textile/Apparel Trade from Mexico to the US

	HS 6 Product-Level Match		Firm-Level Match	
	2004	2007	2004	2007
mean statistics (median)	(a)	(b)	(c)	(d)
(1) Number of Exporters	14.7 (8)	11.4 (6)	1,340	1,036
(2) Number of Importers	19.6 (11.5)	14.9 (9)	2,031	1,541
(3) Number of Exporters Selling to an Importer	1.1 (1)	1.1 (1)	1.4 (1)	1.3 (1)
(4) Number of Importers Buying from an Exporter	1.5 (1)	1.4 (1)	2.1 (1)	1.9 (1)
(5) Value Share of Main Exporter (Number of Exporters > 1)	0.76	0.77	0.75	0.78
(6) Value Share of Main Importer (Number of Importers > 1)	0.74	0.76	0.73	0.76

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

[9] Beyond a particular product and the US-Mexico bilateral relationship, Mexican exporters and US importers may have more partners than our statistics below.

[10] Products with only one exporter and one importer are removed from Table 1, which accounts for 3% of trade. If they are included, the numbers of Columns (1) and (2) decrease, but those in other columns barely change.

[11] Online Appendix F.2 presents versions of Table 1 for 2005 and 2006 and for the regression samples that exclude new exporters and new importers after 2005 that might have started with only one partner. The statistics in Column (3)–Column (6) on the numbers of partners remain very close to those in Table 1.

A potential concern for Table 1's statistics is that they might over-represent small firms that only minimally impact aggregate trade. Therefore, 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. "Main-to-main match" is 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. "Main-to-main share" is the share of trade by main-to-main matches out of the total aggregate trade. If all matching is one-to-one, main-to-main share takes on a maximum value of one. Even if 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

		HS 6 Product-Level Match				Firm-Level Match			
Main-to-Main Share		2004	2005	2006	2007	2004	2005	2006	2007
(1)	All	0.79	0.81	0.81	0.85	0.71	0.75	0.74	0.78
(2)	Quota-bound	0.78	0.82	0.81	0.84	0.73	0.74	0.75	0.78
(3)	Quota-free	0.80	0.78	0.81	0.86	0.73	0.73	0.77	0.80
(4)	Processing	0.77	0.81	0.81	0.83	0.73	0.73	0.76	0.77
(5)	Normal	0.79	0.80	0.83	0.84	0.71	0.72	0.76	0.77

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

Table 2 report main-to-main shares for product-level matching and firm-level matching. In Row (1), the main-to-main share for Mexico's overall textile/apparel exports to the US is approximately 80% for product-level matching and 70% for firm-level matching.[12] Main-to-main matches account for the majority of trade volume.[13] Rows (2) and (3) show the main-to-main share for liberalized products (quota-bound) and other products (quota-free), respectively. Rows (4) and (5)

[12]Online Appendix F.1 investigates main-to-main shares at the product-year level. The median main-to-main share is 0.97 and the 25th percentile is 0.86.

[13]Both one-to-one matches and "non one-to-one" matches account for these high shares. The share of trade by one-to-one matches out of the total trade is around 33% for product-level matching. The difference between 33% and the 80% main-to-main share is due to the concentration of trade in main-to-main matches among firms trading with multiple partners. See Online Appendix F.2.

show the share for Maquiladora/IMMEX processing trade and other normal trade, respectively. Stable and high shares suggest that one-to-one matching is a fair approximation of product-level matching in Mexico–US textile/apparel trade.

Partner Switching after the MFA's end Stable main-to-main share does not imply stable partner relationship. Instead, exporters and importers actively switch partners during liberalization. Panel A in Table 3 reports changes in Mexican textile/apparel exports to the US between 2004 and 2007 by incumbent exporters in 2004, separately for liberalized products (quota-bound) and other products (quota-free). The changes in total exports in Column (1) are decomposed into two traditional margins, *extensive margin* in Column (2) by exiters that stopped exporting by 2007 and *intensive margin* in Column (3) by continuing exporters in 2007.[14] Consistent with standard heterogeneous exporter models, the extensive margin plays a large role in liberalized industries.

Export changes previously treated as the intensive margin actually involve substantial partner switching. Columns (4)–(6) decompose Column (3) into three margins of partner changes: *Partner Staying* in Column (4) expresses changes in exports to continuing buyers in 2004 and 2007; *Partner Adding* in Column (5) does those to new buyers in 2007 that did not import from the exporter in 2004; *Partner Dropping* in Column (6) does those to dropped partners that imported from the exporter in 2004 but not in 2007. Parentheses in Columns (5) and (6) report the share of export changes by *Partner Switchers* that simultaneously add and drop partners. Since its share is more than 80%, most partner changes are in fact partner switching.

The prevalence of partner switching is at odds with anonymous market models. In such models where buyers are indifferent for exporters, partner changes should be minimized to save costs of partner changes. Exporters may either add or drop buyers, but should not switch among surviving buyers. In view of these models, *excess reallocation* in Column (8), $|(5)| + |(6)| - |(5) + (6)|$, is expected to be zero. The large excess export reallocation is has been masked in typical exporter

[14]In Online Appendix F.4, the extensive margin is decomposed into dropping products and leaving the US market.

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

	Total	Traditional Margins		Partner Margins			Excess
		Extensive	Intensive	Stay	Add	Drop	Reallocation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Aggregate decomposition							
Quota-bound	-950.6	-887.4	-63.4	-25.1	83.5	-121.9	167.0
% of (3)			100%	39.5%	-131.7%	192.3%	263.64%
Switcher share					(0.95)	(0.82)	
Quota-free	-223.0	-179.6	-43.4	-24.0	37.5	-56.9	75.0
% of (3)			100%	55.4%	-86.5%	131.1%	172.8%
Switcher share					(0.79)	(0.87)	
B. HS 6 digit product-level regression coefficients							
Binding	-4.441**	-4.052**	-0.389	-0.132	0.388**	-0.645**	0.706**
(s.e.)	(2.046)	(1.883)	(0.306)	(0.230)	(0.165)	(0.274)	(0.296)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: (Panel A) 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 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 |Column (5)|+|Column (6)|- |Column (5)+Column (6)|. (Panel B) each column reports product-level regressions of each margin on quota-bound product dummy (Binding) with HS 2 digit fixed effects. Standard errors are clustered at the HS 6-digit product level. Significance: * 10 percent, ** 5 percent, *** 1 percent.

data, without matching information being provided.

As the importance of main parters in Table 2 suggests, the switching of main partners plays a major role in the intensive margin adjustment. In Table 4, the intensive margin in Column (1) is decomposed according to the involvement of main partners: export changes not involving main partners in Column (2); exports to continuing main partners in 2004 and 2007 in Column (3); those to new main buyers in 2007 that were not main buyers in 2004 in Column (4); those to dropped main buyers that were main buyers in 2004 but not in 2007 in Column (5). Column (6) reports excess reallocation associated with main partners, i.e. $|(4)| + |(5)| - |(4) + (5)|$.

The above decompositions show the aggregate importance of partner switching. To examine the impact of liberalization on each margin at the disaggregate product-level, in Panel B of Table 3 and Table 4, we regress each margin of HS 6 digit product level exports on the dummy variable of quota liberalization (the Binding dummy) with HS 2 digit fixed effects and report the estimated coefficients. Large and statistically significant coefficients in Columns (5)–(7) in Table 3 and Column (4)–(6) in Table 4 confirm the significant roles of partner switching.

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

	Intensive Margin	Non-Main Partner	Main Partner Margins			Main Partner Excess Reallocation
			Stay	Add	Drop	
	(1)	(2)	(3)	(4)	(5)	(6)
A. Aggregate decomposition						
Quota-bound	-63.4	-15.2	-13.7	72.9	-107.4	145.8
% of (1)	100%	24.0%	21.6%	114.9%	169.3%	229.8%
Quota-free	-43.4	-14.2	-10.9	38.7	-56.9	77.4
% of (1)	100%	32.7%	25.1%	89.2%	131.3%	178.4%
B. HS 6 digit product-level regression coefficients						
Binding	-0.389	-0.080	-0.095	0.332**	-0.545**	0.602**
(s.e.)	(0.306)	(0.082)	(0.205)	(0.141)	(0.238)	(0.240)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: (Panel A) each column reports changes in Mexican textile/apparel exports to the US between 2004 and 2007 by exporters in 2004, for quota-bound products and other quota-free products. Intensive margin changes by survivors in (1) is decomposed to: (2) exports to non-main partners; (3) exports to continuing main partners; (4) exports to new main partners; (5) exports to dropped main partners. Column (6) is |Column (4)|+|Column (5)|- |Column (4)+Column (5)|. (Panel B) each column reports the coefficients of product-level regressions of each margin on the dummy of quota-bound products (Binding) with HS 2 digit fixed effects. Standard errors are clustered at the HS 6-digit product level. Significance: * 10 percent, ** 5 percent, *** 1 percent.

3 The Model

The dominance of partner switching in trade liberalization is puzzling in anonymous market models. This section develops a simple matching model of exporters and importers where partner switching is the principal margin of adjustment.

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.[15] 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.[16] 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. In Stage 2, teams compete in the US final-good market in a monopolistically competitive fashion. The frictionless one-to-one 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.[17] Section 5.6 discusses its extension for many-to-many matching.

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 identical distribution with the c.d.f. $G(y)$ and continuous support $[y_{min}, y_{max}]$. For simplicity, a Chinese supplier is a perfect substitute for a Mexican supplier of the same capability. The identical distribution of Chinese and Mexican suppliers is assumed only for graphical exposition. Online Appendix A.1 derives the main predictions without the assumption.

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

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

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

[17] 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.

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.[18] For simplicity, we assume firm's marginal costs depend on the 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).

[18] 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.

Backward induction obtains an equilibrium. All calculations are in Online Appendix A.1.

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:[19]

$$\pi_x(x) = [A\theta(x, m_x(x)) - f] - \pi_y(m_x(x)) = \max_y A\theta(x, y) - \pi_y(y) - f;$$

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

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

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.[20] 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

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

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) Case C (Complement) $\theta_{12} > 0$; (2) Case I (Independent) $\theta_{12} = 0$; (3) Case S (Substitute) $\theta_{12} < 0$.[21] 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

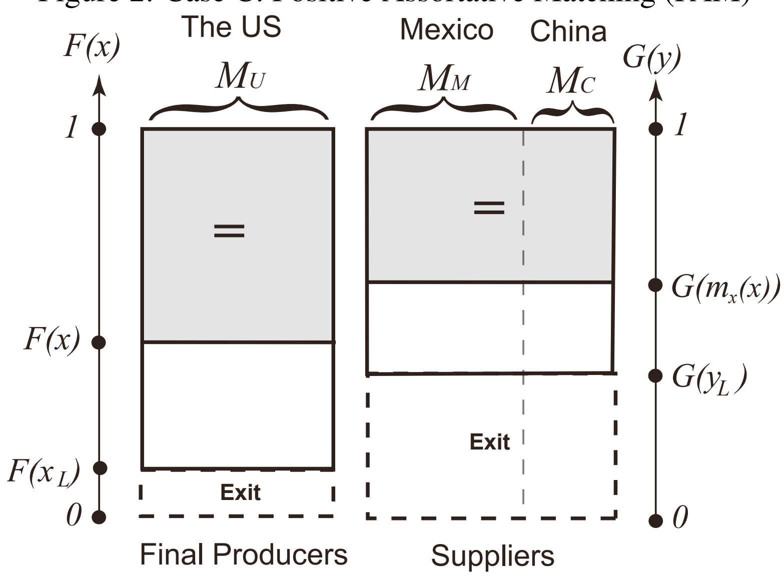
[20]The use of differentiation and continuums of agents is a convenient shortcut for deriving the sorting pattern. Online Appendix E.2 presents a general proof of sorting that can be applied for finite agents.

[21]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.

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 and independent of capability in Case I.

Case I is a useful benchmark because it represents two important classes of standard trade models. The first is anonymous market models where each firm is indifferent about partner capability. The second is heterogenous firm trade models with one-sided heterogeneity where firm heterogeneity exists either among exporters ($\theta_1 = \theta_{12} = 0$) or among importers ($\theta_2 = \theta_{12} = 0$). Therefore, we focus on Case C and Case I in the main text and examine Case S in Online Appendix B.1.

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



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

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

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 $m_x(x)$. Figure 2 describes how matching function $m_x(x)$ is determined for a given $x \geq x_L$. The width of the left rectangle 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 $\Theta(x_L) = M_U \int_{x_L}^{\infty} \theta(x, m_x(x))\, dF(x)$ and the capability cutoff $\theta_L(x_L) = \theta(x, m_x(x_L))$ 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, $\Theta(x_L) = M_U \int_{x_L}^{\infty} \theta^x(x)\, dF(x) + (M_M + M_C) \int_{y_L(x_L)}^{\infty} \theta^y(y) dG(y)$ and $\theta_L(x_L) = \theta^x(x_L) + \theta^y(y_L(x_L))$ become functions of x_L. From (1), (4) and $A = \delta/\sigma\Theta$, the team with the capability cutoff earns zero profits:

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

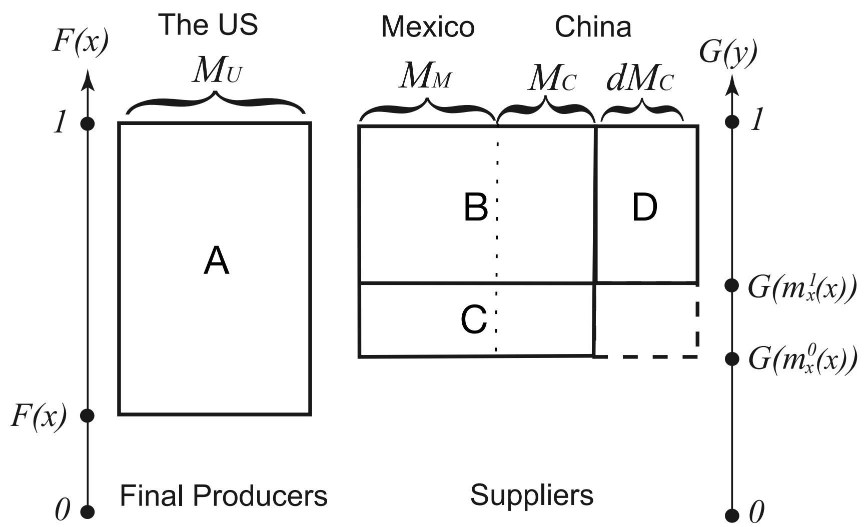
In both Case C and Case I, (7) uniquely determines x_L since $\Theta(x_L)$ is decreasing and $\theta_L(x_L)$ is increasing in x_L. Finally, we define a stable matching equilibrium as follows.

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 exit the US market, which is proved in Appendix B.

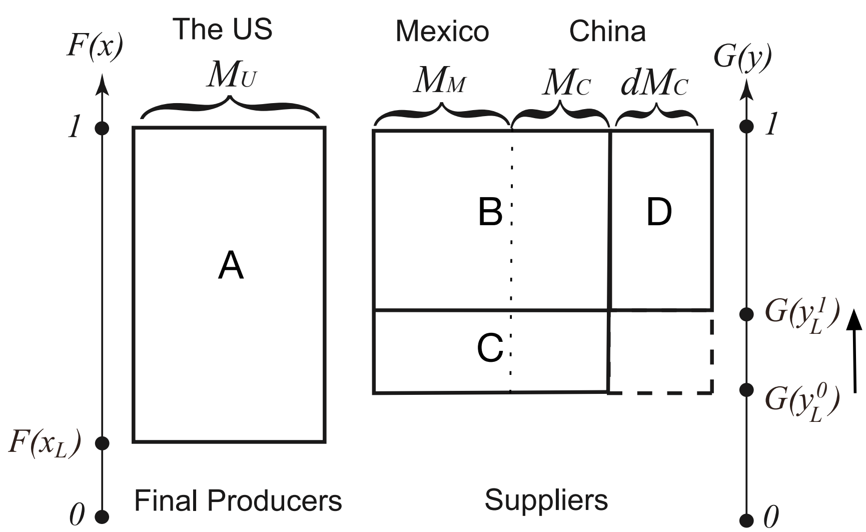
Our data on Mexico–US trade only record rematching by firms engaging in Mexico–US trade both before and after the MFA's end. We call these firms *US continuing importers* and *Mexican continuing exporters*. Then, we obtain three predictions for Case C as follows.

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.

Figure 4: Case I: Response of Matching to the MFA's End



Case I Figure 4 shows that the entry of Chinese suppliers raises the capability cutoff for suppliers from y_L^0 to y_L^1, which is proved in Online Appendix B. As low capability suppliers in Area C exit, US importers who matched with them switch to new Chinese suppliers in Area D. 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 and independent of capability before and after the MFA's end.

I3: The capability cutoff for Mexican exporters rises.

Rematching Gain from Trade The MFA's end 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. This rematching corresponds to partner excess reallocation in Tables 3 and 4. We show both adjustments improve the consumer welfare.

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 Online Appendix B).

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).[22] In Case I, the rematching gain is zero because matching is irrelevant for firms. Note that Case I nests standard trade models, perfectly competitive models and Krugman/Melitz models with one-sided heterogeneity. Therefore, the absence of the partner rematching gain in Case I implies that it is a new mechanism of gains from trade that is absent in these standard models. If data observe rematching consistent with Case C, the model interprets it as a process of improving global buyer–supplier matching and consumer welfare. The rematching gains from trade also indicates inefficiency of "matching diversion" caused by a preferential trade agreement. High capability US final producers are diverted to match with low capability Mexican suppliers instead of high capability Chinese suppliers.[23]

4 Empirical Strategies

4.1 Proxy for Capability Rankings

Testing predictions C1–C3 and I1–I3 requires data on the ranking of firm capability. We use the ranking of firm's product-level trade before the liberalization as its proxy, using properties of the model. For Case C, let $I(x)$ be the import of the intermediate good by an US importer with capability x and let $X(y)$ be the export by a Mexican exporter with capability y. For Case I, let $\bar{I}(x)$ be the expected imports by a US importer with capability x and let $\bar{X}(y)$ be the expected exports 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 (the proof is in Online Appendix A.1.4).

[22] 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).

[23] Ornelas, Turner, and Bickwit (2019) theoretically analyze "matching diversion" by the preferential trade agreement in a model of one-sided heterogeneity.

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.*

Note that Lemma 2 is about product-level trade with the main partners. Thus, we use product-level trade to create the ranking of firm's product-level capability in each product market.[24]

Using Lemma 2, we create the capability ranking of firms as follows. For each HS 6-digit product, we create a ranking of all US importers in 2004 by the value of their imports of the product from their main partner in 2004 before the MFA's end. Similarly, for each HS 6-digit product, we rank all Mexican exporters in 2004 by the value of their exports of the product 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. The correlation of trade ranks in 2004 and 2007 are higher than 0.85 for all products and similar between the treatment and control groups. Therefore, we assume that the capability ranking is stable in a short run and use the rank measured from 2004 data for the same firm throughout our sample period.

Using these rankings, we first create three variables: (1) firm i's own rank in product g in country c, $OwnRank_{ig}^{c}$; (2) rank of the firm's main partner of product g in 2004 before the MFA's end, $OldPartnerRank_{ig}^{c}$; and (3) rank of the firm's main partner of product g in 2007 after the MFA's end, $NewPartnerRank_{ig}^{c}$. We choose the period 2004–07 to avoid potential confounding from the impact of 2008 Lehman crisis on Mexican exports. Note that $OldPartnerRank_{ig}^{c}$ differs from $NewPartnerRank_{ig}^{c}$ 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 (e.g., 1st rank means the best). Finally, we create variables of partner changes as follows. Partner upgrading dummy Up_{igs}^{c} equals one if $NewPartnerRank_{igs} < OldPartnerRank_{igs}$. Partner downgrading dummy $Down_{igs}^{c}$ equals one if $NewPartnerRank_{igs} > OldPartnerRank_{igs}$.

[24] When firms trade multiple products, firm's total trade may also be increasing in capability. However, if a firm's product capability is the sum of firm capability and idiosyncratic components as in a multi-product firm in Bernard, Redding and Schott (2011), the relationship between total trade and firm capability could be attenuated by idiosyncratic components. To reduce measurement errors, we create the ranking from product-level trade.

4.2 Specifications

Partner Changes (C1 and I1) The following regressions test predictions C1 and I1:

$$Up_{igs}^{c} = \beta_U^c Binding_{gs} + \lambda_s + \varepsilon_{Uigs}^{c}$$

$$Down_{igs}^{c} = \beta_D^c Binding_{gs} + \lambda_s + \varepsilon_{Digs}^{c}, \tag{8}$$

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.[25] ε_{Uigs}^{c} and ε_{Dijs}^{c} are error terms. Online Appendix C.5 explains the 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 β_U^c and β_D^c in (8) 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 estimate its impact on the probability that firms switch from their initial main partner to one with higher and lower capabilities, respectively. HS 2-digit fixed effects control for basic product characteristics such as textile/apparel and knit/woven.

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, some idiosyncratic shocks appearing as error terms in (8) could induce partner changes. Considering this point, we reformulate Prediction I1: no difference should exist in the probability of partner

[25] 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 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.

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 could produce a mechanical positive correlation regardless of the sign of sorting.[26] 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 ranking should appear in error terms ε_{Uigs}^c and ε_{Digs}^c, 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 unobservables, β_U^c and β_D^c are consistently estimated.[27]

Another advantage of (8) is to control for various unobservable determinants of firm's partner ranks. First, idiosyncratic shocks to demand and cost may change firm capability and generate partner switching. As long as these shocks appearing as error terms in (8) are uncorrelated to

[26]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.

[27]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.

the MFA liberalization, they should not bias our estimate. Second, the dependent variables are constructed from time differences in partner ranks. The time differencing controls 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:

$$NewPartnerRank_{ig}^{c} = \alpha^{c} + \gamma^{c} OldPartnerRank_{ig}^{c} + \varepsilon_{ig}^{c} \tag{9}$$
$$\text{for firm } i \text{with } NewPartnerRank_{ig}^{c} \neq OldPartnerRank_{ig}^{c}.$$

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 independent of capability 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 treatment and control groups since Prediction C2 should hold for both groups in Case C.[28]

Capability Cutoff Changes (C3 and I3) We test predictions C3 and I3 by two models. First, we estimate a product-level difference-in-difference of export cutoffs for two periods, pre-liberalization (2001–04) and post-liberalization (2004–07):[29]

$$\ln ExportCutoff_{gsr} = \delta_1 Binding_g + \delta_2 Binding_g * After_r + \delta_3 After_r + \lambda_s + u_{gsr}. \tag{10}$$

[28] 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.

[29] We thank a referee for suggesting the product-level regression of the export cutoff.

For surviving exporters in the end year of period r, the minimum of their exports of product g in the initial year of period r proxies for the capability cutoff, $ExportCutoff_{gsr}$. Since importer information is unavailable before 2004, we use Mexican exporter's total product exports as capability proxy, which is highly correlated with exports with the main partners in the 2004–07 data. Regression (10) uses the *level* of exports instead of the *rank* of exports because the level of capability determines firm's exit, while the rank of capability determines matching. Dummy variable $After_r$ equals one if period r is 2004–07, λ_s represents HS 2-digit level fixed effects and u^c_{igs} are error terms.

We use the difference-in-difference specification to test predictions about the cutoff *changes*. In (10), the cutoff increase in Prediction C3/I3 implies $\delta_2 > 0$ as the coefficient of interest. On the other hand, δ_1 estimates the difference in the *levels* of the cutoffs between the liberalized and non-liberalized products. We perform a placebo check of no difference in prior trends in cutoffs by estimating the same equation (10) for two pre-liberalization periods (1998–2001 and 2001–04).

The product-level regression (10) may raise two potential concerns. First, it fails to control for firm heterogeneity within products. Second, a rise in the export cutoff may not imply more firm exit. Therefore, we estimate a threshold model of firm's exit. In each period r, Mexican supplier i receives a random i.i.d. shock ε_{ir} to its profit, which captures idiosyncratic factors inducing firm exit in absence of trade liberalization (e.g., Eaton et. al., 2014). The firm chooses to exit if ε_{ir} is below a threshold $\bar{\varepsilon}_{ir}(y)$. Case C and Case I have two predictions: (i) the MFA's end increases threshold $\bar{\varepsilon}_{ir}(y)$ for a given capability y; and (ii) threshold $\bar{\varepsilon}_{ir}(y)$ is a decreasing function in the firm's capability y. Then, we estimate the following firm-level regression for Mexican firm i who exports product g to the US in the initial year of period $r \in \{2001-04,\, 2004-07\}$:

$$\begin{aligned} Exit_{igsr} = {} & \delta_1 Binding_g + \delta_2 Binding_g * After_r + \delta_3 After_r + \delta_4 \ln Exports_{igr} \\ & + \delta_5 After_r * \ln Exports_{igr} + \lambda_s + u_{igsr}. \end{aligned} \tag{11}$$

Dummy variable $Exit_{igsr}$ equals one if the firm stops exporting during period r. $\ln Exports_{igr}$ is the log of the firm's total exports of product g in the initial year of period r, which proxies firm capability. The above mentioned predictions (i) and (ii) are expressed as follows: (i) $\delta_2 > 0$, i.e., the end of the MFA increased exit probability for a given capability level; (ii) $\delta_4 < 0$ and $\delta_4 + \delta_5 < 0$, i.e., small low capability firms are more likely to exit.[30]

5 Results

5.1 Partner Changes

Table 5 reports regressions for partner changes during 2004–07 using linear probability models.[31] Columns with odd numbers report estimates of β_d^c ($c = US, Mex$ and $d = U, D$) from baseline regressions (8). We find that β_U^{US} in Column (1) and β_D^{Mex} in Column (7) are positive and statistically significant, while β_D^{US} in Column (3) and β_U^{Mex} in Column (5) are close to and not statistically different from zero. These signs on β_d^c 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 percentage points.[32] These effects are quantitatively large when compared with the sample averages of Up_{igs}^{US} and $Down_{igs}^{Mex}$, which are 3 percentage points and 15 percentage points, respectively.[33]

Columns with even numbers in Table 5 report the regressions adding the firm's own rank and its

[30]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 exports. 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 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.

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

[32]β_D^{Mex} is estimated larger than β_U^{US} because the actual matching is not exactly one-to-one and includes the following "within match" partner changes. Suppose a Mexican exporter had been exporting to two US importers in 2004 and these two US importers buy only from the exporter. Then, in 2007 the exporter stopped exporting to its 2004 main partner and exported only to the second importer. This is counted as partner downgrading for the exporter but not as partner upgrading for the two importers. This causes β_D^{Mex} estimated larger than β_U^{US} . In Appendix F.3.4, we distinguish firm's main partner change within and across match. If we use only main partner switching across match,

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.

interaction with the binding dummy. Both large and small firms switch their partners as the model predicts. Figure 5 visualizes these results by drawing kernel-weighted local mean regressions of partner change dummies on the firm's own rank for apparel products. Dashed lines and areas represent the regression lines with 90% confidence bands for the treatment group, while solid lines and area for the control group.[34] The higher probability of US importers' upgrading and Mexican exporters' downgrading in the treatment group is found uniformly for all capability ranks. In contrast, little difference between the two groups is found in the probability of US importers' downgrading and Mexican exporters' upgrading.

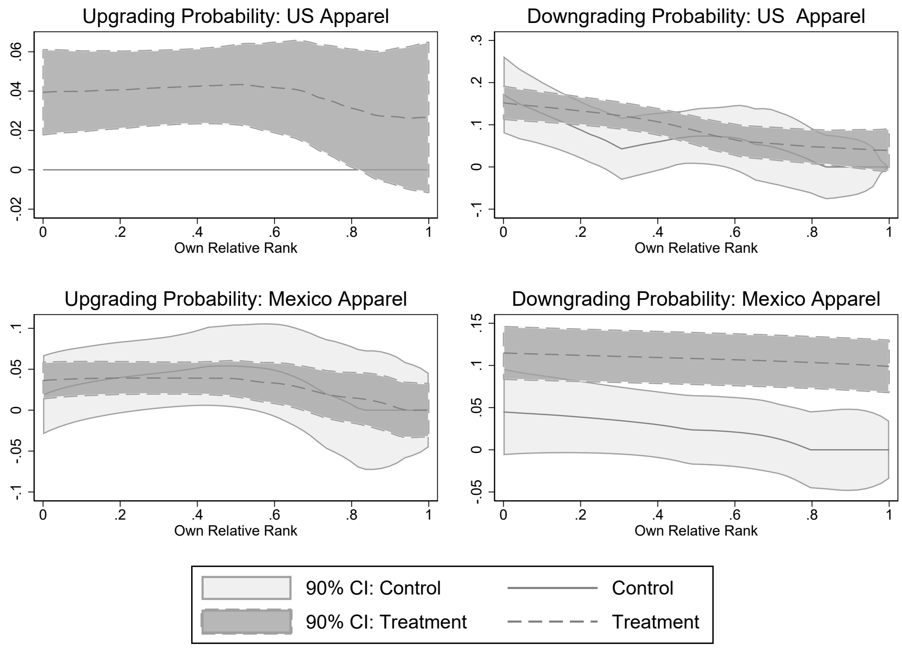
Table 6 examines partner changes in later periods of 2007–11 and 2009–11 in order to check

the estimates of β_U^{US} and β_D^{Mex} become very close to each other.

[33]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.

[34]Graphs are drawn by Stata with default parameters (the Epanechnikov kernel with the rules of thumb bandwidth).

Figure 5: Partner Change during 2004–2007 and Initial Capability Ranks: Apparel Products



Note: Dark gray lines and areas represent kernel weighted local mean regression lines with 90% confidence bands for the treatment group, while light gray lines and area for the control group.The confidence interval for US upgrading for the control group is degenerated because no upgrading occurred there.

our assumption that both treatment and control groups exhibit similar partner change patterns if the treatment was absent.[35] For each period, we re-construct capability rankings based on trade 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. Table 6 reports very small and insignificant estimates for β_U^{US} and β_D^{Mex} in 2007–11 [Columns (1) and (4)] and 2009–11 [Columns (3) and (6)]. These results support our assumption.[36]

Online Appendix F.3 conducts several robustness checks. First, we include the number of

[35]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 exports before MFA quota removal in 2005.

[36]The period 2008–11 [Columns (2) and (5)] 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: Placebo Checks: Partner Change in Different Periods

	Partner Change in Different Periods: Linear Probability Models					
	Up^{US}			$Down^{Mex}$		
	2007–11	2008–11	2009–11	2007–11	2008–11	2009–11
	(1)	(2)	(3)	(4)	(5)	(6)
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: see the footnote of Table 5 for the definitions of variables. 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.

products and its interaction with the binding dummy to address potential within firm interaction at multi-product firms. Second, we include as additional controls, several product-level and firm-product level characteristics that are statistically different between the two groups.[37] Third, we further decompose main partner changes into those across match and within match. Finally, we use alternative windows of two years and four years. Our main results are robust to all of them.

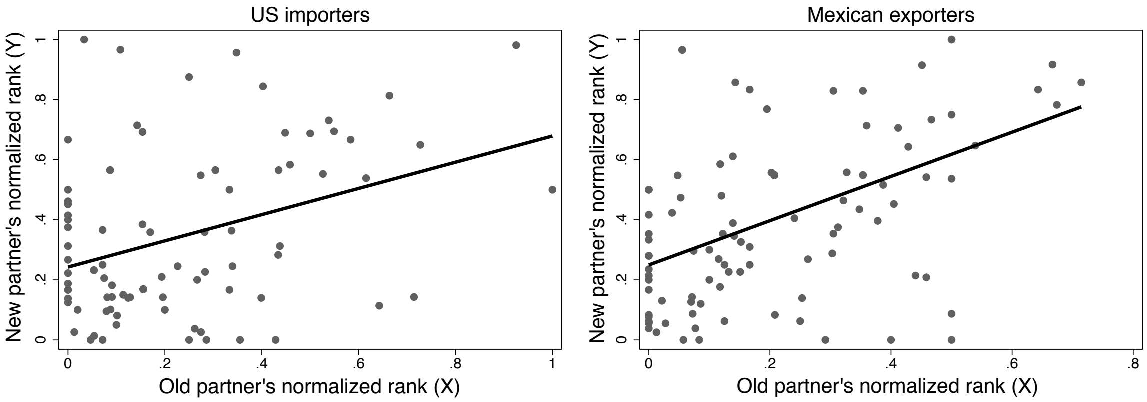
5.2 New and Old Partners Ranks

Figure 6 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 6 and the regressions show significant positive relationships. Firms who match with relatively high capability partners in 2004 switch to relatively high capability partners in 2007.

[37] Those product-level characteristics are: number of exporters, number of importers, log product trade, 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. Those firm-product level characteristics are: log of firm's product trade volume with the main partner, share of Maquladora/IMMEX trade in firm's product trade, number of partners, and dummy of whether a US importer is an intermediary firm such as wholesalers and retailers. 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.

This result again supports Case C PAM and rejects Case I independent matching.

Figure 6: 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 7 reports the results of tests of predictions C3 and I3. Column (1) reports the baseline specification of product-level regression (10) and Columns (2) includes, as additional control variables, product characteristics for the initial year of each period and their interactions with the After dummy. These controls are the same ones in footnote 37 that are available.[38] Estimates of positive and significant δ_2 confirm the prediction that the MFA's end increased the capability cutoff for Mexican exporters. Column (5) reports the baseline specification of firm-level regression (11) and Columns (6) includes product and firm characteristics variables and their interactions with the After dummy.[39] Estimates of positive and significant δ_2 confirm that the MFA's end increased their exit probability for a given capability level. Also, negative estimates of δ_4 and $\delta_4 + \delta_5$ confirm that small exporters are more likely to exit.

[38]They are number of exporters, log product trade, share of Maquiladora/IMMEX trade and product type dummies.
[39]They include share of firm's Maquiladora/IMMEX trade as an additional firm characteristics.

Columns (3) and (7) conduct placebo checks, estimating the regression (10) and (11) with two periods before the MFA liberalization, 1998–2001 and 2001–04, respectively. Column (4) includes control variables. The placebo for (11) is presented without additional controls because several control variables are not available for the period. In all placebo checks, estimated δ_2 is close to zero and statistically insignificant, which confirm no prior difference in the trend between the treatment and control groups.

Table 7: Mexican Exporter's Exit from the US market

	Product-Level Difference-in-Difference				Firm-Level Difference-in-Difference		
	$\ln ExportCutoff_{gsr}$				$Exit_{igsr}$		
Period 1	2001–04		1998–2001		2001–04		1998–2001
Period 2	2004–07		2001–04		2004–07		2001–04
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Binding	-1.255***	-0.668***	-1.074***	-0.786***	-0.040***	-0.035***	-0.021
(δ_1)	(0.281)	(0.246)	(0.248)	(0.249)	(0.014)	(0.013)	(0.015)
Binding	1.031**	1.188**	0.106	0.324	0.076***	0.099***	-0.003
$\times$After (δ_2)	(0.479)	(0.490)	(0.178)	(0.244)	(0.016)	(0.020)	(0.013)
After	-3.402***	-0.863	-0.230	0.809	-0.361***	-0.331***	-0.119***
(δ_3)	(0.364)	(1.620)	(0.151)	(0.785)	(0.042)	(0.069)	(0.034)
$\ln Export$					-0.058***	-0.059***	-0.069***
(δ_4)					(0.002)	(0.002)	(0.003)
$\ln Export$					0.020***	0.026***	0.011***
$\times$After (δ_5)					(0.003)	(0.003)	(0.003)
Controls	No	Yes	No	Yes	No	Yes	No
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	696	696	652	652	22,625	22,624	24,043

Note: $\ln ExportCutoff_{gsr}$ is the log of the minimum of firm-product level export in the initial year of period r. $Exit_{igsr}$ 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) and (4) include product-level controls and Column (6) also include product-firm level controls. 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.

5.4 Alternative Capability Rankings

In Appendix F.5, we present our tests using two alternative rankings: the ranking of firm's total product trade in 2004 and that of firm's unit price of the product's trade with the main partners in 2004, respectively. 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 capability ranking. On the other hand, if capability mainly reflects productivity, the unit price ranking may become the exact reversal of the capability ranking.

The main results are robust to the use of alternative rankings as shown in Table A.18 in Appendix F.5. The results from price rankings suggests that exporter's capability mainly reflects its quality. This is consistent with previous findings from export data that quality is an important determinant of firm's export participation. Quality also determines a firm's export partner.[40]

5.5 Alternative Explanations

Our empirical tests have confirmed all of PAM's predictions C1, C2, and C3. Independent 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 some roles because the goodness of fit of PAM's predictions is not perfect.

Online Appendix D examines four alternative hypotheses for our findings. The first hypothesis is negative assortative matching where trade rankings may not agree with true capability rankings. The second hypothesis is repeated random matching. Suppose random partner change occurs in every period and exhibits mean reversion. The exit of low capable Mexican exporters in liberalized industries may create a positive correlation between the binding dummy and the downgrading by

[40]See e.g., Kugler and Verhoogen (2012), Manova and Zhang (2012). Regressions using price rankings report smaller coefficients than the baseline results. This may be because exporters are differentiated by productivity in some products (e.g., Baldwin and Ito, 2011; Mandel, 2009).

Mexican exporters. The third “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 hypotheses, we conduct additional analyses and show that these do not fully explain our results.

5.6 Extensions for Many-to-Many Matching

Our analysis has focused on one-to-one matching because product-level matching is approximately one-to-one in our dataset. There might be two potential concerns about the validity of our approach under many-to-many matching: first, whether our approach can be applied when product-level matching is many-to-many; second, whether our finding of product-level PAM is consistent with previous studies where matching is typically defined at the firm level. To address these two concerns, we present two extensions to many-to-many matching in Online Appendix E. The first model shows that all Predictions C1–C3 and I1–I3 and our empirical strategy continue to be valid even if product-level matching is many-to-many. The second model reconciles product-level PAM with firm-level negative degree assortativity found by Blume et al. (2010) and Bernard et al. (2018) in a unified framework. The following is sketches of the two models.

Model 1: Many-to-Many Matching in One Intermediate Good Market A final producer produces multiple products/varieties form one intermediate good. A supplier of the intermediate good owns multiple production lines, where each production line specializes for a particular variety. The maximum number of production lines is given for a supplier, possibly because of the span of control, i.e. internal resources (e.g., managers) are required for collaborating with different final producers. In this extension, one-to-one PAM occurs between a final producer’s product and a supplier’s production line, following the exactly the same mechanism of the main model.

As in multi-product firms in Bernard, Redding and Schott (2011), a final producer's capability vary across products so that it matches with multiple suppliers. Similarly, a supplier's capability vary across product-lines so that it matches with multiple final producers. Therefore, the resulting matching between final producers and suppliers is many-to-many at the product level.

The model predicts PAM for main partners from the same Beckerian mechanism. Therefore, all predictions C1–C3 and I1–I3 and our empirical tests continue to be valid even when product-level matching is many-to-many. The model also makes useful predictions. First, our approach is valid even when data cannot observe US importers' trade with suppliers in other countries like our dataset. Second, main partner switching may occur either within and across initial match. These two predictions justify the approach in the main text. Third, in response to liberalization, both Mexican firms and US firms drop their partners. Appendix presents evidence for the last prediction.

Model 2: Product-level PAM and Firm-level Negative Degree Assortativity The model features the love of variety in horizontally differentiated intermediate goods and multi-product suppliers that produce multiple intermediate goods. Following the mechanism of Bernard et al. (2018), firms select in importing and exporting based on match-specific fixed costs and capabilities. Firm-level matching exhibits the degree of negative degree assortativity. At the same time, in each intermediate product market, final producers matches in one-to-one with suppliers as in our main model. This reconciliation has a testable implication: the degree of negative degree assortativity becomes weaker when the definition of matching changes from at the firm level to the firm-product level. Appendix presents evidence supporting for the prediction.

6 Concluding Remarks

During the last two decades, trade research has flourished by incorporating for 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, which is puzzling to standard trade models. 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 interprets partner switching as a new mechanism of gains from trade that is absent in standard trade models.

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 improves 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.[41] 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.

[41] 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 (2019) 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)

A Proofs

A.1 Solving the Model (with different distributions of China and Mexico)

A.1.1 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

$$\frac{\delta \theta \left(\omega\right)^{\alpha} q \left(\omega\right)^{\rho-1}}{\int_{\omega' \in \Omega} \theta(\omega')^{\alpha} q(\omega')^{\rho} d\omega'} = p\left(\omega\right) \text{ for all } \omega \in \Omega. \tag{A1}$$

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

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

where $P \equiv \left[\int_{\omega \in \Omega} p(\omega)^{1-\sigma} \theta\left(\omega\right)^{\alpha\sigma} d\omega\right]^{1/(1-\sigma)}$ is the price index. Substituting this into (A1), we obtain the demand function:

$$
\begin{aligned}
\frac{\delta \theta\left(\omega\right)^{\alpha} q\left(\omega\right)^{\rho-1}}{\int_{\omega' \in \Omega} \theta(\omega')^{\alpha} q(\omega')^{\rho} d\omega'} &= p\left(\omega\right) \\
\delta \theta\left(\omega\right)^{\alpha} q\left(\omega\right)^{\rho-1} \left(\frac{\theta(\omega)^{\alpha(\sigma-1)} p\left(\omega\right)^{1-\sigma}}{q(\omega)^{\rho} P^{1-\sigma}}\right) &= p\left(\omega\right) \\
q(\omega) &= \frac{\delta \theta\left(\omega\right)^{\alpha\sigma}}{P^{1-\sigma}} p(\omega)^{-\sigma}. \qquad \text{(A2)}
\end{aligned}
$$

A.1.2 Stage 2: Team profit maximization

Facing the demand function (A2), 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

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

A.1.3 Stage 1

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

$$M_U[1-F(x_L)] = M_M[1-G_M(y_L)] + M_C[1-G_C(y_L)] \tag{A3}$$

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,

$$M_U[1-F(x)] = M_M[1-G_M(m_x(x))] + M_C[1-G_C(m_x(x))] \text{ for } x \geq x_L, \tag{A4}$$

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 and $G(y)$ is defined by

$$1 - G(y) \equiv \frac{M_M[1-G_M(y)] + M_C[1-G_C(y)]}{M_M + M_C}.$$

Note that $\Theta\left(x_L\right)$ 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.

Prediction C1 when the Capability Distribution differs between Mexico and China The proof for Prediction C3/I3 will be given in A.2. Let y^C_{max} be the maximum capability of Chinese suppliers. Define x' such that $m_x(x') = y^C_{max}$. If $x < x'$, then the matching market clearing condition is (A4) and

$$\frac{dm_x(x)}{dM_C} = \frac{1 - G_y(m_x(x))}{M_M g_M(m_x(x)) + M_C g_C(m_x(x))}. \tag{A5}$$

If $x \geq x'$, then the matching market clearing condition is (A4) is

$$M_U[1 - F(x)] = M_M[1 - G_M(m_x(x))]$$

and $dm_x(x)/dM_C = 0$. Thus, the change in the matching function is expressed by (A5). The following summarizes partner change under Case C.

C1 Let y^C_{max} be the maximum capability of Chinese suppliers. (1) US importers with $x \geq x'$ and Mexican exporters with $y \geq y^C_{max}$ do not change their partners. (2) For other firms, US continuing importers upgrade Mexican partners, while Mexican continuing exporters downgrade US partners to those with lower capability.

A new prediction is that (1) very high capability firms do not change their partners even in Case C.

The results in Table 5 and Figure 5 find this is not the case. Partner switching occurs for firms at all capability levels as in the main model.

A.1.4 Proof for Lemma 2

Trade 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 imports by US importers $I(x) = T(x, m_x(x))$ and exports by Mexican suppliers $X(y) = T(m_y(y), y)$ increase in their own capabilities, respectively. In Case I, both mean imports by US importers, $\bar{I}(x) = [1 - G(y_L)]^{-1} \int_{y_L}^{y_{max}} T(x, y) dG(y)$, and mean exports 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.

B 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. The following proof allows the capability distribution to differ between Mexico and China.

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 $\Theta^I > \Theta^J$ □

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 $y_L^A > y_L^B$. □

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. □

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 $y_L^A > y_L^{NR}$. $\square$

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 $\Theta^A > \Theta^{NR}$. $\square$

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

B.1 Negative Assortative Matching

B.1.1 Solving the Model

In Case S, the market clearing condition becomes

$$M_U[1 - F(x)] = (M_M + M_C)\left[G\left(m_x\left(x\right)\right) - G(y_L)\right] \text{ for all } x \geq x_L. \tag{A6}$$

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 (A6) 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

$$\begin{aligned} A\theta\left(x_L, y_{max}\right) - f &= A\int_{m_x(x_{max})}^{y_{max}} \theta_2(m_y(t), t)dt \\ \frac{\delta}{\sigma\Theta(x_L)}\left[\theta\left(x_L, y_{max}\right) - \int_{m_x(x_{max})}^{y_{max}} \theta_2(m_y(t), t)dt\right] &= f. \end{aligned} \tag{A7}$$

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), (A6) and (A7).

B.1.2 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 (A7) 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

$$\begin{aligned}
\int_{y_L^B}^{y_{max}} \int_{m_y^A(t)}^{m_y^B(t)} \theta_{12}(z,t)dzdt &= \int_{y_L^B}^{y_{max}} \left[\theta_2(m_y^B(t),t) - \theta_2(m_y^A(t),t)\right] dt \\
&= \int_{y_L^B}^{y_{max}} \theta_2(m_y^B(t),t)dt - \int_{y_L^B}^{y_{max}} \theta_2(m_y^A(t),t)dt \\
&\geq \int_{y_L^B}^{y_{max}} \theta_2(m_y^B(t),t)dt - \int_{y_L^A}^{y_{max}} \theta_2(m_y^A(t),t)dt \\
&> 0. \qquad \text{(A8)}
\end{aligned}$$

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 $y \geq y_L^B$,

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

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

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

which contradicts with (A8). □

B.1.3 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 (A6), we obtain the partner change of importers with capability x:

$$dm_x(x) = \frac{\Gamma(x)}{g(m_x(x))}, \Gamma(x) \equiv g(y_L)dy_L - \frac{G(m_x(x)) - G(y_L)}{(M_M + M_C)} dM_C. \tag{A9}$$

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.

C Data Construction

C.1 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.

C.2 Assign Importer IDs

We used a series of methods developed in record-linkage research to assign importer-ID.[42]

[42] 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.

Format Standardization 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.) that account for only small shares. 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.[43] Third, we removed generic words in company names that did not help identify a particular company such as legal terms (e.g., Co., Ltd., etc.). Forth, we dropped EINs that did not follow the regular format.

Lists of Variations in Names, Addresses and EINs We prepared lists of possible variations in Names, Addresses and EINs from Orbis by Bureau van Dijk, which covers 20 millions company branches, subsidiaries, and headquarters in the US. From Orbis, we created 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. The primary provider of US company information in Orbis (2012 version) was Dun&Bradstreet. We used Orbis information for manufacturing firms and intermediary firms (wholesalers and retailers) due to the capacity of our workstation (16 cores and 256GB memory). These lists are used as "dictionaries" of possible variations to which the customs records are matched.

Matching by one variable Using these data, we conduct matching of the customs data and the lists from Orbis by each of linking variables (EINs, names, and addresses) and matching of the customs data and the same customs data within each HS 2-digit industry.

EIN matching is simple exact matching of EINs. In matching of names and addresses, we used fuzzy matching techniques allowing small typographical errors and abbreviations. Fuzzy matching is to conclude that the two names (or addresses) compared are "fuzzy matched" if they are close to

[43] Another way of standardizing addresses could be to use Google geocoding API, which could not be purchased in 2012 when this dataset was constructed.

each other in terms of some *edit distance*. The Levenshtein distance and the Jaro-Winkler distance are two commonly used distances in the natural language processing and functions calculating them are available in the Record Linkage package of R. Both distances basically measures the amount of corrections needed to convert the one word to the other word compared. From trials using a subsample, we find the Jaro-Winkler distance performs better. The Jaro-Winkler distance JW takes a value in $[0, 1]$ where $JW = 1$ if the two words perfectly match and $JW = 0$ if the two words are completely different (see, e.g. Herzog et. al., 2007, for details).

Two types of errors may occur in fuzzy matching: "false matching" (matching records that should not be matched) and "false unmatching" (not matching records that should be matched). The criteria for fuzzy matching is chosen to minimize false unmatching because while false matching is easier to identify by manual checks than false unmatching.

From trials and errors using subsamples, we set the following criteria. Two names are matched if one of the followings is satisfied: (1) the Jaro-Winkler distance metric JW is $JW \geq 0.9$; (2) they agree on the number of the first n letters ($n = 15$); (3) $JW \geq 0.85$, the length of the shorter name l satisfies $l \geq 7$, and the longer of the two names includes the shorter one.

To increase the accuracy of fuzzy matching, we additionally do the following. First, we made a list of words that frequently appearing in the company name in the textile/apparel industry (e.g., "apparel", "mill"). We remove those words from the two names compared if the word simultaneously appears in both names. Second, 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, while matching of zip codes uses exact matching. The criterion is $JW \geq 0.9$ both for street names and for city names.

Aggregation From these operations, we obtain matched pairs of names, addresses and EINs within each HS 2-digit industry. Then, using these matched relations, we created clusters of information (names, addresses, and EINs) in which one cluster identifies one firm. We identified a cluster utilizing the following 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 criterion is intentional and follows a conventional technique in record linkage research. It aims to minimize false unmatching at the cost of false matching. Since the probability that randomly chosen two entries match is very low, it is extremely difficult to manually find false unmatching. It is much easier to loosely match entries and to manually find false matching than the other way.

Then, we manually checked every cluster that includes multiple names unmatched. If unmatched names are reasonably similar or we find some relationship that connects unmatched names from search engines or the firms' websites, then we conclude they represent the same firm; otherwise, we separate the cluster into different groups. After this extensive manual checks, we assigned temporally importer-ID to each cluster.

These temporary importer-IDs are assigned at the HS 2 digit level. To construct importer-ID throughout the textile and apparel industries, we match clusters across HS 2 digit industries by the same fuzzy matching techniques above and aggregate them to create larger clusters. After manually checking every cluster, we assigned importer-IDs to each cluster.

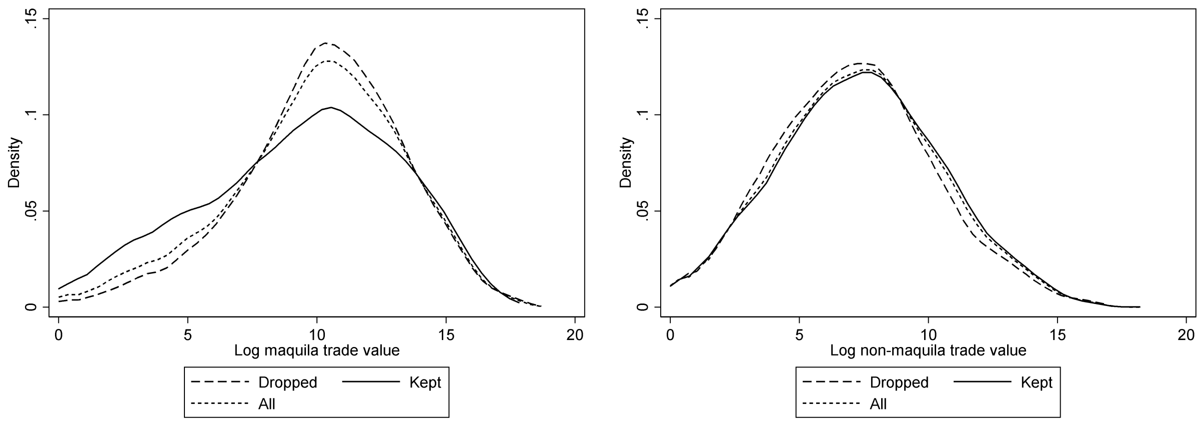
C.3 Data Cleaning

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.[44] Fourth, we removed products that have only one exporter or one importer. 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 normal exports remain in the final sample.

Figure A.1 examines sample selection due to the data cleaning. The left panel draws the distributions of log HS 6-digit product trade in 2004 by Maquiladora/IMMEX exporters, while the right panel does those by other normal exporters. Each panel presents estimated trade 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

[44] 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 A.1: Sample Selection



Note:

C.4 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 in 2004, separately for Maquiladora/IMMEX exporters and for other normal exporters.[45] 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 A.1 are very similar to those in Table 5. Thus, our results are not driven by sample selection due to the data cleaning.

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

Table A.1: 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.

C.5 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 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:

$$Binding_g = I\left\{\frac{\sum_{j\in J(g)} x^m_{j2004} I\{\text{quota on } j \text{ was binding in 2004}\}}{\sum_{j\in J(g)} x^m_{j2004}} \geq 0.5\right\}, \tag{A10}$$

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 of product g in 2004 .

Firm-Level and Firm-Product-Level Characteristics $OwnRank_{igs}$ is firm's normalized rank in terms of trade in product g that falls in $[0, 1]$. For exporter i, define $ExRank_{igs}$ as firm i's rank based on its trade of product g with the main partner in 2004 among exporters of product g in 2004 (small $ExRank_{igs}$ means large exports). 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 of product g over the firm's total trade of product g in 2004. $\ln TotalTrade_{gs}$ is the log of total trade 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 of product g with the main partner over firm i's total trade of product g in 2004. $\ln Trade_{igs}$ is the log of firm i's total trade of product g in 2004.

D 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 may not be monotonically increasing in capability. The import of US importers with capability x, $I(x)$, and export 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.

Mean Reversion in Repeated Independent Random Matching An alternative explanation for partner changes is "mean reversion in repeated random matching" where firms are forced to change partners randomly in every period and the time-series change in matching exhibits mean reversion. In this case, the exit of low capable Mexican exporters in liberalized industries may mechanically create a positive correlation between the binding measures and the downgrading by Mexican exporters in our regression. If this happens, it is a mechanical result of survival bias and cannot be interpreted as support for PAM.

If the hypothesis is true, Mexican exporters upgrade more frequently in non-liberalized industries where more low capable Mexican exporters survive than in liberalized industries. Therefore, we should observe a negative and significant estimate of β_U^{Mex} in (8). However, columns (5) and (6) in Table 5 show β_U^{Mex} is close zero, which rejects the hypothesis.

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 A.2 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 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 A.2 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 A.2: 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 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.

E Extensions to Many-to-Many Matching

E.1 Model 1: Multiple Final Goods and One Input

E.1.1 Model

Setting Final producers produce multiple final products, following Bernard, Redding and Schott (2011). There are N final products that use one common intermediate good. Though these final products may be different varieties of a product or different segments like women's/mens', for expositional purpose, we call them "products". The consumer's utility is given by

$$U=\sum_{i=1}^{N}\frac{\delta}{\rho}\ln\left[\int_{\omega\in\Omega_i}\theta(\omega)^{\alpha}q(\omega)^{\rho}d\omega\right]-\sum_{i=1}^{N}\int_{\omega\in\Omega_i}p(\omega)q(\omega)d\omega+I.$$

A final producer potentially produces one variety in each of N products. Let $x_i=\chi+\lambda_i$ be the *product capability* of a firm in producing product i where χ is the *firm capability* and λ_i is an *idiosyncratic capability* that follows an i.i.d. across products with $E\left(\lambda_i\right)=0$ and is independent of firm capability of final producers and suppliers. The marginal densities of χ and λ are given by $f(\chi)$ and $h(\lambda)$, respectively. Let λ_{min} and λ_{max} be the minimum and maximum values of λ.

A supplier may match multiple final producer. A supplier owns multiple production lines and each production line specializes for a particular final good variety. Let v be the firm capability of a supplier, which will be more specified below. A supplier with firm capability v owns $n(v)$ production lines and $n(v)$ is weakly increasing in v. The number of production lines determines the capacity of buyers. An interpretation of these capacities is span of control. A firm requires manager's resource for collaborating with each buyer.

A production line of a supplier with firm capability v has *line capability* $y=v+\varepsilon$ where ε is an *idiosyncratic capability* that follows an i.i.d. across product lines with $E\left(\varepsilon\right)=0$ and is independent of firm capability of final producers and suppliers. Let the marginal density of v and ε be $g(v)$ and $k(\varepsilon)$, respectively. The density $g(v)$ is common for Mexican suppliers and Chinese suppliers for simplicity. Let ε_{min} and ε_{max} be the minimum and maximum values of ε. In other respects, the production technology is the same as in the main model.

Equilibrium A match is now defined between a final product with capability x and a supplier production line with capability $y=m_x(x)$. The joint profit from a match is $\Pi\left(x,y\right)=A\theta\left(x,y\right)-f$ as in the main model, where f is fixed cost per product. Therefore, the stability conditions continue to be (2) and the sign of θ_{12} determines the sign of sorting.

Let $\tilde{M}_U \equiv M_U N$ be the total potential mass of final product varieties. Define $n \equiv \int_{-\infty}^{\infty} n(t)g(t)dt$. Then, $\tilde{M}_M \equiv M_M n$ and $\tilde{M}_C \equiv M_C n$ are the total production lines of Mexican suppliers and Chinese suppliers, respectively. The cdfs of product capability $x = \chi + \lambda$ is

$$\tilde{F}(x) = \int_{x_{min}}^{x} \int_{\lambda_{min}}^{\lambda_{max}} f(s-\lambda)h(\lambda)d\lambda ds.$$

The cdf of supplier's *line capability* $y = \upsilon + \varepsilon$ is

$$\tilde{G}(y) \equiv \int_{y_{min}}^{y} \int_{\varepsilon_{min}}^{\varepsilon_{max}} \frac{n(s-\varepsilon)g(s-\varepsilon)k(\varepsilon)}{n} d\varepsilon ds.$$

From the above notations, the matching market clearing condition under Case C is given by

$$\tilde{M}_U[1-\tilde{F}(x)] = \left(\tilde{M}_M + \tilde{M}_C\right)[1-\tilde{G}(m_x(x))]. \tag{A11}$$

The matching market clearing condition is isomorphic to the one in the main model. The conditions for Case I and Case S can be derived analogously with the capability distributions with tildes.

Production lines with capability below these cutoffs are shut down. The cutoff capability of final product lines x_L and that of supplier product lines y_L are determined to satisfy

$$\tilde{M}_U[1-\tilde{F}(x_L)] = \left(\tilde{M}_M + \tilde{M}_C\right)[1-\tilde{G}(y_L)]. \tag{A12}$$

A final producer with firm capability χ produce products with product capability $x \geq x_L$, that is, if $\lambda \geq \lambda_L \equiv \max\{\lambda_{min}, x_L - \chi\}$. A supplier with firm capability υ operates product lines with line capability $y \geq y_L$, that is, if $\varepsilon \geq y_L - \upsilon$. A firm exits the market if its entire production shuts down. Therefore, the cutoffs for firm capability are $\chi_L = x_L - \varepsilon_{max}$ for final producers and

$\upsilon_L = y_L - \varepsilon_{max}$ for suppliers.

E.1.2 Predictions

We show this extended model continues to predict predictions C1–C3 and I1–I3 regarding the main partners.

PAM for Mean Main Partner Capability In Case C, PAM holds for matching between a product and a production line. A final producers match with multiple suppliers with firm capability. To define main partners in the current setting of continuous agents, we consider a set of suppliers matching with the most capable products of a final producers. For some small $\delta > 0$, define an interval $\Lambda(\delta) \equiv [\lambda_{max} - \delta, \lambda_{max}] \subset \mathbb{R}$. Let $\chi + \Lambda(\delta) = [\chi + \lambda_{max} - \delta, \chi + \lambda_{max}]$ be the set of the most capable products of a final producer with capability χ. As a continuous analogue, we define the final producer's main partners as a set of suppliers matching with the most capable products. The mean capability of the final producer's main partner is:

$$
\begin{aligned}
E\left[v \middle| \chi, \lambda \in \Lambda(\delta)\right] &= E\left[y - \varepsilon \middle| \chi, \lambda \in \Lambda(\delta)\right] \\
&= E\left[y \middle| \chi, \lambda \in \Lambda(\delta)\right] \\
&= E\left[m_x\left(\chi + \lambda\right) \middle| \chi, \lambda \in \Lambda(\delta)\right] \\
&= \frac{1}{1 - H\left(\lambda_{max} - \delta\right)} \int_{\lambda_{max}-\delta}^{\lambda_{max}} m_x(\chi + \lambda) h(\lambda) d\lambda.
\end{aligned}
$$

Using the L'Hospital's rule, we take the limit of the mean main partner capability with $\delta \to 0$:

$$
\begin{aligned}
\lim_{\delta \to 0} E\left[v \middle| \chi, \lambda \in \Lambda(\delta)\right] &= \lim_{\delta \to 0} \frac{m_x(\chi + \lambda_{max} - \delta) h(\lambda_{max} - \delta)}{h(\lambda_{max} - \delta)} \\
&= m_x(\chi + \lambda_{max}).
\end{aligned}
$$

We consider this limit as the mean capability of the main partner. From similar steps for suppliers, we obtain the mean capability of the main partner of a supplier with firm capability v is $m_y(v + \varepsilon_{max})$. Since m_x and m_y are increasing functions, the mean capability of a firm's main partner is increasing in the firm's capability.

Lemma 7. *In Case C, PAM holds for the mean main partner capability in the following sense. Consider a final producer with firm capability χ and a supplier with firm capability v. The mean firm capability of the final producer's main partner is $m_x(\chi + \lambda_{max})$ and increasing in χ. The mean firm capability of the supplier's main partner is $m_y(v + \varepsilon_{max})$ and increasing in v.*

In Case I, firms are indifferent across partners. Therefore, matching is random and idenpendent of capability.

Effects of the MFA liberalization Since the matching market clearing condition (A11) and (A12) are isomorphic to those in the main model (6) and (4), the MFA liberalization causes the same results on matching functions and capability cutoffs.

Lemma 8. *Suppose the mass of Chinese firms increases. In Case C, the cutoff of supplier production line capability y_L and the cutoff of supplier firm capability $v_L = y_L - \varepsilon_{max}$ both rise; $m_x(x)$ increase for given x; and $m_y(y)$ decreases for given y. In Case I, the cutoff of supplier production line capability y_L and the cutoff of supplier firm capability $v_L = y_L - \varepsilon_{max}$ both rise.*

In Case C, a product of a US final producer upgrades its partner production line. A production line of a Mexican supplier downgrades its partner final product. In Case I, no product and no product line change their partners as long as the current partners have higher capability than the new cutoffs.

From Lemma 7, we obtain the same predictions C1–C3 about partner switching and the mean main partner capability in Case C.

C1 US continuing importers upgrade the mean capability of their main partners, while Mexican continuing exporters downgrade the mean capability of their main partners.

C2 PAM holds for the mean main partner capability before and after the end of the MFA.

C3 The firm capability cutoff for Mexican exporters rises.

For Case I, we continue to have the same predictions I1–I3 in Case I.

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

I2 The mean main partner capability of a firm is independent of the firm's capability before and after the end of the MFA.

I3 The firm capability cutoff for Mexican exporters rises.

Remark 1. All predictions C1-C3 and I1-I3 continue to hold if product-level matching is many-to-many.

Within Match Main Partner Switching A firm's main partner switching could happen within an initial match. For example, suppose that a Mexican exporter traded with two final producers. After the liberalization, the most capable final producer left the exporter and the second capable final producer became the main partner of the exporter. We call this change in the main partner within an initial match "within match" main partner switching. If the switch happens across different initial matches, we call it "across match" main partner switching.

In the model, firms are indifferent between within and across match partenr switching.

Remark 2. Main partner switching can occur either across match or within match. Predictions C1–C3 hold for main partner switching both across and within match. This justifies our approach in the main text that does not distinguish main partner switching both across and within match.

Number of Partners The model features many-to-many matching at the firm-level. The mean number of total production lines matching with a final producer with firm capability χ is

$$N^T(\chi) = N \int_{\max\{\lambda_{min}, x_L - \chi\}}^{\lambda_{max}} h(\lambda) d\lambda.$$

$N^T(\chi)$ is a weakly increasing function. The mean number of production lines in Mexico matching with the above final producer is

$$N^M(\chi) = \left(\frac{M_M}{M_M + M_C}\right) N^T(\chi) \tag{A13}$$

Since these $N^M(\chi)$ production lines are heterogeneous in capability, the probability that one supplier provides multiple production lines to the same final producer is negligible for the case of continuum of agents and small for the case of finite agents. Therefore, we interpret $N^M(\chi)$ as an approximation of the number of Mexican suppliers that match with a final producer with capability χ. Similarly, the mean number of final products matched with a supplier with firm capability υ is

$$N^S(\upsilon) = n(\upsilon) \int_{\max\{\varepsilon_{min}, y_L - \upsilon\}}^{\varepsilon_{max}} k(\varepsilon) d\varepsilon. \tag{A14}$$

Similarly to $N^M(\chi)$, we interpret $N^S(\upsilon)$ as an approximation of the number of US final producers matching with a Mexican supplier with capability υ.

Remark 3. The mean number of partners of Mexican exporters and that of US importers both weakly increase in firm capability.

Empirical Strategy Testing C1–C3 and I1–I3 The empirical strategy in the main text for testing C1–C3 and I1–I3 remains valid. Let $T(x, y)$ be the export by product line with capability y for a product with capability x where $T(x, y)$ are increasing in x and y.

(1) Case C. We first consider the case of PAM. The export by a supplier with firm capability υ to the mean main partner is

$$X(\upsilon) = T(m_y(\upsilon + \varepsilon_{max}), \upsilon + \varepsilon_{max}).$$

$X(\upsilon)$ is an increasing function in firm capability υ as in the main text. The import of a final producer with firm capability χ from the mean main partner is

$$I(\chi) = T\left(\chi + \lambda_{max}, m_x\left(\chi + \lambda_{max}\right)\right)$$

$I(\chi)$ is an increasing function in firm capability χ as in the main text.

(2) Case I. The mean export value by a supplier with firm capability υ to a random partner is

$$\bar{X}(\upsilon) = \int_{y_L - \upsilon}^{\infty} \int T(x, \upsilon + \varepsilon) \tilde{f}(x) k(\varepsilon) dx d\varepsilon,$$

where $\tilde{f}(x) = \tilde{F}'(x)$ is the density of product capability. $\bar{X}(\upsilon)$ is an increasing function in firm capability υ as in the main text. The mean import of a final producer with firm capability χ from a random partner is

$$\bar{I}(\chi) = \int_{x_L - \chi}^{\infty} \int T(\chi + \lambda, y) \tilde{g}(y) h(\varepsilon) dy d\lambda,$$

where $\tilde{g}(y) = \tilde{G}'(x)$ is the density of line capability. $\bar{I}(\chi)$ is an increasing function in firm capability χ as in the main text.

Therefore, we can use the pre-shock ranking of export and import values as proxies for the pre-shock capability ranking of suppliers and final producers, respectively.

Remark 4. The ranking of pre-shock trade corresponds to the ranking of capability on average. Therefore, the empirical strategy testing C1–C3 and I1–I3 in the main text continues to be valid when product-level matching include many-to-many matching.

In the above model, China can be interpreted as the rest of the world or a country that is not observed in our dataset.

Remark 5. The empirical strategy testing C1–C3 and I1–I3 in the main text is valid when US firms simultaneously match Mexican suppliers and suppliers in other countries.

E.1.3 Empirical Evidence for the Change in the Number of Partners

The model provides two testable predictions about the effect of the MFA liberalization on the number of partners *within a product market*. First, the number of total intermediate products exported from Mexico to the US decreases as y_L rises. Therefore, both US importers and Mexican exporters reduce the number of partners from (A13) and (A14). Second, since $N^M(v)$ weakly decreases for a given v, low capability Mexican suppliers decrease more partners than high capability ones.[46]

N1 US importers and Mexican exporters weakly decrease the number of partners.

N2 Low capability Mexican suppliers decrease more US partners than high capability Mexican suppliers.

To test the above predictions, we regress the changes in the number of partners during 2004–07 on the binding dummy for US importers and for Mexican exporters, respectively, in Column (1) and (3) in Table A.3. The negative and significant coefficients of the binding dummy in Columns (1) and (3) confirm prediction N1 that both US importers and Mexican exporters reduce the number of partners in liberalized industries. To test prediction N2, Column (2) includes an estimate of Mexican exporter's firm capability χ and its interaction with the binding dummy. Firm capability is estimated by the log of a Mexican firm's export in the product per buyer in 2004. The coefficient

[46]The relationship between a change in the number of US final producer's Mexican partners and the US final producer's capability is difficult to investigate in our data. This is because US importers may stop importing from Mexico either because it switches to a Chinese supplier as in N3 or because it stops importing the product at all. Our data do not distinguish the two reasons.

of the Binding dummy remains negative and the interaction term is positive, which are consistent with N2. As the standard deviation of the firm capability estimate is 3.35, most firms decrease the number of partners and the one standard deviation difference in capability leads to the difference in the change in the number of partners by 0.34.

Table A.3: Changes in the number of partners during 2004–07

	Change in Number of Partners		
	Mexico		US
	(1)	(2)	(3)
Binding	-0.68**	-1.63**	-0.12*
	(0.32)	(0.63)	(0.06)
Binding		0.10*	
× Firm Capability		(0.06)	
Firm Capability		-0.12***	
		(0.04)	
HS2 FE	Yes	Yes	Yes
Obs.	601	601	718

Note: Dependent variables are the change in the number of partners during 2004–07. $Binding_{gs}$ is a dummy variable indicating whether product g from China faced a binding US import quota in 2004.Firm capability is estimated by the log of a Mexican firm's export in the product per buyer 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.

E.2 Model 2: Multiple Inputs and Multi-Product Suppliers

E.2.1 Replication of Firm-Level Negative Degree Assortativity

Table A.4 replicates the regression of the negative degree assortativity in Bernard et al. (2018, Figure 1) under two different definitions of match. For each Mexican exporter i, let x_{it} be the number of US importers that the Mexican exporter i sells to in year t. These US buyers of the Mexican exporter i may also import from other Mexican exporters. Let y_{it} be the average number of Mexican exporters that the US buyers of Mexican exporter i import from in year t. Then, consider the following regression of log-demeaned y_{it} on log-demeaned x_{it}:

$$\ln\left(\frac{y_{it}}{\bar{y}_t}\right) = \beta \ln\left(\frac{x_{it}}{\bar{x}_t}\right) + u_{it}$$

where $\bar{y}_t$ and $\bar{x}_t$ are means of y_{it} and x_{it},,respectively. If the coefficient β is negative, then the negative degree assortativity holds. If a Mexican exporter trades with few buyers, its US buyers tends to trade with many Mexican exporters. If a Mexican exporter trades with many US buyers, its US buyers tends to trade with few Mexican exporters.

Table A.4 reports the coefficient of β for each year of 2004 and 2007. In columns (1) and (2), matches are defined at the firm level as in Bernard et al. (2018), while in the other columns (3) to (6), matches are defined at the firm-product level as in our main analysis. In columns (1) and (2), the slope of the coefficient is negative and statistically significant, though the coefficients are slightly smaller than -0.13 in Bernard et al. (2018), which seems reasonable because our dataset only includes textile/apparel products and one destination, the US. In 2007, a 10% increase in number of buyers is associated with 1.1% decline in average connections among buyers. Therefore, firm-level matching shows the negative degree assortativity. In columns (3) and (4), the coefficients become significantly smaller and close to zero. The negative degree assortativity disappeared for product-level matching. This is robust in columns (5) and (6) with product-fixed effects where the identification is from comparisons within products.

In sum, Table A.4 shows that the negative degree assortativity holds at firm-level but almost disappears at firm-product-level. This suggests the negative degree assortativity is a first order feature of exporter-importer matching *at the firm level*, but may not be *at the product level*, at least in our dataset. The negative degree assortativity seems better applied for firm's choice of partners across different products rather than within narrowly defined products. Based on this observation, we extend the main model by introducing multiple intermediate products below.

Table A.4: Negative Degree Assortativity under Different Match Definitions

	Log average number of sellers per buyer					
Definition of Match	Firm-Level		Firm-Product-Level			
	2004	2007	2004	2007	2004	2007
	(1)	(2)	(3)	(4)	(5)	(6)
Log buyers per exporter	-0.077***	-0.108***	-0.006	-0.020	-0.001	-0.016
	(0.027)	(0.026)	(0.046)	(0.042)	(0.019)	(0.016)
Product Fixed effects	–	–	No	No	Yes	Yes
Obs.	1402	1094	4131	3112	4131	3112

Note: The table reports coefficients of the regressions of the log mean number of sellers by the importer related to a giving exporter on the log of the number of the buyers per exporter. Matches are defined at the firm level in columns (1) and (2) and at the firm-product level in columns (3) to (6). Standard errors are clustered at the product level. Significance: * 10 percent, ** 5 percent, *** 1 percent.

E.2.2 Reconciliation of product-level PAM and firm-level negative degree assortativity

A final producer produces one variety of one final product as in the main model. The consumer utility function is the same as before:

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

where $\theta^d(\omega)$ is team's capability index for demand. The production of a final good uses K different intermediate goods and labor with a CES production function:

$$q = x\left(\sum_{k=1}^{K}\left(y_k^\beta d_k\right)^{\frac{\eta-1}{\eta}}\right)^{a\eta/(\eta-1)}(l - n_m f_x - f)^{1-a}, \tag{A15}$$

where $\eta > 1$ is the elasticity of substitution, q is output, x is the capability of a final producer, y_k is the product capability of the intermediate good k, d_k is the input of the intermediate good k, l is the input of labor, K and n_m are the number of intermediate goods and matches, respectively, both of which are endogenously chosen, f_x is match-specific fixed costs, and f is fixed costs for production. The wage is normalized to one. To save f_x, a final producer matches with at most one supplier for each intermediate good.

A supplier may produce multiple intermediate goods from $k = 1, ..., K$. For a supplier with capability y_k, the cost function of producing q unit of intermediate k is $c_y (y_k)^{\gamma} q + f_y$ where f_y is per-match fixed costs. Let $M_S^k \equiv M_M^k + M_C^k$ be the total mass of suppliers of intermediate k. Without loss of generality, the index of intermediate goods is ordered so that

$$M_S^1 > M_S^2 > ... > M_S^K. \tag{A16}$$

The cdfs of Mexican supplier's capability and Chinese supplier's capability are the same and given by $y_k \sim G(y)$ with strictly positive support $Y \subset R_{++}$ so that 0 can be used to denote "not matching" as we will explain below.

A team is expressed by a $K + 1$ dimensional "team capability" vector $z \equiv (x, y_1, ..., y_K)$ where $y_k = 0$ if a team includes no supplier for intermediate goods k. Team's cost function is $\frac{c}{\theta^c(z)} q + n_m f_m + f$, where $f_m \equiv f_x + f_y$ is the total fixed costs per match and $\theta^c(z) \equiv x \left(\sum_{k=1}^{K} y_k^{(\beta-\gamma)(\eta-1)} \right)^{a/(\eta-1)}$ is the team capability index for costs. Team's joint profit becomes

$$\Pi(z) = A\theta(z) - n_m f_m - f$$

where $\theta(z) \equiv \theta^d(z)^{\alpha\sigma} \theta^c(z)^{\sigma-1}$ is the team capability. We consider Case C where θ is increasing and its all cross-derivatives are positivity, which implies that θ is strict supermodular.[47]

Assumption 2. *θ is symmetric with respect to $(y_1, ..., y_K)$, twice continuously differentiable and strict supermodular, which implies (1) for any permutation σ of $(y_1, ..., y_K)$, $\theta(x, y_1, ..., y_K) = \theta(x, \sigma(y_1), ..., \sigma(y_K))$; (2)$\partial\theta(z)/\partial x > 0, \partial\theta(z)/\partial y_k > 0$, $\partial^2\theta(z)/\partial x \partial y_k > 0$ and $\partial^2\theta(z)/\partial y_j \partial y_k >$*

[47] A sufficient condition for Assumption 2 is that θ^d is supermodular and $\alpha \geq 1$ and that σ is sufficiently larger than η.

0 *for all* $j, k = 1, ..., K$.

Consider a stable matching in a frictionless matching market. Let $\pi_x(x)$ and $\pi_k(y_k)$ be the profit schedules of final producers and those of intermediate k suppliers, respectively. A final producer with capability x matches with an intermediate k supplier having capability $m_k(x)$. If a final producer with x may not match with an intermediate k' producer, let the matching function be $m_k(x) = 0$.

A stable matching satisfies the following two conditions: (i) *individual rationality*: $\pi_x(x) \geq 0$ and $\pi_k(y) \geq 0$ for all x, y, and k; (ii) *pair-wise stability*:

$$\begin{aligned}\pi_x(x) &= A\theta\left(x, m_1(x), ..., m_K(x)\right) - \sum_{i=1}^{K} I\{m_i(x) \neq 0\}\left(\pi_i(m_i(x)) - f_m\right) - f \\ &= \max_{y' \in (Y \cup \{0\})^K} A\theta\left(x, y'\right) - \sum_{i=1}^{K} I\{y'_i \neq 0\}\left(\pi_i(y'_i) - f_m\right) - f\end{aligned}$$

and

$$\begin{aligned}\pi_k(m_k(x)) &= A\theta\left(x, m_1(x), ..., m_K(x)\right) - \sum_{i=1, i\neq k}^{K} I\{m_i(x) \neq 0\}\left(\pi_i(m_i(x)) - f_m\right) - f \\ &= \max_{\left(x', y'_{-k}\right) \in X \times (Y \cup \{0\})^{K-1}} A\theta\left(x, y_k, y'_{-k}\right) - \sum_{i=1, i\neq k}^{K} I\{y'_i \neq 0\}\left(\pi_i(y'_i) - f_m\right) - f\end{aligned}$$

where $\pi_i(0) = 0$, and $I\{y'_i \neq 0\}$ indicates whether the team includes intermediate i supplier or not. As in the case of one-to-one matching, stable matching is PAM. The proof is given at the end of this section.

Lemma 9. *Stable matching is PAM.*

The matching market clearing condition for an intermediate good k is expressed as:

$$M_U[1 - F(x)] = M_S^k\left[1 - G(m_k(x))\right]. \tag{A17}$$

From (A16) and (A17), the order of product capability across intermediates within a team is

$$m_1(x) > m_2(x) > ... > m_K(x). \tag{A18}$$

Final producers with low x may prefer to match with fewer than K partners to save fixed costs of matching. From (A18), a final producer drops suppliers from low capability ones: first, Kth intermediate, second, $K-1$th intermediate, and so forth. Let x_{kL} be the threshold capability of final producers such that a final producer matches with a supplier of intermediate k if and only if $x \geq x_{kL}$. The threshold x_{KL} is determined by

$$\begin{aligned} &A\theta\left(x_{KL}, m_1(x_{KL}), ..., m_{K-1}(x_{KL}), m_K(x_{KL})\right) \\ &\qquad -A\theta\left(x_{KL}, m_1(x_{KL}), ..., m_{K-1}(x_{KL}), 0\right) = f_m. \end{aligned}$$

In general, thresholds x_{kL} is determined by

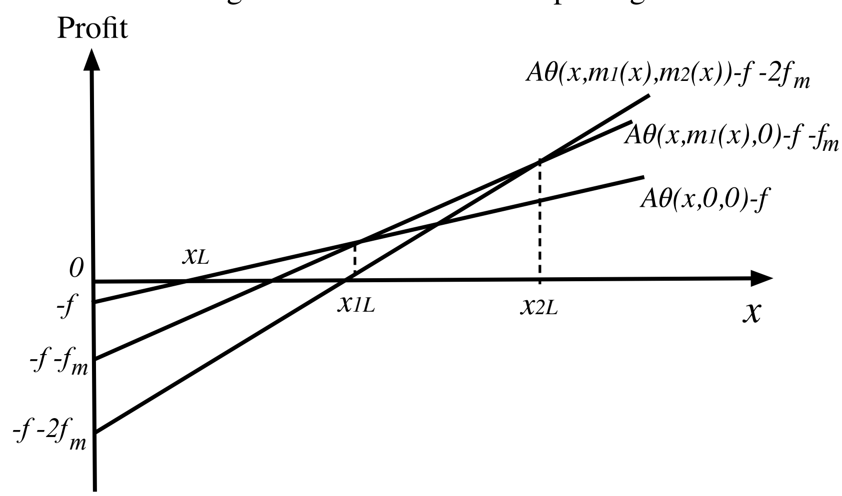
$$\begin{aligned} &A\theta\left(x_{kL}, m_1(x_{kL}), ..., m_{k-1}(x_{kL}), m_k(x_{kL}), 0, .., 0\right) \\ &\qquad -A\theta\left(x_{kL}, m_1(x_{kL}), ..., m_{k-1}(x_{kL}), 0, 0, .., 0\right) = f_m. \end{aligned} \tag{A19}$$

The threshold x_L for final good production is given by

$$A\theta\left(x_L, 0, .., 0\right) = f.$$

Figure A.2 draws the above selection mechanism for the case of $K = 2$. Each line represents team profit as a function of final producer's capability. The steepest line represents the profit of teams importing two intermediates; the second steepest line does that of teams importing one intermediate; the flattest line does that of teams importing no intermediate. The cutoff capabilities are determined by a similar mechanism in standard heterogeneous firm trade models. The number of imported goods and that of foreign suppliers are increasing in the capability of a final producer.

Figure A.2: Selection of Importing



Note: each line represents team profit as a functions of final producers capability. The steepest one represents teams importing two intermediates; the second steepest one does teams importing one intermediate; the flattest one does teams importing no intermediate.

Denote the cutoff capability of intermediate k by $y_{kL} = m_k(x_{kL})$ such that intermediates k with $y_k < y_{kL}$ are not exported. To see the order of y_{kL}, first note that the cutoff conditions (A19) for x_{kL} and x_{k-1L} can be rewritten as:

$$A\int_0^{y_{kL}} \frac{\partial\theta\left(x_{kL}, m_1(x_{kL}), ..., m_k(x_{kL}), t, 0, .., 0\right)}{\partial y_k} dt = f_m$$
$$A\int_0^{y_{k-1L}} \frac{\partial\theta\left(x_{k-1L}, m_1(x_{k-1L}), ..., m_{k-1}(x_{k-1L}), t, 0, .., 0\right)}{\partial y_k} dt = f_m. \tag{A20}$$

Second, Assumption 2 and PAM imply

$$\frac{\partial\theta\left(x_{k-1L}, m_1(x_{k-1L}), ..., m_{k-2}(x_{k-1L}), t, 0, .., 0\right)}{\partial y_{k-1}}$$
$$< \frac{\partial\theta\left(x_{kL}, m_1(x_{kL}), ..., m_{k-2}(x_{kL}), m_{k-1}(x_{kL}), t, 0, .., 0\right)}{\partial y_k}.$$

Therefore, from (A20), $y_{kL} < y_{k-1L}$. The cutoff capabilities of final producers and suppliers are summarized as follows.

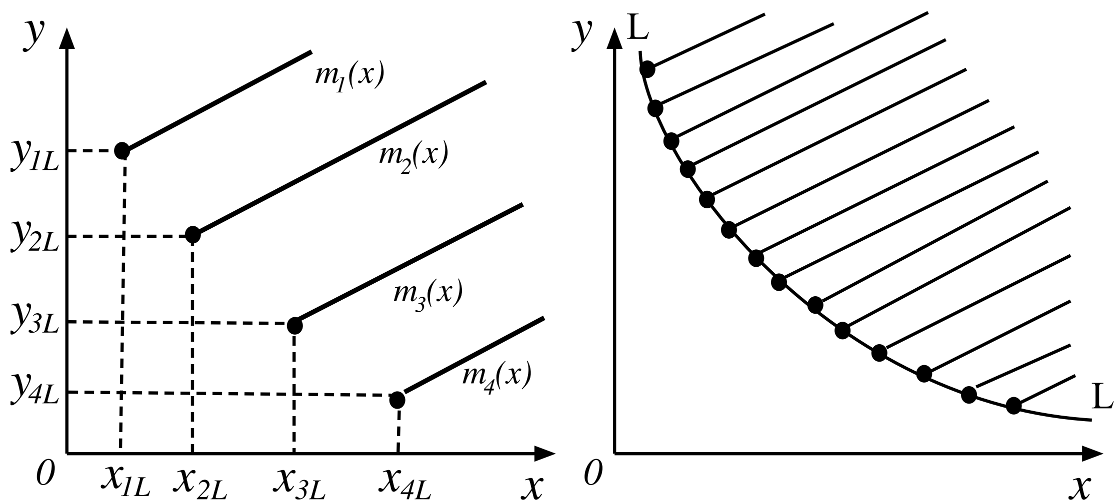
Lemma 10. *x_{kL} is increasing in k and y_{kL} is decreasing in k.*

Lemma 10 implies the negative degree assortativity of firm-level matching. The left panel in Figure A.3 describes matching functions $m_k(x)$ and the cutoff capabilities x_{kL} and y_{kL} for the case of $K = 4$. Matching functions $m_k(x)$ are upward sloping (not necessarily straight lines) and do not cross with each other from (A18). The number of a firm's partners is increasing in the firm's own capability. Matches between low capability firms are not possible because they cannot afford fixed costs. A low capability final producer with $x \in [x_{1L}, x_{2L})$ matches with only one supplier with higher capability than y_{1L} who matches with four final producers. On the other hand, a low capability supplier with $y \in [y_{4L}, y_{3L})$ matches with only one final producer with higher capability than x_{4L} who matches with four suppliers. Therefore, a small firm matching with few partner matches with a large firm matching with many partners.

The above mechanism of the negative degree assortativity is essentially the same as the one in Bernard et al. (2018). The number of partners is determined by the interaction of match specific fixed costs and capability. The right Panel in Figure A.3 shows the case when K is large. The combination of x_{kL} and y_{kL} converges to a downward sloping LL curve, which is the lower bound of capabilities in profitable matches. As K approaches to infinity, matching functions effectively cover the upper right area of the LL curve since matching functions do not cross with each other from (A18). With a dataset of finite data points, matches are scattered over the upper right area of the LL curve.

Figure A.3: Firm-level Negative Degree Assortativity

Case of $K = 4$ (Left) and Case of large K (Right)



Note: the left panel shows matching functions $m_k(x)$ and the cutoff capabilities x_{kL} and y_{kL} for intermediate k the case of $K = 4$. The right panel shows the case of many intermediate goods. Each dot represents a combination of x_{kL} and y_{kL} , while each line represents matching function $m_k(x)$.

Testable Prediction The above reconciliation of PAM and negative degree assortativity has a testable prediction. Define matching at firm-level and matching at firm-product level as follows.

Definition 3. When a match is defined at the firm level, a firm's partners are firms with which the firm trades in some textile/apparel product. When a match is defined at the firm-product level, a firm's partners are firms with which the firm trades in the particular textile/apparel product.

In Figure A.3, firm-level matching shows the negative degree assortativity, while firm-product level matching shows PAM. This model has the following proposition.

Proposition 1. *The negative degree assortativity holds at the firm level, while PAM holds at the firm product level.*

The results in Table A.4 supports Proposition 1 as we explained above.

Proof for Lemma 9 For $x, y \in R^{K+1}$, define $x \wedge y = (\min(x_1, y_1), ..., \min(x_{K+1}, y_{K+1}))$ and $x \vee y = (\max(x_1, y_1), ..., \max(x_{K+1}, y_{K+1}))$. From Topkis (1978, Theorem 3.2), the strict supermodularity of θ implies that for any two team capability vectors z and z', if $z \neq z'$, $z \neq z \vee z'$ and $z' \neq z \vee z'$, then

$$\theta\left(z \vee z'\right) + \theta(z \wedge z') > \theta(z) + \theta(z'). \tag{A21}$$

Suppose a stable matching is not PAM. Then, there exist two teams with capability vectors $z \equiv (x, .y_1, ..., y_K)$ and $z' \equiv (x', y_1', ..., y_K')$ such that $z \neq z'$, $z' \neq z \vee z'$ and $z \neq z \vee z'$. Without loss of generality, suppose $x > x'$, z has n intermediates, and z' has n' intermediates. The stability condition implies that team's joint profit is fully distributed to the team members:

$$A\theta\left(z\right) - nf_m - f = \pi_x(x) + \sum_{i=1}^{K} \pi_i(y_i)$$
$$A\theta\left(z'\right) - n'f_m - f = \pi_x(x') + \sum_{i=1}^{K} \pi_i(y_i').$$

From (A21),

$$\begin{aligned} A\theta\left(z \vee z'\right) + A\theta\left(z \wedge z'\right) - \left(n + n'\right) f_m - 2f &> A\theta\left(z\right) + A\theta\left(z'\right) - \left(n + n'\right) f_m - 2f \\ &= \pi_x(x) + \sum_{i=1}^{K} \pi_i(y_i) + \pi_x(x') + \sum_{i=1}^{K} \pi_i(y_i') \\ &= \pi_x(x) + \pi_x(x') + \sum_{i=1}^{K} \pi_i(y_i \vee y_i') + \sum_{i=1}^{K} \pi_i(y \wedge y_i'). \end{aligned} \tag{A22}$$

Since z' is a stable match, the profit of final producer with x' must be maximized with the current partners, which implies

$$\pi_x(x) \geq A\theta\,(z \vee z') - n' f_m - f - \sum_{i=1}^{K} \pi_i(y_i \vee y_i').$$
$$\Rightarrow \pi_x(x) + \sum_{i=1}^{K} \pi_i(y_i \vee y_i') \geq A\theta\,(z \vee z') - n' f_m - f \tag{A23}$$

(A22) and (A23) imply

$$\begin{aligned} A\theta\,(z \wedge z') - n f_m - f > & \ \pi_x(x) + \pi_x(x') + \sum_{i=1}^{K} \pi_i(y_i \vee y_i') + \sum_{i=1}^{K} \pi_i(y \wedge y_i') \\ & - [A\theta\,(z \vee z') - n' f_m - f] \\ \geq & \ \pi_x(x') + \sum_{i=1}^{K} \pi_i(y_i \wedge y_i'). \end{aligned}$$

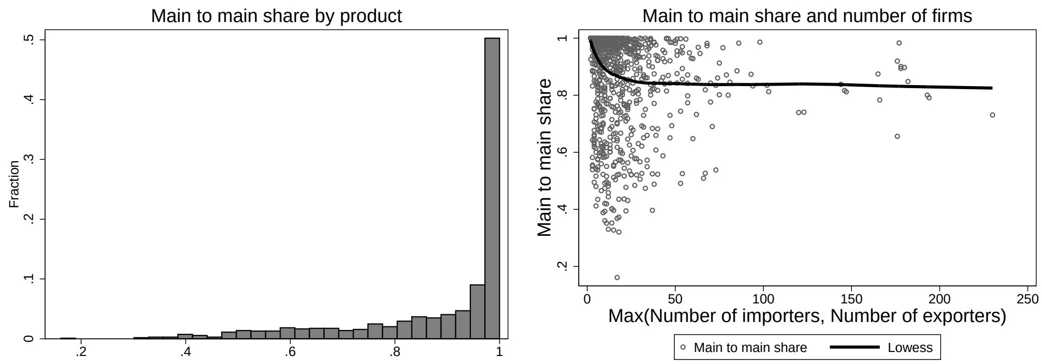
That is, forming a team with capability vector $z \wedge z' = (x', y \wedge y')$ is a profitable deviation, which contradicts with stable matching. QED.

F Additional Figures and Tables

F.1 Main-to-Main Share at Product Level

Two panels in Figure A.4 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 A.4 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 A.4 remains very similar when the horizontal axis expresses either n_m or n_x.

Figure A.4: 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.

F.2 Table 1 for Alternative Samples

Table 1 for 2005 and 2006 Table A.5 reports statistics in Table 1 for 2005 and 2006. They show very similar patterns as Table 1.

Table A.5: Summary Statics

	HS 6 Product-Level match		Firm-Level match	
mean statistics (median)	2005	2006	2005	2006
(1) N of Exporters	14.1(7)	11.7 (6)	1,275	1,136
(2) N of Importers	18.7 (10)	15.5 (9)	1,874	1,702
(3) N of Exporters Selling to an Importer	1.1 (1)	1.1 (1)	1.4 (1)	1.3 (1)
(4) N of Importers Buying from an Exporter	1.5 (1)	1.5 (1)	2.0 (1)	1.9 (1)
(5) Value Share of Main Exporter (Number of Exporters > 1)	0.77	0.76	0.76	0.77
(6) Value Share of Main Importer (Number of Importers > 1)	0.75	0.77	0.75	0.76

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

Table 1 for Regression Sample Table A.6 and Table A.7 report statistics in Table 1 for the regression sample. They show very similar patterns as Table 1.

Table A.6: Summary Statics for Product-Level Matching: Regression Samples

Product-Level Matching	2004	2005	2006	2007
(1) Number of Exporters*	20.6	18.9	19.0	17.6
(2) Number of Importers‡	20.5	18.3	17.9	18.0
(3) Number of Exporters Selling to an Importer*	1.4 (1)	1.4 (1)	1.3 (1)	1.2 (1)
(4) Number of Importers Buying from an Exporter‡	2.2 (1)	2.3 (1)	2.2 (1)	1.9 (1)
(5) Value Share of the Main Exporter* (Number of Exporters > 1)	0.75	0.75	0.75	0.78
(6) Value Share of the Main Importer‡ (Number of Importers > 1)	0.73	0.76	0.78	0.79

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

Table A.7: Summary Statics for Firm-Level Matching: Regression Samples

Firm-Level Matching	2004	2005	2006	2007
(1) Number of Exporters*	475	462	394	397
(2) Number of Importers‡	804	744	666	636
(3) Number of Exporters Selling to an Importer*	2.0 (1)	2.0 (1)	1.8(1)	1.7 (1)
(4) Number of Importers Buying from an Exporter‡	3.2 (1)	3.2 (1)	2.9 (1)	2.6 (1)
(5) Value Share of the Main Exporter* (Number of Exporters > 1)	0.73	0.74	0.76	0.78
(6) Value Share of the Main Importer‡ (Number of Importers > 1)	0.71	0.74	0.75	0.77

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

Shares of trade by one-to-one match, one-to-many match and many-to-many match

Table A.8 shows the shares of trade by one-to-one matches, one-to-many matches and many-to-many matches out of the total trade as well as the main to main share. In a "one-to-one" match, the exporter and the importer are the only partner of each other in the year in the dataset. In a "one Mexico-to-Many US" match, the exporter trade only with the importer while the importer trade with other Mexican exporters. In a "many-to-many" match, both the exporter and the importer trade with more than one partners.

Both one-to-one matches and the concentration of trade in main-to-main matches in "non one-to-one" matches account for these high shares. The share of trade by one-to-one matches out of the total trade is around 33% for product-level matching. The difference between 33% and the 80% main-to-main share is due to the concentration of trade in main-to-main matches among firms trading with multiple partners.

Table A.8: Shares of trade by one-to-one match, one-to-many match and many-to-many match out of the total trade

		HS 6 Product-Level Match				Firm-Level Match			
	Share	2004	2005	2006	2007	2004	2005	2006	2007
(1)	One-to-one	0.33	0.34	0.30	0.33	0.11	0.15	0.12	0.10
(2)	One Mexico-to-Many US	0.27	0.32	0.33	0.30	0.22	0.25	0.28	0.26
(3)	Many Mexico-to-one US	0.22	0.21	0.21	0.20	0.41	0.42	0.36	0.36
(4)	Many-to-Many	0.18	0.13	0.17	0.18	0.26	0.18	0.24	0.28
(5)	Main-to-Main	0.79	0.81	0.81	0.85	0.71	0.75	0.74	0.78

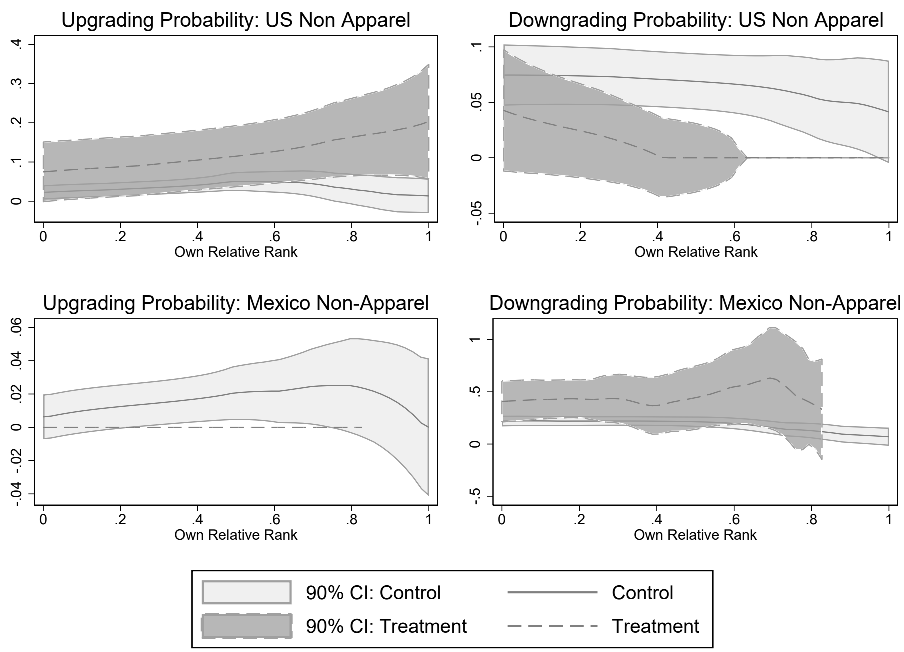
Note: Each row the shares of trade by one-to-one matches, one-to-many matches and many-to-many matches out of the total trade as well as the main to main share. In a "one-to-one" match, the exporter and the importer are the only partner of each other in the year in the dataset. In a "one Mexico-to-Many US" match, the exporter trade only with the importer while the importer trade with other Mexican exporters. In a "many-to-many" match, both the exporter and the importer trade with more than one partners. In a "main-to-main" match, both the exporter and the importer trade are the main partner of each other.

F.3 Partner Switching Regressions

F.3.1 Figure5 for Non-Apparel Products

Figure A.5 shows the same figures in Figure 5 for non-apparel products. In US upgrading (up-left) and Mexican downgrading (down-right), the regression lines of the treatment group lies above those of the control group. In US downgrading (up-right) and Mexican upgrading (up-left), the regression lines of the two groups are close (notice the scale). These results are consistent with the main regressions in Table 5 and the predictions of PAM.

Figure A.5: Partner Change during 2004–2007 and Initial Capability Ranks: Non-Apparel Products



Note: Dark gray lines and areas represent kernel weighted local mean regression lines with 90% confidence bands for the treatment group, while light gray lines and area for the control group.

F.3.2 Additional Controls of Product and Firm Characteristics

Summary Statistics and Treatment Control Group Comparison of Product and Firm Characteristics Table A.9 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 then the control group. In the regressions below, we include LnTotalTrade and all product type dummies since #Exporters, #Importers and LnTotalTrade are highly correlated.

Table A.10 reports similar summary statistics for importer-product level characteristics. Even with HS 2-digit fixed effects, the treatment group shows more trade and a higher share of processing trade (Maquiladora/IMMEX).

Table A.11 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 A.9: 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 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 A.10: 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 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 A.11: 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 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.

Partner Change Regressions with Additional Controls Tables A.12 and A.13 include, as additional control variables, those characteristics that are statistically different between the two groups within HS 2-digit product categories. Each column includes each set of control variables one by one, while Column (9) include all control variables. Estimates of β_U^{US} and β_D^{Mex} remain mostly statistically significant and similar in magnitude. In Column (9) of Table A.12, β_U^{US} is 73% of the benchmark estimate with p-value 0.12. If we use the probit model, the coefficient remains 5%

significant even if we include all control variables.

Table A.12: Partner Change during 2004–07 with Additional Controls: US Upgrading

	Up^{US} : Linear Probability Models								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Binding	0.052**	0.053**	0.051**	0.052**	0.043**	0.044*	0.049**	0.042*	0.038
	(0.022)	(0.022)	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)	(0.024)	(0.024)
Firm-Product Level Controls									
LnTrade	0.000								0.002
	(0.003)								(0.002)
Maquiladora		-0.015							-0.022
		(0.017)							(0.014)
#Partners			0.007***						0.002
			(0.002)						(0.002)
US Intermediary				0.012					0.021
				(0.013)					(0.013)
HS 6-digit Product Level Controls									
#Exporters					0.001***				0.001***
					(0.000)				(0.000)
#Importers						0.0003**			-0.000
						(0.0001)			(0.000)
LnTotalTrade							0.002		0.001
							(0.004)		(0.000)
Women								-0.040**	-0.026*
								(0.018)	(0.015)
Men								0.005	0.023
								(0.022)	(0.020)
Cotton								0.020	-0.003
								(0.020)	(0.015)
Wool								-0.045**	-0.040**
								(0.020)	(0.020)
Man-Made								0.014	-0.001
								(0.019)	(0.017)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	718	718	718	718	718	718	718	718	718

Note: Dependent variable Up^{US}_{igs} is a dummy variable indicating whether during 2004-07 US importer i switched its main Mexican partner of HS 6-digit product g to one with a higher capability rank. $Binding_{gs}$ is a dummy variable indicating whether product g from China faced a binding US import quota in 2004. $LnTrade_{ig}$ is the log of firm i's trade 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. $Intermediary\,Info\,Missing_{ig}$ is a dummy variable indicating the information of $US\,Intermediary_{ig}$ is not available (% of US importers and % of Mexican exporters). $\#Exporters_g$ and $\#Importers_g$ are numbers of exporters and importers of product g in 2004, respectively. $LnTotalTrade_g$ is the log of trade for product g in 2004.$LnTotalTrade_g$ is the log of trade for product g in 2004. Women, Men, Cotton, Wool, and Man-Made are product type dummies (Silk is the omitted type). 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 A.13: Partner Change during 2004–07 with Additional Controls: Mexico Downgrading

	$Down^{Mex}$: Linear Probability Models								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Binding	0.115***	0.127***	0.103***	0.128***	0.122***	0.125***	0.123***	0.130***	0.118***
	(0.035)	(0.035)	(0.037)	(0.034)	(0.035)	(0.037)	(0.038)	(0.037)	(0.039)
Firm-Product Level Controls									
LnTrade	0.008								0.008*
	(0.005)								(0.004)
Maquiladora		-0.025							-0.054**
		(0.024)							(0.026)
#Partners			0.036***						0.037***
			(0.009)						(0.010)
US Intermediary				0.046					0.034
				(0.031)					(0.032)
HS 6-digit Product Level Controls									
#Exporters					0.000				0.001***
					(0.000)				(0.000)
#Importers						0.000			-0.001*
						(0.000)			(0.000)
LnTotalTrade							0.002		-0.006
							(0.007)		(0.009)
Women								0.041	0.040
								(0.037)	(0.040)
Men								0.090*	0.072
								(0.049)	(0.053)
Cotton								-0.042	-0.037
								(0.039)	(0.037)
Wool								-0.010	-0.027
								(0.051)	(0.053)
Man-Made								-0.079**	-0.090**
								(0.039)	(0.039)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	718	718	718	718	718	718	718	718	718

Note: Dependent variable $Down^{Mex}_{igs}$ is a dummy variable indicating whether during 2004-07 Mexican exporter i switched its US main partner of HS 6-digit product g to one with a lower capability rank. $Binding_{gs}$ is a dummy variable indicating whether product g from China faced a binding US import quota in 2004. $LnTrade_{ig}$ is the log of firm i's trade 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. $Intermediary\,Info\,Missing_{ig}$ is a dummy variable indicating the information of $US\,Intermediary_{ig}$ is not available (% of US importers and % of Mexican exporters). $\#Exporters_g$ and $\#Importers_g$ are numbers of exporters and importers of product g in 2004, respectively. $LnTotalTrade_g$ is the log of trade for product g in 2004.$LnTotalTrade_g$ is the log of trade for product g in 2004. Women, Men, Cotton, Wool, and Manmade are product type dummies (Silk is the omitted type). 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.

F.3.3 Multi-product firms

In data, some firms exports multiple products. Multi-product exporters may decide partners differently from single product exporters. To address this concern, Table A.14 includes the number of products a firm trade in 2004 and its interaction with the Binding dummy. The main results are robust.

Table A.14: Partner Change Regression Controlling for Multi-Product Firms

	Liner Probability Models							
	Up^{US}		$Down^{US}$		Up^{Mex}		$Down^{Mex}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Binding	0.051**	0.056**	-0.019	0.000	-0.004	-0.002	0.128***	0.199***
	(0.021)	(0.025)	(0.026)	(0.033)	(0.020)	(0.025)	(0.035)	(0.045)
N of products	-0.001**	-0.001	-0.002	-0.001	-0.001**	-0.001*	0.001	0.005**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.002)
Binding*		-0.001		-0.002		-0.000		-0.007**
N of products		(0.001)		(0.002)		(0.001)		(0.003)
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 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. ; N of products for a US importer is the number of HS 6-digit textile/apparel products that the firm imports from Mexico in 2004, while N of products for a Mexican exporter is the number of HS 6-digit textile/apparel products that the firm exports to the US 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.

F.3.4 Main Partner Changes Across and Within Match

In data, some firms may trade with multiple firms other than main partners. Main partner switching may be "within match", where the firm and the new main partner in 2007 were in an initial match in 2004, as well as "across match", where the firm and the new main partner in 2007 were not in an initial match in 2004. It may appear that "within match" main partner switching contradicts with our theory, but it does not. A model extended to many-to-many matching in Appendix E1 allows main partner switching (US importer's main partner upgrading and Mexican main exporter's partner downgrading) to be either within or across match. This prediction justifies our approach in the main text where we do not distinguish across- and within match main partner switching.

Table A.15 also shows partner switching regressions that distinguishes across- and within match main partner switching where e.g., the indicator of across match main partner upgrading is one if and only if partner upgrading occurs across an initial match. The table confirms prediction C1 of US importer's upgrading and Mexican exporter's downgrading even when within match main partner switching are removed.

Table A.15: Main Partner Changes Across and Within Match

	Liner Probability Models							
	Up^{US}		$Down^{US}$		Up^{Mex}		$Down^{Mex}$	
	Across	Within	Across	Within	Across	Within	Across	Within
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Binding	0.040**	0.012	-0.000	-0.017	-0.011	0.009	0.046**	0.080**
	(0.019)	(0.009)	(0.018)	(0.021)	(0.017)	(0.006)	(0.019)	(0.033)
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 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.

F.3.5 Different Time Windows

Table A.16 reports estimates of β_U^{US} and β_D^{Mex} after changing the end year to 2006, 2007 and 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.

Table A.16: 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

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.

F.4 Further decomposition of the extensive margin

Table A.17: Decomposition of Extensive Margin

	Extensive Margin	Leaving	Product Dropping
	(1)	(2)	(3)
Quota-bound	-887.4	-718.5	-168.9
% of (1)	100%	81%	19%
Quota-free	-179.6	-122.1	-57.5
% of (1)	100%	68%	32%

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 the extensive margin in (1) are decomposed to exporter's leaving in (2) by exporters that left the US market for all textile/apparel products and to product dropping in (3) by exporters that remain to export some textile/apparel product.

F.5 Alternative Capability Ranking

Then, we estimate partner change regression (8) and new and old partner ranks regression (9) using these two rankings. The baseline exit regression (11) already uses firm's total product trade as capability. Since price data before 2004 are very noisy, we do not estimate the exit regression using price data.

Table A.18 reports partner change regressions in Panel A and regressions of new and old partner ranks in Panel B. Columns labeled "Total" and "Price" report estimates using total trade rankings and price rankings, respectively. The main results are robust to alternative rankings. The results from price rankings also imply that exporter's capability mainly reflects its quality. This is consistent with previous findings from export data that quality is an important determinant of firm's export participation. Quality also determines a firm's export partner.[48]

Table A.18: Alternative Capability Rankings

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

	Up^{US}		$Down^{US}$		Up^{Mex}		$Down^{Mex}$	
	Total	Price	Total	Price	Total	Price	Total	Price
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Binding	0.052**	0.047**	-0.017	0.006	0.001	0.037	0.123***	0.069**
	(0.021)	(0.018)	(0.027)	(0.023)	(0.019)	(0.031)	(0.035)	(0.028)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	718	672	718	672	601	559	601	559

B: Old and New Partners 2004–07: OLS

	New Partner Rank			
	US Importers		Mexican Exporters	
	Total	Price	Total	Price
	(9)	(10)	(11)	(182)
Old Partner	0.44***	0.17*	0.68***	0.47***
Rank	(0.13)	(0.10)	(0.13)	(0.12)
Constant	0.24***	-0.44***	0.25***	0.30***
	(0.04)	(0.06)	(0.04)	(0.07)
R^2	0.15	0.04	0.21	0.14
Obs.	88	80	104	98

Note: Rankings are based on firm's product total trade in 2004 in "Total" and on firm's unit price of product in 2004 in "Price". (Panel A) and (Panel B) replicate regressions in Table 5 and Figure 6, respectively. Significance: * 10 percent, ** 5 percent, *** 1 percent.

[48] See e.g., Kugler and Verhoogen (2012), Manova and Zhang (2012). Regressions using price rankings report smaller coefficients than the baseline results. This may be because exporters are differentiated by productivity in some products (e.g., Baldwin and Ito, 2011; Mandel, 2009).

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