Assortative Matching of Exporters and Importers*

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Abstract

This paper examines how exporting and importing firms match based on their capability by investigating how trade liberalization reshapes such exporter–importer matching. During the recent liberalization on the Mexico-US textile/apparel trade, exporters and importers often switch their main partners as well as change trade volumes. We develop a many-to-many matching model of exporters and importers where partner switching is the principal margin of adjustment, featuring Beckerian positive assortative matching by capability. Trade liberalization achieves efficient global buyer–supplier matching and improves consumer welfare by inducing systematic partner switching. The data confirm the predicted partner switching patterns.

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 in which firms seek and compete for capable buyers and suppliers globally. A case example is Boeing's 787 Dreamliner team that comprises the most capable suppliers from all over the world. Trade research in the last two decades has revealed the tremendous heterogeneity in the capability of exporters and importers (e.g., their productivity and product quality). Thus, how heterogeneous exporters and importers match along the supply chains may determine the aggregate capability of the industry.

This study examines how exporters and importers match based on their capability by investigating how trade liberalization reshapes such exporter–importer matching. From a newly constructed matched exporter–importer dataset of Mexican and US firms, we report a new fact that the change in a firm's exports during trade liberalization involves substantial *partner switching*, defined as the simultaneous adding and dropping of partners. Motivated by this fact, we develop a many-to-many matching model of exporters and importers featuring Beckerian positive assortative matching (PAM) by capability. The model shows that trade liberalization achieves efficient global buyer–supplier matching and improves consumer welfare by inducing systematic partner switching. The data confirm the predicted systematic partner switching patterns.

We use Mexico's customs administrative records to construct our matched exporter–importer dataset for Mexican textile/apparel exports to the United States from 2004 to 2007, a period of large-scale trade liberalization. In 2005, the United States 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), this liberalization effectively removed protection for Mexican products in the US market and forced them to compete with imports from third countries, principally China. The liberalization varied across products substantially and was arguably exogenous because the liberalization schedule was decided at the GATT Uruguay Round (1986–94) when China's export growth were not expected.

The MFA's end substantially changed many of the partnerships between Mexican exporters and US importers. Mexican exports to the United States decreased by the extensive margin (stopping exports) and intensive margin (reducing export values). The intensive margin adjustment involved substantial partner switching, often including the exporter's largest partners. Partner switching accounted 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. As we explain in Section 2, this prevalence of main partner switching in trade liberalization was at odds with anonymous market models (e.g., neoclassical models, oligopoly models), love-of-variety models (the Krugman–Melitz model), and some recent exporter–importer matching models (e.g., Bernard, Moxnes, and Ulltveit-Moe, 2018) that combine the love-of-variety model and match-level fixed costs.

Motivated by this new fact, we develop a many-to-many matching model of exporters and importers in an intermediate good market in which partner switching is the principal margin of adjustment. The model combines Sattinger's (1979) frictionless assignment model of a continuum of agents, Melitz's (2003) standard heterogeneous firm trade model, and Bernard, Redding, and Schott's (2011) multi-product firm trade model. The model consists of final producers (importers) in the United States and suppliers (exporters) in Mexico and China. Final producers produce multiple products, while suppliers own multiple production lines. A final producer's variety-level capability depends on its firm-level capability and idiosyncratic capability, while a supplier's production-line-level capability depends on its firm-level capability and idiosyncratic capability. A final variety matches a production line one-to-one, resulting in the many-to-many matching of final producers and suppliers. The Beckerian PAM of varieties and production lines arises as a stable equilibrium when a variety's capability and production's capability are complements.

The model predicts that the MFA's end induced systematic partner switching that led to efficient buyer–supplier matching and improved consumer welfare. As empirically documented by

Khandelwal, Schott, and Wei (2013), at the MFA's end, Chinese suppliers at various capability levels entered the US market. The entry of Chinese suppliers lowered the capability ranking of each Mexican supplier in the market. Therefore, to achieve PAM, Mexican exporters switched to US importers with lower capability, while US importers switched to Mexican exporters with higher capability. We call these types of partner switching "partner downgrading" and "partner upgrading," respectively. Allowing capable Chinese suppliers to match with capable US final producers, this rematching achieved PAM in the global market, which improved aggregate capability and consumer welfare. By contrast, in an anonymous market in which matching is independent of capability, rematching should not occur in a systematic way or result in an efficiency gain.

We take the model's predictions on partner switching to data. Guided by the theory, we estimate the rankings of firm-level capability of Mexican exporters and US importers by the rankings of their 2004 pre-liberalization product trade with their main partners. We then compare the partner switching patterns between liberalized products (the treatment group) and other textile/apparel products (the control group) within Harmonized System (HS) two-digit industries. We find the partner switching patterns to be consistent with PAM. First, US importers upgrade their Mexican partners more often in the treatment group than in the control group. At the same time, Mexican exporters downgrade their US partners more often in the treatment group than in the control group. Second, among firms that switch their main partners, the capability rankings of new partners are positively correlated with those of old partners. Together, these findings provide strong support for PAM and reject independent random matching. Furthermore, we confirm the model's predictions on firm exit and the number of partners. First, the capability cutoff for Mexican exporters increases. Second, US importers and Mexican exporters decrease their number of partners.

To the best of our knowledge, detecting Beckerian PAM by capability in this way is a novel approach to addressing the endogeneity problem in the conventional approach. When matching matters for a firm's performance, most firm characteristics observable in typical production and customs data (e.g., inputs, outputs, and productivity measures) may reflect partners' unobserved capability as well as the firm's own capability. Therefore, the simple correlation of those characteristics across matches may suffer from endogeneity.[1] Instead, our approach utilizes the MFA's end as an exogenous negative shock on the capability ranking of Mexican exporters.

As matched exporter-importer data become available to researchers, the last decade saw the burgeoning literature on buyer-supplier relationships in international trade.[2] Our paper contributes to a strand of this literature studying matching of heterogenous exporters and importers. Rauch (1996), Casella and Rauch (2002), and Rauch and Trindade (2003) pioneered the theoretical literature by using the assignment model of symmetric and horizontally differentiated firms, while our model contributes by featuring firms with heterogeneous capabilities, as in Melitz (2003). Antras, Garicano, and Rossi-Hansberg (2006) analyzed offshoring as the PAM of managers and workers by skills across countries. The assignment model captures two distinctive features in exporter-importer relationships. First, trading with high capability firms improves firm's performance, but the opportunity to trade with them is scarce and something that firms compete for. This view echoes with recent empirical evidence that trading with high capability foreign firms improves local firm's performance through various channels.[3] Second, buyer–supplier matching is an allocation of those scarce trading opportunities. Thus, trade liberalization induces partner switching to achieve a globally efficient buyer–supplier matching. We provide the first evidence for this matching mechanism from actual matching data.

Bernard et al. (2018) recently developed another approach combining match-level fixed costs and the love-of-variety (CES) production function.[4] A buyer and a supplier are matched when the

[1]For instance, Oberfield (2018) showed that a buyer's employment is positively correlated with a seller's employment in a model of a buyer–seller network in which buyers match sellers randomly and independently of capability.

[2]Data on domestic buyer-supplier relationships have also recently become available for studying domestic production networks (e.g. Bernard, Moxnes, and Saito, 2019; Dhyne, Kikkawa, Mogstad, and Tintelnot, 2021).

[3]See e.g., De Loecker (2007) and Atkin, Khandelwal, and Osman (2017) for learning technologies; Macchiavello (2010) and Macchiavello and Morjaria (2015) for reputation building; Tanaka (2020) for improving management; and Verhoogen (2008) for quality upgrading. Trading with foreign multinational firms is also found to improve firm's performance (e.g., Javorcik, 2004).

[4]Bernard, Dhyne, Magerman, Manova, and Moxnes (2021) and Lim (2018) introduced idiosyncratic match-level

match surplus exceeds the match-level fixed costs. As the match surplus monotonically increases in the buyer's capability and the supplier's, all the matches are realized except those between low capability firms.[5] Thus, the model can predict the negative degree assortativity reported by Blum, Claro, and Horstmann (2010), Bernard et al. (2018), and others that a buyer's number of partners is negatively correlated with the average number of firms to which the buyer's partners sell.

Our finding of PAM can be compatible with negative degree assortativity both theoretically and empirically. In Appendix D, we present a two-tier model of exporter–importer matching that unifies Bernard et al.'s (2018) model and ours to predict negative degree assortativity for the firm-level matching and PAM for the product-level matching. In the model, a buyer (e.g., a car maker) has a love-of-variety production function with respect to intermediate goods and decides whether to make or buy each intermediate good (e.g., tires, seats), considering the match surplus and match-level fixed costs, as in Bernard et al. (2018). For each intermediate good (e.g., a set of four tires), a buyer matches a supplier following PAM as in our model. Our data confirm the model's prediction by finding that negative degree assortativity holds when a match is defined at the firm level, but becomes weaker and statistically insignificant when a match is defined at the product level.

Another important strand of the literature studies the dynamics of an exporter's and importer's partner choice in a steady-state environment. Macchiavello (2010) introduced reputation building in an assignment model to explain an exporter's partner upgrading over time. Eaton, Eslava, Jinkins, Krizan, and Tybout (2014) and Eaton, Jinkins, Tybout, and Xu (2015) developed models incorporating search and learning frictions in partner acquisitions.[6] Eaton, Kortum, and Kramartz (2016) modeled random meeting and competition among multiple buyers and suppliers. Monarch

fixed costs in the model of Bernard et al. (2018) and analyzed the formulation of domestic production networks. Carballo, Ottaviano, and Volpe Martincus (2018) applied the ideal variety approach instead of using the love-of-variety model, which incorporates the interaction between the buyer's taste for ideal varieties and the seller's productivity.

[5]By contrast, the match surplus is a non-monotonic function in the assignment model. When a buyer's capability is fixed, the match surplus is maximized at the capability of its partner in stable matching, which is expressed as the stability condition (2) in our model.

[6]As a related study, Lu, Mariscal, and Mejia (2017) analyzed importers' switching of intermediates in a search and learning model.

(2021) estimated partner switching costs in a dynamic discrete choice model. Heise (2020) documented the dependence of exchange rate pass-through on the age of trade relationships.

Benguria (2021) and Dragusanu (2014) documented positive correlations between the size and productivity measures of exporters and importers in France–Colombia trade and India–US trade, respectively. Our model featuring Beckerian PAM also predicts these findings. Benguria (2021) and Dragusanu (2014) developed search effort models of the Stigler (1961) type to explain their findings by a different mechanism: a high productivity exporter spends greater search efforts finding a high productivity importer. Their models, however, do not explain Mexican exporters' partner downgrading at the MFA's end. In their models, search costs are sunk and importers are willing to trade with all exporters. Thus, Mexican exporters should continue to trade with pre-liberalization US partners instead of downgrading partners by paying additional search costs.

Another related literature investigates non-anonymous contracts in given exporter-importer relationship by using matched exporter-importer data. Macchiavello and Morjaria (2015) examined the surplus of long-term relationships relative to anonymous spot trade. Cajal-Grossi, Macchiavello, and Noguera (2020) found higher markups in long-term relational trade than spot trade. Bernard and Dhingra (2019) studied investment on relationship as a measure to avoid inefficiency in spot trade. Ignatenko (2019) reports exporter's price discriminations across importers. Our paper complements this literature by showing that exporters and importers choose their partners in an non-anonymous way, too.

The rest of this paper is organized as follows. Section 2 discusses our dataset and documents new facts on partner switching during trade liberalization. Section 3 presents our model and derives predictions. Section 4 describes our empirical strategy. Section 5 presents the main empirical results and robustness checks. Section 6 provides concluding remarks. The Appendix provides the calculations, proofs, data construction, extended models, robustness checks, and additional analyses rejecting alternative explanations of our results.

2 Mexico–US Textile/Apparel Trade

Mexico–US textile/apparel trade is particularly suitable for tracking the changes in exporter–importer matching during trade liberalization. First, since Mexico and the United States are large trading partners, trade between them includes numerous heterogeneous exporters and importers.[7] Second, Mexico–US textile/apparel trade experienced large-scale liberalization, the end of the MFA.

2.1 The End of the MFA

The MFA and its successor, the Agreement on Textiles and Clothing, are agreements about the quotas on textile/apparel imports among GATT/WTO countries. At the GATT Uruguay Round (1986–94), the United States (together with Canada, the European Union, and Norway) promised to abolish the 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 imports in 1990.

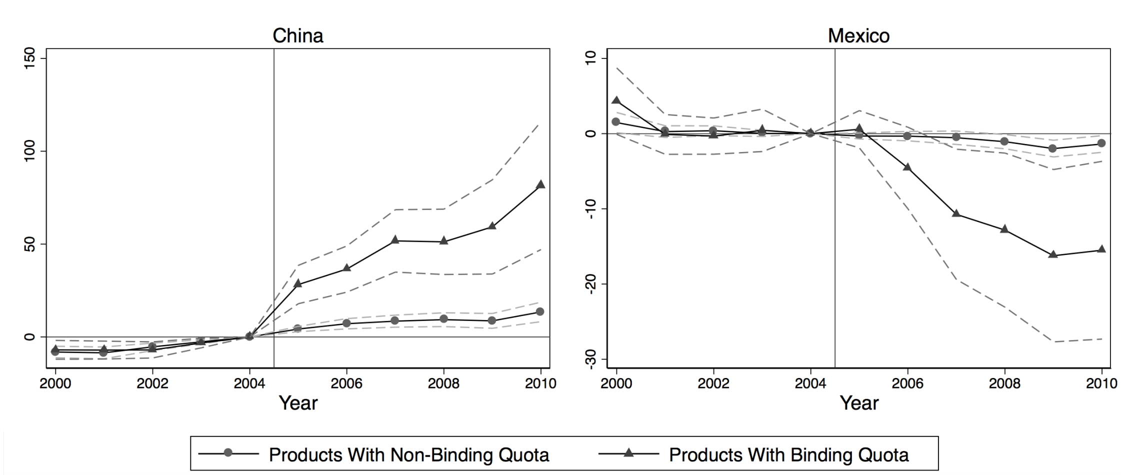
Three facts (taken from previous studies) about the consequences resulting from the MFA's end motivate our analysis.

Fact 1: Surge in Chinese Exports to the United States According to Brambilla, Khandelwal, and Schott (2010), US imports from China disproportionally increased by 271% in 2005, while imports from most other countries decreased. Using Brambilla et al.'s (2010) US import quota data, we classify each HS six-digit textile/apparel product into two groups (see Appendix B.5 for details). The first treatment group consists of Chinese exports subject to the binding 2004 US import quota. The second control group consists of other textile/apparel products. We regress the HS six-digit product-year-level exports of China and Mexico on the annual year dummies and product fixed effects separately for the treatment group and control group. Figure 1 plots the

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

coefficients of the annual year dummies with triangles for the treatment group and circles for the control group for China and Mexico. The difference in the coefficients between the two groups expresses the impacts of the MFA's end on Chinese and Mexican exports after controlling for product-specific effects. The left plot shows the coefficients for Chinese exports, while the right panel shows those for Mexican exports. In the left panel for Chinese exports, while the coefficients before 2005 are stable and virtually identical between the two groups, after the 2005 quota removal, the coefficient for the treatment group increases much faster than that for the control group.[8]

Figure 1: The Effects of the MFA's End on Chinese and Mexican Textile/Apparel Exports to the United States



Note: The left panel plots the coefficients of the annual year dummies in the regression of the HS six-digit product-year-level exports of China on the annual year dummies and product fixed effects separately run for the products on which the United States had imposed binding quotas against China in 2004 (the treatment group, triangles) and other textile/apparel products (the control group, circles). The right panel expresses the same information for exports from Mexico to the United States. Data source: UN Comtrade.

Fact 2: Mexican Exports Faced Competition from China By 2003, Mexico already had tariff- and quota-free access to the US market through NAFTA. With the MFA's end, Mexico lost its advantage over third-country exporters and faced increased competition from Chinese exporters in

[8]After this substantial surge in import growth, the United States and China had agreed to impose new quotas until 2008, but imports from China never returned to their pre-2005 levels because (1) the new quota system covered fewer product categories than the old system (Dayaratna-Banda and Whalley, 2007) and (2) the new quotas were substantially greater than the MFA levels (see Table 2 in Brambilla et al., 2010).

the US market, as the right panel of Figure 1 shows.[9] While the two groups are stable and almost identical before 2005, the treatment group significantly declines thereafter.

Fact 3: Exports by New Chinese Entrants with Various Capability Levels From Chinese customs transaction data, Khandelwal et al. (2013) decomposed the increases in Chinese exports to the United States in liberalized products after the removal of the quota into the intensive and extensive margins. Increases in Chinese exports were mostly driven by the entry of new exporters that had not previously exported products. These new exporters have different capability levels to those of incumbent exporters, with many more capable than incumbents.[10]

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 United States. For each match of a Mexican exporter and a US importer, the dataset contains the following information: exporter ID, importer ID, HS six-digit product code, annual shipment value (USD), quantity and unit, an indicator of a duty-free processing reexport program (Maquiladora/IMMEX), and other information.

We assign the exporter ID and importer ID throughout the dataset. The exporter ID is the tax number unique to each firm in Mexico. Assigning importer IDs to US firms is challenging. Although the customs records report the name, address, and employment identification number (EIN) of the US importer for each transaction, none of these can uniquely identify a firm because

[9] In theory, Mexican firms can import materials from China, and produce and export textile/apparel products to the United States; however, the number of such cases is negligible because NAFTA sets restrictive rules of origin. The basic rule is informally called "yarn forward" (US CBP, 2014). To be qualified as NAFTA products, the yarn must be made in Mexico from fibers that could be imported from China. However, Mexico imported USD 7 million of fibers from China in 2004, which accounts for only 0.08% of Mexico's textile/apparel exports to the United States.

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

it can use multiple names or change names, own multiple plants/establishments, or change tax numbers. Furthermore, a firm's name and address may be written in multiple ways and suffer from typographical errors. Therefore, simply counting combinations of names, addresses, and employment identification numbers would wrongly assign more than one ID to one US importer and overestimate the number of US buyers for each Mexican exporter.

We therefore assign the importer ID by applying a series of record linkage techniques.[11] First, we prepare 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 EIN from Orbis by Bureau van Dijk, which covers 20 million company branches, subsidiaries, and headquarters in the United States. These lists are used as dictionaries to which customs records are matched. Second, the address format is standardized using software certified by the US Postal Office. Third, we match the lists from Orbis to each of the linking variables (name, address, EIN) in the customs data by fuzzy matching. Two types of errors can 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 are chosen to minimize false unmatching because false matching is easier to identify by manual checks. Fourth, binary matched records are aggregated into clusters so that each record matches another record in that cluster. A resulting cluster represents a firm. Fifth, we manually check each cluster and remove falsely matched records. Finally, we assign the importer ID to each cluster. Appendix B explains the data construction process in detail.

Data cleansing drops some observations. First, since the dataset only covers observations from June to December 2004, we drop the observations from January to May in other years to make the information in each year comparable. We obtain similar results when January–May observations are included. Second, while importer information is reported for most normal trade transactions, it

[11] An excellent reference for record linkage is Herzog, Scheuren, and Winkler (2007). In addition, we benefitted from the lecture slides on "Record Linkage" by John Abowd and Lars Vilhuber.

is sometimes missing for processing trade transactions under the Maquiladora/IMMEX program in which exporters do not have to report an importer for each shipment.[12] We drop exporters that do not report the importer information for most transactions. To address the potential selection issues caused by this action, we distinguish normal trade and processing trade in the analyses below and conduct weighted regressions in Appendix B.4.

Table 1 reports the summary statistics for the product-level and firm-level matching. A product-level match occurs if an importer and exporter trade in a particular product, while a firm-level match occurs if an importer and exporter trade in some products. Columns (a) and (b) in Table 1 report the mean and median of the product-level matching.[13] 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.[14] Rows (5) and (6) show that even for firms that trade with multiple partners, more than 70% of their trade occurs with their single main partners.[15]

Excess Partner Switching after the MFA's end Our new finding is that exporters and importers actively switch partners during liberalization. Panel A in Table 2 reports the changes in Mexican textile/apparel exports to the United States 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 the *extensive margin* in Column (2) by exiters that stopped exporting by 2007 and *intensive margin* in Column (3) by continuing exporters in 2007.[16]

[12]The Maquiladoras program started in 1986 and was replaced by the IMMEX program in 2006. Under the Maquiladoras/IMMEX programs, firms in Mexico can import the materials and equipment to be used for exports duty free. Exporters must register the importer's information in advance but need not report it for each shipment.

[13]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 in Columns (1) and (2) decrease, whereas those in the other columns barely change.

[14]Appendix E.1 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 on the numbers of partners in Columns (3)–(6) remain close to those in Table 1.

[15]The large shares of trade with main partners in Table 1 are not driven by small firms that affect total trade to an only small extent. In an earlier version of this paper, we reported that main-to-main matches, where the exporter is the importer's main partner for the product and the importer is the exporter's main partner, account for around 80% of total trade.

[16]In Appendix E.2, the extensive margin is decomposed into dropping products and leaving the US market.

Table 1: Summary Statistics for the HS Six-Digit Product-Level Matching and Firm-Level Matching in Textile/Apparel Trade from Mexico to the United States

	Product-Level Match		Firm-Level Match	
	2004	2007	2004	2007
mean statistics (median)	(a)	(b)	(c)	(d)
(1) Number of Exporters	15.6 (8)	11.8 (6)	1,340	1,036
(2) Number of Importers	20.3 (11)	15.2 (8)	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	0.77	0.73	0.76

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

Consistent with standard heterogeneous exporter models, the extensive margin plays a large role in liberalized industries.

Export changes previously treated as the intensive margin in the literature actually involve substantial partner switching. Columns (4)–(6) decompose Column (3) into three margins of partner changes: *Partner Staying* in Column (4) expresses the changes in exports to continuing buyers in 2004 and 2007, *Partner Adding* in Column (5) expresses those to new buyers in 2007 that did not import from the exporter in 2004, and *Partner Dropping* in Column (6) expresses those to dropped partners that imported from the exporter in 2004 but not in 2007. The parentheses in Columns (5) and (6) report the share of export changes by *Partner Switchers* that simultaneously add and drop partners. Since this share is more than 80%, most partner changes are in fact partner switching. Column (7) reports the excess reallocation associated with main partners, i.e., $|(5)| + |(6)| - |(5) + (6)|$.

As the importance of main partners in Table 1 suggests, the switching of main partners plays a major role in the adjustment. In Table 3, the intensive margin in Column (1), which is Column (3)

Table 2: Changes in Mexican Textile/Apparel Incumbent Exports to the United States 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	-950.9	-887.4	-63.4	-25.1	83.5	-121.9	167.1
% of (3)			100%	39.5%	-131.7%	192.2%	263.4%
Switcher share					(0.95)	(0.82)	
Quota-free	-223.0	-179.6	-43.4	-24.0	37.5	-56.9	75.1
% of (3)			100%	55.4%	-86.6%	131.1%	173.2%
Switcher share					(0.79)	(0.87)	
			B. HS six-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: In Panel A, each column reports the changes in Mexican textile/apparel exports to the United States between. 2004 and 2007 by incumbent exporters in 2004 for quota-bound products and other quota-free products. The changes in total exports in (1) are decomposed into the extensive margin by exiters in (2) and the intensive margin by survivors in (3). The intensive margin in (3) is decomposed into (4) exports to continuing partners, (5) exports to new partners, and (6) exports to dropped buyers. Column (7) is |(5)|+|(6)|- |(5)+(6)|. In Panel B, each column reports the product-level regressions of each margin on the quota-bound product dummy (Binding) with the HS two-digit fixed effects. Standard errors are clustered at the HS six-digit product level. Significance: * 10%, ** 5%, *** 1%.

in Table 2, is decomposed according to main partner's involvement: 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), and those to dropped main buyers that were main buyers in 2004 but not in 2007 in Column (5). Column (6) reports the excess reallocation associated with main partners, i.e., $|(4)| + |(5)| - |(4) + (5)|$.

The prevalence of main partner switching is at odds with that in anonymous market models (perfectly competitive and oligopoly models) and love-of-variety models (the Krugman–Melitz model) including some recent models of firm-to-firm production networks (e.g., Bernard et al., 2018). First, as we show in Section 3, in anonymous market models in which buyers are indifferent about exporters, partner changes should be minimized to save costs associated with switching partners. Exporters may either add or drop buyers, but should not switch among surviving buyers.

Table 3: Intensive Margin Changes in Mexican Textile/Apparel Incumbent Exports to the United States 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%	32.8%	25.1%	89.2%	131.3%	178.4%
B. HS six-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: In Panel A, each column reports the changes in Mexican textile/apparel exports to the United States between 2004 and 2007 by exporters in 2004 for quota-bound products and other quota-free products. The intensive margin changes by survivors in (1) are decomposed into (2) exports to non-main partners, (3) exports to continuing main partners, (4) exports to new main partners, and (5) exports to dropped main partners. Column (6) is |(4)|+|(5)|- |(4)+(5)|. In Panel B, each column reports the coefficients of the product-level regressions of each margin on the dummy of quota-bound products (Binding) with the HS two-digit fixed effects. Standard errors are clustered at the HS six-digit product level. Significance: * 10%, ** 5%, *** 1%.

Therefore, the excess reallocation in Column (7) in Table 2 and Column (6) in Table 3 should be zero. Second, in production network models combining the love-of-variety model and match-specific fixed costs, firms usually add and drop marginally important partners rather than main partners. Thus, the large main partner excess export reallocation in Column (6) in Table 3 is puzzling to those models.

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

3 The Model

This section develops an exporter–importer matching model in which partner switching is the principal margin of adjustment. We first consider the case of one-to-one matching in Section 3.1 and show partner switching as a new mechanism of gains from trade in Section 3.2. In Section 3.3, we introduce many-to-many matching and derive predictions that we take to the data in Section 4.

3.1 Matching Model of Exporters and Importers

The model includes three types of a continuum of firms, namely, US final producers, Mexican suppliers, and Chinese suppliers.[17] The model has two stages. In Stage 1, 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. Suppliers tailor intermediate goods and transact them only within the team. Firms match under perfect information and each firm joins only one team. This one-to-one frictionless matching model is the simplest model predicting assortative matching. Introducing search frictions does not change the qualitative predictions that we take to the data.[18] In Stage 2, teams compete in the US final good market in a monopolistically competitive fashion.

The US representative consumer maximizes the CES 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 the set of available differentiated final goods, ω is the 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 the team producing ω, q_0 is the consumption of the numeraire good, I is the exogenously given income.

[17] US final producers may be retailers or wholesalers. Our model is a partial equilibrium version of that of Sugita (2015), who presented a two-country general equilibrium model with endogenous firm entry.

[18] A body of the theoretical literature examines matching with search frictions (e.g. Smith (2011) is an excellent survey). The general conclusion of the literature is that as long as the complementarity within matches is large enough, matching becomes positive assortative on average, as in the frictionless matching model that we consider.

$\alpha \geq 0$ and $\delta > 0$ are the 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.

The team's capability $\theta = \theta(x, y)$ is increasing in the final producer's capability x and supplier's capability y in that team, i.e., $\theta_1 \equiv \partial\theta(x, y)/\partial x > 0$ and $\theta_2 \equiv \partial\theta(x, y)/\partial y > 0$. There exists a fixed mass M_U of final producers in the United States, M_M of suppliers in Mexico, and M_C of suppliers in China. The cumulative distribution function (CDF) for US final producers' capability is $F(x)$ with support $[x_{min}, x_{max}]$. For simplicity, a Chinese supplier is a perfect substitute for a Mexican supplier of the same capability. The capability of Mexican and Chinese suppliers follows an identical distribution with the CDF $G(y)$ and support $[y_{min}, y_{max}]$.[19]

Production technology is of the Leontief type. When a team with capability θ produces q units of final goods, the team supplier produces q units of intermediate goods at costs $c_y\theta^\beta q + f_y$; then, the final producer assembles these intermediate goods into final goods at costs $c_x\theta^\beta q + f_x$, where c_i and f_i are positive constants ($i = x, y$). The team's total costs are $c(\theta, q) = c\theta^\beta q + f$, where $c \equiv c_x + c_y$ and $f \equiv f_x + f_y$. The externalities within teams make firms' marginal costs dependent on both their partner's capability and their own capability.[20] For simplicity, we assume that the firm's marginal costs depend on the team's capability. The team's capability θ shifts both demand and marginal costs depending on α and β. Therefore, θ may represent productivity (e.g., Melitz, 2003) and/or quality (e.g., Baldwin and Harrigan, 2011; Verhoogen, 2008).

[19]The identical distribution of Chinese and Mexican suppliers is assumed only for graphical exposition. Appendix A.1 derives the main predictions without this assumption.

[20]An example of a within-team externality is the costs of quality control. Producing high-quality final goods might require extra costs of quality control in each production stage because one defective component could destroy the whole product (Kremer, 1993). Another example is productivity spillovers. Through the teaching and learning (e.g., joint R&D) within a team, each member's marginal cost may depend on the entire team's capability.

Stage 2 We obtain an equilibrium by backward induction. The 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 each team takes $A \equiv \frac{\delta}{\sigma}\left(\frac{\rho P}{c}\right)^{\sigma-1}$ as given and $\gamma \equiv \alpha\sigma - \beta(\sigma - 1) > 0$ is assumed so that the team's profit increases in θ. All the calculations are in Appendix A.1. We normalize $\gamma = 1$ by choosing the unit of θ as the comparative statics on α, β and σ is not our main interest. The price index $P = c/\left(\rho\Theta^{1/(\sigma-1)}\right)$ decreases in the team's aggregate capability $\Theta \equiv M\int\theta dH(\theta)$, where M and $H(\theta)$ are active teams' mass and capability distribution, respectively.

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. $m_y(y)$ is 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 profits, $\pi_x(x) \geq 0$ and $\pi_y(y) \geq 0$ for all x and y; and (ii) *pair-wise stability*, wherein each firm is the optimal partner for the other team member:[21]

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

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

From the envelop theorem, we obtain

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

which proves that profit schedules increase in capability.[22] Thus, the capability cutoffs 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 cutoffs satisfy

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

That is, the number of active final producers equals that of active suppliers.

Differentiating (3) by x, we obtain the derivative of the matching function:

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

Since the denominator in (5) is positive from the second-order condition, the sign of θ_{12} is the same as the sign of $m_x'(x)$, namely, the sign of sorting in stable matching (e.g., Becker, 1973). For simplicity, we consider three cases in which the sign of θ_{12} is constant for all x and y: (1) Case C (Complement) $\theta_{12} > 0$, (2) Case I (Independent) $\theta_{12} = 0$, and (3) Case S (Substitute) $\theta_{12} < 0$.[23] In Case C, we have PAM ($m_x'(x) > 0$): high capability firms match with high capability firms, whereas low capability firms match with low capability firms. In Case S, we have negative assortative matching ($m_x'(x) < 0$): high capability firms match with low capability firms. In Case

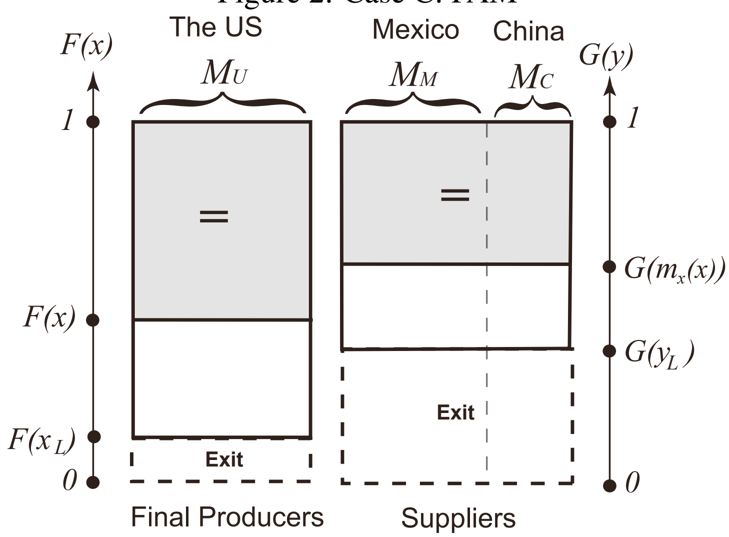
[22]The use of differentiation is a convenient shortcut for deriving the sorting pattern, following Sattinger (1979). Lemma 7 in Appendix D presents a general proof of sorting that can be applied to finite agents.

[23]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 the 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 of Case S is technological spillovers through learning and teaching. Gains from learning from highly capable partners might be greater for low capability firms. Grossman and Maggi (2000) provided further examples of Case C and Case S.

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 that matching is random and independent of capability in Case I.

Case I is a useful benchmark because it nests two important classes of standard models. The first is anonymous market models in which each firm is indifferent about partner capability. The second is heterogeneous firm trade models with one-sided heterogeneity in which firm heterogeneity exists either among exporters ($\theta_1 = \theta_{12} = 0$) or among importers ($\theta_2 = \theta_{12} = 0$). In the following, we focus on Case C and Case I in the main text and examine Case S in Appendix A.3.

Figure 2: Case C: PAM



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

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

Figure 2 describes condition (6). The left rectangle has width M_U and the right one has M_M+M_C. The left vertical axis expresses the value of $F(x)$ and the right one the value of $G(y)$. The left gray area equals the mass of final producers with higher capability than x, $M_U\left[1-F(x)\right]$, while the right gray area equals the mass of suppliers that match with them, $\left(M_M+M_C\right)\left[1-G\left(m_x(x)\right)\right]$.

The matching function $m_x(x)$ equalizes the size of the two gray areas.

Finally, we obtain the cutoff x_L as follows. 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, $m_x(x)$ determines 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, let $\theta(x, y) \equiv \theta^x(x) + \theta^y(y)$. Condition (4) determines $y_L(x_L)$ as a function of x_L. 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:

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

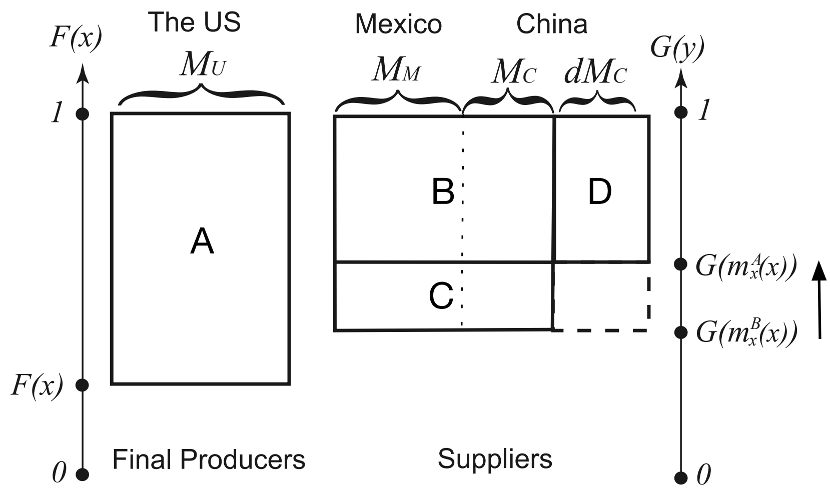
(7) uniquely determines x_L since $\Theta(x_L)$ is decreasing and $\theta_L(x_L)$ is increasing in x_L.

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

This section analyzes the effect of the MFA's end on matching. Motivated by Fact 3 shown in Section 2 that new Chinese entrants had different levels of capability, we model the event as an increase in the mass of Chinese suppliers ($dM_C > 0$). We assume that a firm changes its partner only if it strictly prefers the new match over the current match. We denote the variables and functions before the MFA's end by "B" (before) and variables after the MFA's end by "A" (after).

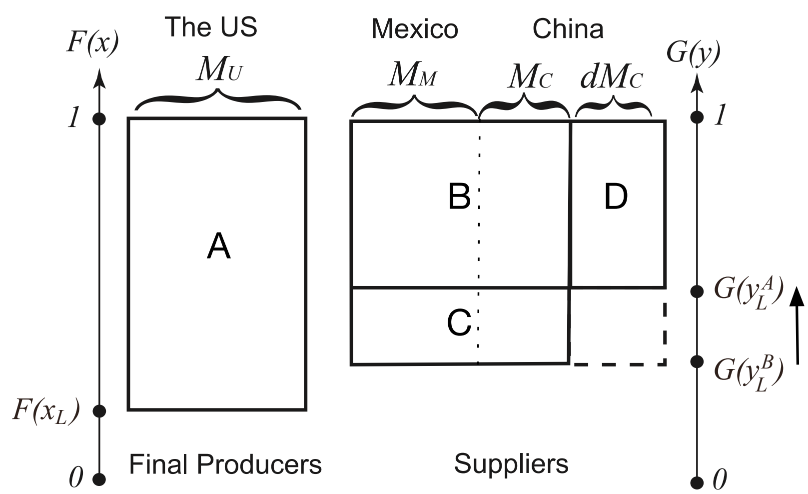
Case C Figure 3 shows how matching changes from $m_x^B(x)$ to $m_x^A(x)$ for the given capability x. Area A expresses US importers with capability higher than x. They initially match with suppliers in areas $B + C$ that have higher capability than $m_x^B(x)$. After the MFA's end, the original matches become unstable because some US importers are willing to switch to the new entrants. In the new matching, final producers in area A match with suppliers in areas $B + D$ that have higher

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



capability than $m_x^A(x)$. A US final producer with capability x switches its main partner from one with capability $m_x^B(x)$ to one with higher capability, namely, $m_x^A(x)$. We call this change "partner upgrading" by US final producers. This in turn implies "partner downgrading" by Mexican suppliers. Mexican suppliers with capability $m_x^A(x)$ match with final producers with strictly higher capability than x before the MFA's end. Not all Mexican suppliers can match with new partners, however, and those with low capability exit the market, as proven in Appendix A.2.1.

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



Case I Figure 4 shows that the MFA's end increases the supplier's cutoff from y_L^B to y_L^A, as proven in Appendix A.2.1. Since whether x_L increases or decreases is generally ambiguous, the figure depicts the case in which x_L unchanged. As low capability suppliers in Area C exit, US importers that matched with them switch to new Chinese suppliers in Area D. Other firms do not change their partners, although they change the price and quantity of goods traded. Firms are indifferent about their partners as long as those partners have a capability level above the cutoffs.

Rematching Gains from Trade The MFA's end causes two adjustments. First, new Chinese suppliers with high capability enter the market and Mexican suppliers with low capability exit. This *replacement effect* occurs in both Cases C and I, and it corresponds to the extensive margin adjustment in Table 2. Second, incumbent firms rematch. This *rematching effect* occurs only in Case C and corresponds to the partner excess reallocation in Tables 2 and 3.

We show that the rematching effect in Case C is a new mechanism of gains from trade that did not exist in standard trade models nested in Case I (perfectly competitive models and Krugman–Melitz models with one-sided heterogeneity). We consider a hypothetical "no-rematching" equilibrium at which firms switch partners only if their current partners exit the market and denote variables in this equilibrium by "NR." The following proposition compares the price indices across the three cases (the proof is in Appendix A.2.1).

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

The effect of liberalization on the price index $P^B - P^A$ can be decomposed into the replacement effect $P^B - P^{NR}$ and rematching effect $P^{NR} - P^A$. The gain from the replacement effect is well known in the heterogeneous firm trade literature. In Case C, the rematching effect creates an additional consumer gain. The proof applies a classic theorem in matching theory that stable matching maximizes the aggregate payoff, $A\Theta - Mf$, for the given A (Koopmans and Beckmann, 1957; Shapley and Shubik, 1971; Gretsky, Ostroy and Zame, 1992) and proves that aggregate capability increases as $\Theta^A > \Theta^{NR} > \Theta^B$.[24] In other words, trade liberalization improves consumer welfare by improving global buyer–supplier matching and aggregate capability.

Proposition 1 also implies that a preferential trade agreement can create inefficient "matching diversion." High capability US final producers are diverted to match with low capability Mexican suppliers instead of high capability Chinese suppliers.[25]

3.3 Many-to-Many Matching

This section introduces many-to-many matching in an intermediate good market. A final producer produces multiple product varieties and a supplier owns multiple production lines. Matching occurs between varieties and production lines, resulting in many-to-many matching.

There exist N final products and one intermediate good. The consumer's utility is given by

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

where Ω_s is the set of varieties of product s. A final producer produces at most one variety of each product, following Bernard et al. (2011). Let $\chi_{is} = x_i + \eta_{is}$ be the *product capability* of firm i for product s, where x_i is *firm capability* and η_{is} is i.i.d. *idiosyncratic capability* with $E(\eta_{is}) = 0$ and support $[\eta_{min}, \eta_{max}]$. x_i and η_{is} are independent and have densities $f_x(x)$ and $f_\eta(\eta)$, respectively.

A supplier owns multiple production lines. Each line specializes in a particular variety. A supplier with firm capability y owns $n(y)$ production lines and can match with at most $n(y)$ buyers. One reason for such buyer capacities is a manager's span of control. A supplier requires a manager's resource to collaborate with each buyer. We assume that $n(y)$ is weakly increasing in y.

[24] In the case of finite agents, the intuition of the theorem follows from the definition of the 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 the additional technical assumptions shown by Gretsky et al. (1992). Applying the theorem to Proposition 1 is not trivial since A is endogenous in our setting.

[25] Ornelas, Turner, and Bickwit (2019) theoretically analyzed matching diversion by a preferential trade agreement in a model with one-sided heterogeneity.

The production line k of supplier j with firm capability y_j has *line capability* $\upsilon_{jk} = y_j + \varepsilon_{jk}$, where ε_{jk} is i.i.d. *idiosyncratic capability* with $E(\varepsilon_{jk}) = 0$ and support $[\varepsilon_{min}, \varepsilon_{max}]$. y_j and ε_{jk} are independent. Their marginal densities are $g_y(y)$ and $g_\varepsilon(\varepsilon)$, respectively, which are common for both Mexican and Chinese suppliers. We assume that $f_\eta(\eta)$ and $g_\varepsilon(\varepsilon)$ are log-concave.[26] In other respects, the model has the same structure as the one in Section 3.1.

Matching occurs between a final product variety and supplier production line. The conditions for stable variety-to-line matching are similar to those in Section 3.1. Stable matching consists of the matching function $\upsilon = m_\chi(\chi)$ and $\chi = m_\upsilon(\upsilon)$ between product capability χ and line capability υ, the variety's profit schedule $\pi_\chi(\chi)$, and the line's profit schedule $\pi_\upsilon(\upsilon)$. Since a match's joint profit is $\Pi(\chi, \upsilon) = A\theta(\chi, \upsilon) - f$, where f is the fixed cost per product, the stability conditions continue to be (2) and the sign of θ_{12} determines the sign of sorting. The matching market-clearing condition in Case C is similar to that in (6):

$$\tilde{M}_U[1 - \tilde{F}(\chi)] = \left(\tilde{M}_M + \tilde{M}_C\right)\left[1 - \tilde{G}\left(m_\chi(\chi)\right)\right], \tag{8}$$

where $\tilde{M}_U \equiv M_U N$ is the total mass of varieties, $\tilde{M}_M \equiv M_M n$ and $\tilde{M}_C \equiv M_C n$ are the total mass of production lines in Mexico and China, respectively, and $n \equiv \int_{y_{min}}^{y_{max}} n(y) g_y(y) dy$ is the mean mass of production lines. The CDFs of product capability χ and line capability υ are $\tilde{F}(\chi) \equiv \int_{-\infty}^{\chi} f_\chi(t)dt$ and $\tilde{G}(\upsilon) \equiv \int_{-\infty}^{\upsilon} \frac{n(t)}{n} g_\upsilon(t)dt$, respectively, where $f_\chi(\chi)$ and $g_\upsilon(\upsilon)$ are the densities of χ and υ, respectively.[27] The conditions for Cases I and S can be derived analogously. The cutoff capabilities of varieties χ_L and lines υ_L satisfy similar conditions to in (4) and (7).

While variety-to-line matching is one-to-one, firm-to-firm matching is many-to-many. We approximate the number of a final producer's partners by the number of production lines matching

[26] The class of distributions with log-concave densities includes a wide range of unimodal parametric distributions such as normal, uniform, logistic, Frechet and many others.

[27] These densities are obtained as $f_\chi(\chi) = \int_{\max\{x_{min}, t-\eta_{max}\}}^{\min\{\eta_{min}, t-x_{max}\}} f_x(s) f_\eta(t-s) ds dt$ and $g_\upsilon(\upsilon) = \int_{\max\{y_{min}, t-\varepsilon_{max}\}}^{\min\{\varepsilon_{min}, t-y_{max}\}} g_y(s) g_\varepsilon(t-s) ds dt$.

with the final producer, and the number of a supplier's partners by the number of varieties matching with the supplier.[28] The number of a final producer's active products follows a binomial distribution with success probability $[1 - F_\eta(\chi_L - x)]$ and the number of trials N, while the number of a supplier's active production lines follows a binomial distribution with $[1 - G_\varepsilon(\upsilon_L - y)]$ and $n(y)$. The mean number of Mexican partners for a final producer with capability x, $N^M(x)$, and the mean number of partners for a Mexican supplier with firm capability y, $n^S(y)$, are given by:

$$N^M(x) = \frac{M_M N[1 - F_\eta(\chi_L - x)]}{M_M + M_C} \text{ and } n^S(y) = n(y)[1 - G_\varepsilon(\upsilon_L - y)], \tag{9}$$

where F_η and G_ε are the cumulative distribution functions of η and ε, respectively. Thus, the mean number of partners is increasing in firm capability and decreasing in the cutoffs.

Because the equilibrium conditions remain the same as in Section 3.1 the effects of the MFA's end on the matching functions, capability cutoffs, and price indices are qualitatively the same as those in Section 3.2. Let P^t ($t \in \{A, B, NR\}$) be the product-level price indices. Then, the following lemma holds with essentially the same proofs as in Section 3.2.

Lemma 1. *(i) In Case C after the MFA's end:* $m_\chi^A(\chi) > m_\chi^B(\chi)$ *for the given* χ*;* $m_\upsilon^A(\upsilon) < m_\upsilon^B(\upsilon)$ *for the given* υ*;* $\upsilon_L^A > \upsilon_L^B$*; and* $P^A < P^{NR} < P^B$*. (ii) In Case I after the MFA's end,* $\upsilon_L^A > \upsilon_L^B$ *and* $P^A = P^{NR} < P^B$*.*

Predictions of Main Partner Choices, Exit, and Number of Partners We derive the model's predictions of firm-to-firm matching that we take to the data. Our data on Mexico–US trade only record partner switching 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.*

[28] Strictly speaking, the number of a final producer's partners could be fewer than the number of lines matching with the final producer. However, since production lines have different capability levels, the probability that one supplier provides multiple production lines to the same final producer is negligible for the case of the continuum of agents and small for the case of finite agents. Therefore, we interpret the number of production lines matching with the final producer as an approximation of the mean number of its partners.

We examine a firm's main partner choice because of its importance in our dataset. First, consider Case C. Let $\chi_i^* \equiv x_i + \max_s \eta_{is}$ be the highest product capability of final producer i. The mean firm capability of final producer i's main partner is $\bar{y}^t(\chi_i^*) \equiv E\left[y|\, y + \varepsilon = m_\chi^t(\chi_i^*)\right]$ for $t \in \{A, B\}$. Similarly, the mean firm capability of supplier j's main partner is $\bar{x}^t(\upsilon_j^*) \equiv E\left[x|\, x + \eta = m_\upsilon^t(\upsilon_j^*)\right]$ for $t \in \{A, B\}$, where $\upsilon_j^* \equiv y_j + \max_k \varepsilon_{jk}$. A final producer i upgrades its main partner if $\bar{y}^A(\chi_i^*) > \bar{y}^B(\chi_i^*)$, and downgrades if $\bar{y}^A(\chi_i^*) < \bar{y}^B(\chi_i^*)$. Similarly, a supplier j upgrades its main partner if $\bar{x}^A(\upsilon_j^*) > \bar{x}^B(\upsilon_j^*)$, and downgrades if $\bar{x}^A(\upsilon_j^*) < \bar{x}^B(\upsilon_j^*)$.

As shown in Appendix A.2.2, the log-concavity of $f_\eta(\eta)$ and $g_\varepsilon(\varepsilon)$ implies that $E\left[x|\, x + \eta = m_\upsilon(\upsilon_j^*)\right]$ increases in $m_\upsilon(\upsilon_j^*)$ and that $E\left[y|\, y + \varepsilon = m_\chi(\chi_i^*)\right]$ increases in $m_\chi(\chi_i^*)$. Therefore, from Lemma 1, US continuing importers upgrade Mexican main partners, while Mexican continuing exporters downgrade US main partners. Another testable implication is that the relative ranking of main partner's firm capability preserves. For each pair of final producers i and j, if $\bar{y}^B(\chi_i^*) > \bar{y}^B(\chi_j^*)$, then $\bar{y}^A(\chi_i^*) > \bar{y}^A(\chi_j^*)$ holds; similarly, for each pair of suppliers k and h, if $\bar{x}^B(\upsilon_k^*) > \bar{x}^B(\upsilon_h^*)$, then $\bar{x}^A(\upsilon_k^*) > \bar{x}^A(\upsilon_h^*)$ holds. That is, the ranking of new partners' firm capability is positively correlated with the ranking of that of old partners.

In Case I, no systematic partner change occurs. No US continuing importers or Mexican continuing exporters change main partners. The firm capability ranking of new partners is independent of the ranking of old partners. In summary, we establish the following proposition.

Proposition 2. *In Case C after the MFA's end, (C1) US continuing importers upgrade Mexican main partners, while Mexican continuing exporters downgrade US main partners and (C2) the firm capability ranking of new main partners is positively correlated with that of old main partners. In Case I after the MFA's end, (I1) No US continuing importers or Mexican continuing exporters change main partners and (I2) the firm capability ranking of new main partners is independent of the ranking of old main partners.*

We derive the model's predictions of firm exit and the number of partners that holds in both

Cases C and I. First, the firm capability cutoff for Mexican suppliers $y_L = \upsilon_L - \varepsilon_{max}$ increases. Second, from (9), the number of partners $N^M(x)$ and $n^S(y)$ decrease.[29]

Proposition 3. *In Cases C and I after the MFA's end, (E1) the firm capability cutoff for Mexican exporters rises and (E2) both US importers and Mexican exporters reduce their partners.*

4 Empirical Strategy

4.1 Proxy for Firm Capability Rankings

To test the predictions in Propositions 2 and 3, we estimate the ranking of firm capability by ranking each firm's product-level trade with its pre-liberalization main partner using the properties of the model. Let $I(x)$ be the mean imports of the intermediate good by US importers with firm capability x from the main partners and let $X(y)$ be the mean exports by Mexican exporters with firm capability y to the main partners. The following lemma holds from the monotonic relationship between firm capability and within-match trade (the proof is in Appendix A.2.3).

Lemma 2. *In Case C and Case I, $I(x)$ and $X(y)$ are monotonically increasing functions.*

Using Lemma 2, we create the capability ranking of firms as follows. For each HS six-digit product, we rank all the US importers in 2004 using their imports of the product from their main partner in 2004 before the MFA's end. Similarly, for each HS six-digit product, we rank all the Mexican exporters in 2004 using their exports of the product to their main partner in 2004. From Lemma 2, these rankings should agree with the rankings of firm capability on average in Case C and Case I. We use these rankings using 2004 data throughout our sample period (2004–2007) during which the ranking is stable.[30] Section 5.4 presents the results using alternative rankings.

[29] From (9), the relationship between the change in the number of partners and firm capability is generally ambiguous, and it depends on the shapes of F_η, $n(y)$, and G_ε.

[30] The correlations of the rankings in 2004 and 2007 are higher than 0.85 for all the products and similar between the treatment and control groups.

Using these rankings, we first create three variables: (1) firm i's own ranking in product g in country c, $OwnRank^c_{ig}$; (2) the ranking of the firm's main partner of product g in 2004 before the MFA's end, $OldPartnerRank^c_{ig}$; and (3) the ranking of the firm's main partner of product g in 2007 after the MFA's end, $NewPartnerRank^c_{ig}$. We choose 2004–2007 as the sample period to avoid potential confounding from the impact of the 2008 Lehman Brothers crisis on Mexican exports. $OldPartnerRank^c_{ig}$ differs from $NewPartnerRank^c_{ig}$ if and only if the firm switches its main partner during 2004–2007. These rankings are standardized using the number of firms to fall into the range of [0,1]. Smaller rankings indicate higher capability (e.g., first ranking means the best). Finally, we create the partner change variables as follows. The partner upgrading dummy Up^c_{igs} equals one if $NewPartnerRank_{igs} < OldPartnerRank_{igs}$ and the partner downgrading dummy $Down^c_{igs}$ equals one if $NewPartnerRank_{igs} > OldPartnerRank_{igs}$.

4.2 Specifications

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

$$
\begin{aligned}
Up^c_{igs} &= \beta^c_U Binding_{gs} + \lambda_s + \varepsilon^c_{Uigs} \\
Down^c_{igs} &= \beta^c_D Binding_{gs} + \lambda_s + \varepsilon^c_{Digs},
\end{aligned}
\tag{10}
$$

where c, i, g, and s represent the country (United States and Mexico), firm, HS six-digit product, and sector (HS two-digit level), respectively. The dummy variable $Binding_{gs}$ equals one if Chinese exports of product g to the United States faced a binding quota in 2004, which is constructed from Brambilla et al. (2010). λ_s represents the HS two-digit-level fixed effects.[31] ε^c_{Uigs} and ε^c_{Dijs} are the

[31]We include the HS two-digit-level fixed effects instead of the HS four-digit-level fixed effects because of their collinearity with the binding dummy. When the binding dummy is regressed on only the HS four-digit-level fixed effects, R^2 is 0.86 in both the US and the Mexico samples, which means that only 14% of the variation in the binding dummy can be used to estimate β^C_U and β^C_D in (10). On the contrary, when the binding dummy is regressed on only the HS two-digit-level fixed effects, R^2 is 0.48 for the US sample and 0.50 for the Mexico sample, which leave sufficient variation. We also drop those HS two-digit sectors (HS 50, 51, 53, 56, 57, and 59) in which no variation in the binding

error terms. Appendix B.5 explains the construction of the binding dummy and other variables. The regression sample includes both continuing US importers and Mexican exporters.

The coefficients of interest β^c_U and β^c_D in (10) are identified by comparing the treatment and control groups within HS two-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. The HS two-digit fixed effects control for basic product characteristics such as textile/apparel and knit/woven.

Prediction C1 for PAM states that at the MFA's end, all the continuing US importers upgrade their main partners, whereas all the continuing Mexican exporters downgrade. Although the frictionless matching model predicts that all the firms will change their partners, in reality, other factors such as transaction costs are likely to prevent some 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 $\beta^{US}_U > 0$, $\beta^{US}_D = \beta^{Mex}_U = 0$, and $\beta^{Mex}_D > 0$ in (10).

Prediction I1 for independent matching states that at the MFA's end, no continuing US importer and Mexican exporter would change their partners. In reality, some idiosyncratic shocks appearing as error terms in (10) could induce partner changes. Thus, we reformulate Prediction I1 as follows: no difference should exist in the probability of partner changes in any direction between the treatment and control groups, which corresponds to $\beta^{US}_U = \beta^{US}_D = \beta^{Mex}_U = \beta^{Mex}_D = 0$ in (10).

Our regression (10) does not suffer from the endogeneity problem that existed in the conventional correlation approach to detecting PAM that regresses an exporter's characteristics on those of an importer. For instance, the cross-sectional regression of an exporter's rank on an importer's rank could produce a mechanical positive correlation regardless of the sign of sorting.[32] We use firm

dummy at the HS two-digit level occurs.

[32]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 the variations in measured importers' rankings are driven by unobserved exporter's capability, which yields a positive mechanical correlation of

characteristics (trade volume) only to construct the outcome variables on the left-hand side. Any discrepancy between the true capability ranking and trade ranking should appear in the error terms ε^c_{Uigs} and ε^c_{Digs}, which might reflect the capability of the firm and its partners, and other unobservable firm and product characteristics. However, as long as the binding dummy is uncorrelated with these unobservables, β^c_U and β^c_D are consistently estimated.[33]

Another advantage of (10) is controlling for the various unobservable determinants of a firm's partner rankings. 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 (10) are uncorrelated to the MFA liberalization, they should not bias our estimates. Second, the dependent variables are constructed from time differences in partner rankings. Time differencing controls for all the time-invariant firm-specific determinants of the *level* of partner rankings.

Old and New Partner Rankings (C2 and I2) To test Predictions C2 and I2, we estimate the following regression for firms that switched partners during 2004–2007:

$$NewPartnerRank^c_{ig} = \alpha^c + \gamma^c OldPartnerRank^c_{ig} + \varepsilon^c_{ig} \tag{11}$$

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

Prediction C2 predicts $\gamma^c > 0$, while Prediction I2 predicts $\gamma^c = 0$.

Two additional points need to be mentioned. First, if we run (11) only for firms that do not change partners, then γ^c equals one by construction. To avoid this mechanical correlation, we estimate (11) only for firms that change partners. Second, the regression (11) combines both the treatment and the control groups since Prediction C2 should hold for both groups in Case C.[34]

exporters' and importers' rankings. Oberfield (2018, Proposition 6) also formally showed this point.

[33]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 for all their products (maybe to save transaction costs), then this might bias our estimates. However, this is unlikely since such pairs account for only 8% of Mexican exporters that switched partners.

[34]For instance, if an industry-wide shock induces a Mexican exporter's partner to downgrade in both the treatment

Capability Cutoff Changes (E1) We test Prediction E1 using two models. First, we estimate a product-level difference-in-difference model of the export cutoffs for the pre-liberalization (2001–2004) and post-liberalization (2004–2007) periods:[35]

$$\ln ExportCutoff_{gsr} = \delta_1 Binding_g + \delta_2 Binding_g \times After_r + \delta_3 After_r + \lambda_s + u_{gsr}. \quad (12)$$

For surviving exporters in the final 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 exporters' product exports as the capability proxy, which is highly correlated with exports to the main partners in the 2004–2007 data. $After_r$ is an indicator of whether period r is 2004–2007, λ_s represents the HS two-digit-level fixed effects, and u^c_{igs} are the error terms.

We use the difference-in-difference specification to test the predictions about the cutoff *changes*. In (12), the cutoff increase in Prediction E1 implies $\delta_2 > 0$ as the coefficient of interest. On the contrary, 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 the prior trends in the cutoffs by estimating equation (12) for the two pre-liberalization periods (1998–2001 and 2001–2004).

The product-level regression (12) raises 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 exits from the market. Therefore, we also estimate the following threshold model of a firm's exit. In each period r, Mexican supplier i receives a random i.i.d. shock ε_{ir} to its profit, which captures the idiosyncratic factors inducing firm exit in the absence of liberalization (e.g., Eaton et al., 2014). The firm chooses to exit if ε_{ir} is below the threshold $\bar{\varepsilon}_{ir}(y)$. Prediction E1 implies two predictions: (i) the MFA's end increases the threshold $\bar{\varepsilon}_{ir}(y)$ for the given capability y and (ii) the threshold

and the control groups, the model with PAM should predict $\gamma^c > 0$ for both groups. In Appendix E.4, we present the regression (11) only for the treatment group.

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

$\bar{\varepsilon}_{ir}(y)$ is a decreasing function of the firm's capability y. Then, we estimate the following firm-level regression for Mexican firm i that exports product g to the United States in the initial year of period $r \in \{2001-04,\ 2004-07\}$:

$$Exit_{igsr} = \delta_1 Binding_g + \delta_2 Binding_g \times After_r + \delta_3 After_r + \delta_4 \ln Exports_{igr} + \delta_5 After_r \times \ln Exports_{igr} + \lambda_s + u_{igsr}. \quad (13)$$

The 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 for firm capability. Regression (13) uses the *level* of exports instead of their *ranking* because the level of capability determines the firm's exit, while the ranking of capability determines the matching. Predictions (i) and (ii) mentioned above are expressed as follows: (i) $\delta_2 > 0$, i.e., the end of the MFA increased the exit probability for a given capability level, and (ii) $\delta_4 < 0$ and $\delta_4 + \delta_5 < 0$, i.e., small low capability firms are more likely to exit.[36]

Number of Partners (E2) To test Prediction E2, we regress the changes in the number of partners on the binding dummy for US importers and Mexican exporters:

$$\Delta \# Partners^c_{igs} = \zeta^c_1 Binding_{gs} + \lambda_s + \varepsilon^c_{igs},\ c \in \{Mex, US\}, \quad (14)$$

where $\Delta \# Partners^c_{igs}$ is the changes in the number of firm i's partners in product g during 2004–2007, λ_s represents the HS two-digit-level fixed effects, and ε^c_{igs} are the error terms. Prediction E2 implies $\zeta^{Mex}_1 < 0$ and $\zeta^{US}_1 < 0$.

[36]One might think of introducing the triple interaction $Binding_g \times After_r \times \ln Exports_{igr}$ to examine whether the treatment effect on the exit probability decreases in the firm's initial exports. However, this alternative specification is unsuitable for testing Prediction E1. As observed in other customs data (e.g., Eaton et al., 2014), the exit probability of small exporters is high even without liberalization. For instance, the exit rate of the smallest 20% exporters before 2004 is greater than 0.85, while that for the top 20% is around 0.55. Thus, the treatment effect on the exit probability is naturally estimated to be small for these small exporters, but this does not necessarily contradict Prediction E1.

5 Results

5.1 Partner Changes

Table 4 reports the regressions for partner changes during 2004–2007 using linear probability models.[37] The columns with odd numbers report the estimates of β_d^c ($c = US, Mex$ and $d = U, D$) from the baseline regressions (10). 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 of 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.[38] These effects are quantitatively large compared with the sample averages of Up_{igs}^{US} and $Down_{igs}^{Mex}$, which are 3 and 15 percentage points, respectively.[39]

The columns with even numbers in Table 4 add the firm's own ranking and its interaction with the binding dummy. Both large and small firms switch their partners as the model predicts. Figure 5 illustrates these results by drawing the kernel-weighted local mean regressions of the partner change dummies on the firm's own ranking for apparel products.[40] The dashed lines and areas represent the regression lines with 90% confidence bands for the treatment group, while the solid lines and areas represent those for the control group. A higher probability of US importers'

[37]The probit regressions in Appendix E.3.1 provide similar results for all the regressions.

[38]β_D^{Mex} is estimated to be larger than β_U^{US} because of the following partner changes within initial partners, which is consistent with the theoretical model. Suppose that a Mexican exporter had been exporting to two US importers in 2004 and that these two US importers buy only from that 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} to be estimated as larger than β_U^{US}. Appendix E.3.5 shows the results are robust when distinguishing a firm's main partner change within and beyond initial partners.

[39]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 in 2007. In the dataset, only 12% of US importers and 12% of Mexican exporters traded with the same main partner in both 2004 and 2007. The sample averages of Up_{igs}^{US} and $Down_{igs}^{Mex}$ are likely to underestimate the true probabilities of partner changes in the population. In our dataset, partner upgrading and downgrading are observed only if the firm, new partner, and old partner are all continuing firms. Partner switching to firms in other countries and firms that did not exist in 2004 are excluded.

[40]We used the Epanechnikov kernel and chose the bandwidth to minimize the integrated mean squared error. Appendix E.3.2 shows the plot for textile products.

Table 4: 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: The dependent variables Up^c_{igs} and $Down^c_{igs}$ are dummy variables indicating whether during 2004–2007 firm i in country c switched its main partner of HS six-digit product g in country c' to one with a higher or lower capability ranking, 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 ranking of firm i in 2004. All the regressions include the HS two-digit (sector) fixed effects. Standard errors are in parentheses and clustered at the HS six-digit product level. Significance: * 10%, ** 5%, *** 1%.

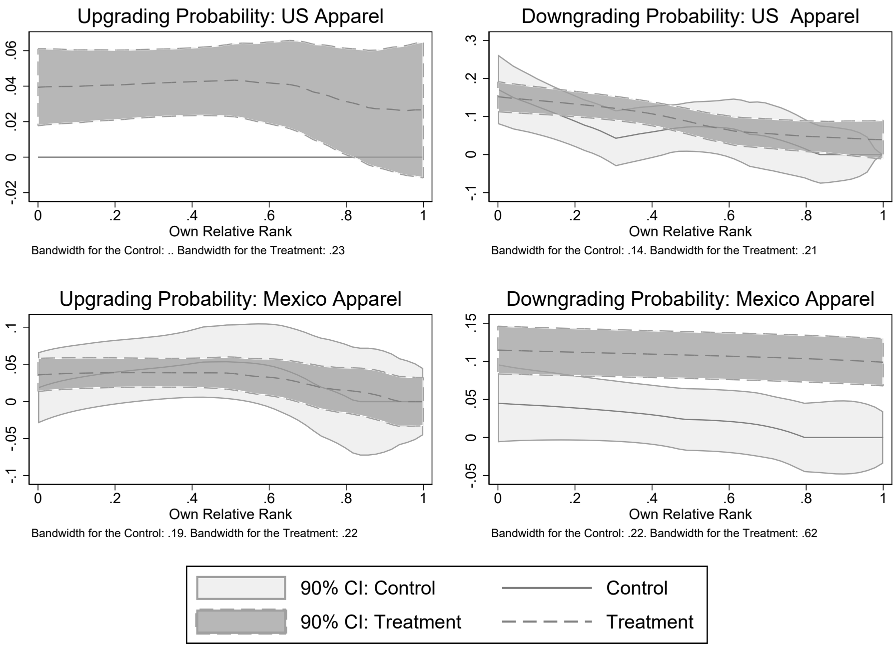
upgrading and Mexican exporters' downgrading in the treatment group is found uniformly for all the capability rankings. By contrast, little difference between the two groups in the probability of US importers' downgrading and Mexican exporters' upgrading is found.

Table 5 examines partner changes in the later periods of 2007–2011 and 2009–2011 to check our assumption that both the treatment and the control groups exhibit similar partner change patterns if the treatment is absent.[41] For each period, we reconstruct the capability rankings based on trade in the new initial years and recreate the upgrading/downgrading dummies. If the transition from the old to the new equilibrium was largely completed by 2007, we should observe no difference in partner changes between the two groups. Table 5 reports 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.[42]

[41]Examining partner changes before 2004 is one way to check this assumption, but this is not feasible since our data only contain partner information from June 2004 onward. At the aggregate level, Figure 1 demonstrates the absence of differential time trends in aggregate exports before the removal of the MFA quota in 2005.

[42]The period 2008–11 shows a different pattern from the other two periods. One possible reason is the Lehman Brothers crisis and the global financial crisis of 2008. Similar to exports from other countries, Mexican exports

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



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

We conduct numerous robustness checks, as shown in Appendix E.3. First, we include as additional controls several product-level and firm-product-level characteristics that statistically differ between the treatment and control groups.[43] Second, to address potential within-firm interactions in firms that trade multiple product and firms that had multiple partners in 2004, we conduct three exercises. We add the number of products that a firm trades and its interaction with the binding dummy, address the case that the main partner switching occurs within initial partners in 2004, and distinguish firms that had a single partner in 2004 and those that had multiple partners. Finally, we adopt alternative variable definitions. We define partner switching using rank bins, define quota

declined markedly in the second half of 2008. This shock might have introduced noise into the rankings.

[43]These product-level characteristics are the 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 textiles. These firm-product-level characteristics are the log of a firm's product trade volume with the main partner, share of Maquiladora/IMMEX trade in a firm's product trade, number of partners, and dummy of whether a US importer is an intermediary firm such as a wholesaler and retailer.

Table 5: 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	-0.007	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 note of Table 4 for variables' definitions. All the regressions include the HS 2 digit (sector) fixed effects. Standard errors in parentheses are clustered at the HS 6 digit product level. Significance: * 10%, ** 5%, *** 1%.

binding under alternative criteria, and use alternative windows of two and four years. Our main results are robust to all of these alternatives.[44]

5.2 New and Old Partners Ranks

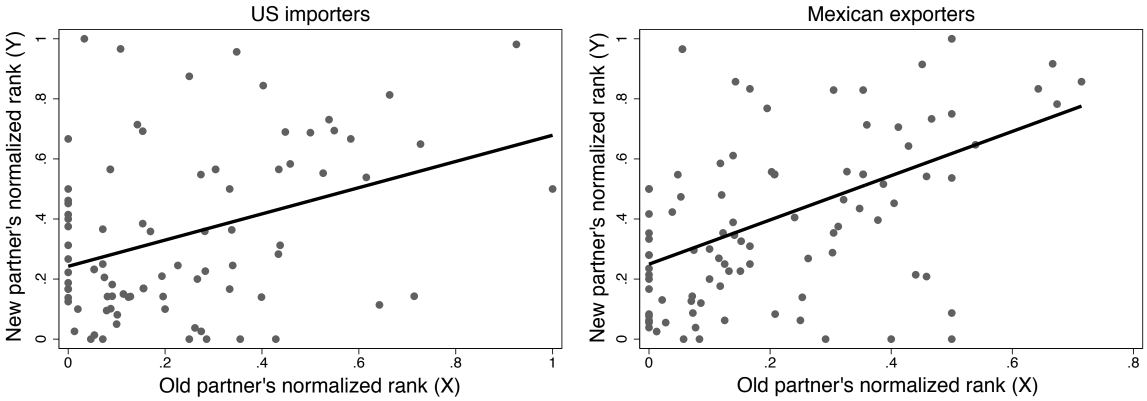
Figure 6 reports regression (11), which tests Predictions C2 and I2, with the corresponding scatterplots. For those US importers that changed their main partners between 2004 and 2007, the left panel displays the rankings of their old partners on the horizontal axis and those of their new partners on the vertical axis. The right panel draws a similar plot for Mexican exporters. The lines represent OLS regression (11). Figure 6 and the regressions show significant positive relationships. Firms that matched with relatively high capability partners in 2004 switched to relatively high capability partners in 2007. This result again supports Case C and rejects Case I.

5.3 Capability Cutoff Changes and Number of Partners

Table 6 reports the tests of Prediction E1. Column (1) reports the baseline specification of product-level regression (12) and Column (2) includes as additional control variables the product character-

[44] One exception is the regression of the US importer when all the product-level and firm-product-level characteristics are included as controls together. The coefficient becomes insignificant, but remains qualitatively the same (β_U^{US} is 73% of the benchmark estimate with p-value 0.12).

Figure 6: Old and New Partner Ranks



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

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

Note: The left panel plots the ranking of new main partners in 2007 against the ranking of old main partners in 2004 for US importers that changed their main partners between 2004 and 2007. The right panel draws similar partner rankings for Mexican exporters. The lines represent OLS fits.

istics for the initial year in each period and their interactions with the after dummy. These controls, when available, are the same as in footnote 43.[45] The estimates of the 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 (13) and Column (6) includes the product characteristic variables and their interactions with the after dummy. The estimates of the positive and significant δ_2 confirm that the MFA's end increased their exit probability for a given capability level. In addition, the negative estimates of δ_4 and $\delta_4 + \delta_5$ confirm that small exporters are more likely to exit the market.

Columns (3) and (7) show placebo checks that estimate regressions (12) and (13) using two periods before the MFA liberalization, 1998–2001 and 2001–2004, respectively.[46] Columns (4) and (8) include the control variables. In all the placebo checks, the estimated δ_2 is close to zero and statistically insignificant, or shows a negative sign. These results reject the concern that the estimate of δ_2 captures a prior difference in the trend between the two groups.

[45] They are the number of exporters, log product trade, and product type dummies.

[46] For this analysis we use the customs transaction dataset for 1998-2004, which does not have US importer information. See Appendix B.1 for the data construction.

Table 6: 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)	(8)
Binding	-1.255***	-0.668***	-1.074***	-0.786***	-0.040***	-0.028**	-0.021	0.009
(δ_1)	(0.281)	(0.246)	(0.248)	(0.249)	(0.014)	(0.013)	(0.016)	(0.014)
Binding	1.031**	1.188**	0.106	0.324	0.076***	0.089***	-0.003	-0.034**
$\times$After (δ_2)	(0.479)	(0.490)	(0.178)	(0.244)	(0.017)	(0.021)	(0.013)	(0.015)
After	-3.402***	-0.863	-0.230	0.809	-0.361***	-0.345***	-0.119***	-0.212***
(δ_3)	(0.364)	(1.620)	(0.151)	(0.785)	(0.042)	(0.077)	(0.034)	(0.056)
$\ln Export$					-0.058***	-0.056***	-0.069***	-0.066***
(δ_4)					(0.002)	(0.003)	(0.003)	(0.003)
$\ln Export$					0.020***	0.020***	0.011***	0.008**
$\times$After (δ_5)					(0.003)	(0.003)	(0.003)	(0.003)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	696	696	652	652	22,625	22,624	24,043	22,142

Note: $\ln ExportCutoff_{gsr}$ is the log of the minimum of firm-product-level exports in the initial year of period r. $Exit_{igsr}$ is a dummy variable 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 exports of product g in the initial year of period r. Columns (2), (4), (6), (8) include the product-level controls. All the regressions include the HS two-digit (sector) fixed effects. Standard errors are shown in parentheses and clustered at the HS six-digit product level. Significance: * 10%, ** 5%, *** 1%.

Table 7: Changes in the Number of Partners during 2004–07

	Change in Number of Partners	
	Mexico	US
	(1)	(2)
Binding	-0.65**	-0.12*
	(0.33)	(0.06)
HS2 FE	Yes	Yes
Obs.	601	718

Note: The dependent variables are the change in the number of partners during 2004–2007. $Binding_{gs}$ is a dummy variable indicating whether product g from China faced a binding US import quota in 2004. All the regressions include the HS two-digit (sector) fixed effects. Standard errors are shown in parentheses and clustered at the HS six-digit product level. Significance: * 10%, ** 5%, *** 1%.

Columns (1) and (2) in Table 7 report regression (14). The negative and significant coefficients of the binding dummy confirm Prediction E2 that both US importers and Mexican exporters reduce the number of partners in liberalized industries.

5.4 Alternative Capability Rankings

In Appendix E.5, we present our tests using three alternative rankings: the ranking of a firm's total product trade in 2004, that of a firm's unit price of the product's trade with the main partners in 2004, and that of a firm's demand-based quality estimated using the method of Khandelwal et al. (2013). We use the total trade ranking as a robustness check and the two other rankings to examine whether an exporter's capability that determines matching is quality or productivity. If the exporter's capability mainly reflects quality rather than productivity, the latter two rankings may agree with the capability ranking. On the contrary, if the exporter's capability mainly reflects productivity, the unit price ranking may become the reverse of the capability ranking.

The main results are robust to the use of alternative rankings, as shown in Table A.24 in Appendix E.5. The results of the price and quality rankings suggest that quality determines exporter–importer matching. Consistent with previous findings that show that quality is an important determinant of a firm's export participation, quality also determines a firm's export partner.[47]

5.5 Alternative Explanations

Our empirical tests confirmed all PAM's predictions. Independent random matching and matching based on idiosyncratic match-specific shocks, both of which predict Predictions I1 and I2, cannot explain these patterns alone. Such randomness in matching could also play some role because the goodness of fit of PAM's predictions is not perfect.

[47] See Kugler and Verhoogen (2012), for example.

Appendix C examines four alternative hypotheses for our findings. The first hypothesis is negative assortative matching under which trade rankings may not agree with true capability rankings. The second hypothesis is repeated random independent matching. Suppose random partner change occurs in every period and exhibits mean reversion. The exit from the market of less capable Mexican exporters may create a positive correlation between the binding dummy and downgrading by Mexican exporters. Third, the segment-switching hypothesis is that Mexican exporters switch a product segment from large-scale production with small markups to small-scale production with large markups. The final hypothesis, the production capacity hypothesis, is that a US importer's partner switches from small to large suppliers to seek large production capacity. For these hypotheses, we conduct additional analyses and show that none of them fully explain our results.

6 Concluding Remarks

This study presented theory and evidence for a simple mechanism of exporter–importer matching: Beckerian PAM by capability. Beckerian PAM offers several new insights into buyer–supplier relationships in international trade. As our model showed, rematching in trade liberalization brings about two new gain-accruing channels. First, at the sector or aggregate levels, trade liberalization improves efficiency by rematching buyers and suppliers. Quantifying these matching-induced gains from trade is an important topic for future research. Second, at the individual level, firms see improved performance when they upgrade their partners. Regarding the second channel, Beckerian PAM has two implications that can be brought to data in future studies. First, the benefits to local firms increase in the capability of foreign partners. Second, only local firms with high capability can maintain stable relationships with high capability foreign firms. The latter suggests the importance of capability development policies to complement trade promotion policies.

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

A Proofs and Derivations

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

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

Consider a final product market i and omit subscript 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

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

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

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

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 $\theta_L(x_L) = \theta\left(x_L, y_L(x_L)\right)$ 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:

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

where $\theta\left(x, y\right) = \theta^x\left(x\right) + \theta^y\left(y\right)$ 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 the increase in y_L will be given in Section A.2.1. 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 4 and Figure 5 find this is not the case. Partner switching occurs for firms at all capability levels as in the main model.

A.2 Proofs

A.2.1 Proof for Proposition 1 and $dy_L > 0$ for Case C and Case I

This section proves Proposition 1 and 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 Proposition 1 Denote the environment after the MFA's end *A-environment,* the environment of the no-rematching equilibrium as *NR-environment*, and the environment before the

MFA's end as *B-environment*.

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

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

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

Proof. Suppose $y_L^{NR} \leq y_L^B$. This means $x_L^{NR} < x_L^B$ and $M^{NR} > M^B$. Since $\theta_L = \theta(x_L, y_L)$ holds in Case C and Case I, $y_L^{NR} < y_L^B$ and $x_L^{NR} < x_L^B$ imply that $\theta_L^{NR} < \theta_L^B$. From $\theta_L = \frac{\sigma f}{\delta}\Theta$ in (7), this means $\Theta^{NR} < \Theta^B$. Since equilibrium matching in the B-environment is feasible in the NR-environment, Lemma 3 and $M^{NR} > M^B$ imply that $\Theta^{NR} > \Theta^B$. This contradiction implies $y_L^{NR} > y_L^B$.

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

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 $\theta_L^{NR} \leq \theta_L^B$ 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 Proposition 1. QED.

A.2.2 Proof for Proposition 2

We prove $E\left[y|\, y + \varepsilon = \upsilon\right]$ is increasing in υ. Let $g_y(y|\upsilon)$ be the density of y conditional on υ, which is given by

$$g_y(y|\upsilon) \equiv \frac{g_{y,\upsilon}\left(y, \upsilon\right)}{g_\upsilon(\upsilon)} = \frac{g_y(y)g_\varepsilon(\upsilon - y)}{\int_{\upsilon-\varepsilon_{max}}^{\upsilon-\varepsilon_{min}} g_y(t)f_\varepsilon(\upsilon - y)dt}. \tag{A6}$$

Consider $y_1 > y_0$ and $\upsilon_1 > \upsilon_0$. The logconcavity of $g_\varepsilon(\varepsilon)$ implies

$$\frac{g_\varepsilon(\upsilon_1 - y_1)}{g_\varepsilon(\upsilon_1 - y_0)} \geq \frac{g_\varepsilon(\upsilon_0 - y_1)}{g_\varepsilon(\upsilon_0 - y_0)}. \tag{A7}$$

See An (1998, Proposition 1) for the proof. From (A6) and (A7), $f_y(y|\upsilon_1)$ and $f_y(y|\upsilon_0)$ satisfy the following monotone likelihood ratio property:

$$\frac{g_y(y_1|\upsilon_1)g_y(y_0|\upsilon_0)}{g_y(y_1|\upsilon_0)g_y(y_0|\upsilon_1)} = \frac{g_\varepsilon(\upsilon_1 - y_1)g_\varepsilon(\upsilon_0 - y_0)}{g_\varepsilon(\upsilon_1 - y_0)g_\varepsilon(\upsilon_0 - y_1)} \geq 1.$$

The monotone likelihood ratio property implies that $g_y(y|\upsilon_1)$ first order stochastically dominates $g_y(y|\upsilon_0)$. Hence, $E\left[y|\upsilon_1\right] \geq E\left[y|\upsilon_0\right]$. That $E\left[x|\, x + \eta = \chi\right]$ is increasing in χ can be proved in a similar way.

A.2.3 Proof for Lemma 2

Consider the model in section 3.3. Trade within a match $T(\chi, \upsilon)$ is equal to the production line's costs and profit:

$$\begin{aligned} T(\chi, \upsilon) &= [c_y q(\theta(\chi, \upsilon)) + f_y] + \pi_\upsilon(\upsilon) \\ &= \left[\frac{c_y}{c}\{C(\theta(\chi, \upsilon)) - f\} + f_y\right] + \pi_\upsilon(\upsilon) \end{aligned}$$

From $C'(\theta) > 0$ from (1), $\partial T(\chi, \upsilon)/\partial \chi > 0$ and $\partial T(\chi, \upsilon)/\partial \upsilon > 0$ hold.

Case C Let $\varepsilon^*(y) \equiv \max_{k=1,\dots,n(y)} \varepsilon_k$ be the maximum among the $n(y)$ draws of idiosyncratic capability by a supplier with firm capability y. Then, $\upsilon^*(y) \equiv \varepsilon^*(y) + y$ is the most capable production line's capability and $T(m_\upsilon(\upsilon^*(y)), \upsilon^*(y))$ is the export by a supplier with firm capability y to the main partner. Let $G_\varepsilon(\varepsilon)$ and $G_{\varepsilon^*(y)}(\varepsilon^*)$ be the CDFs of ε and $\varepsilon^*(y)$. Let $g_{\varepsilon^*(y)}(\varepsilon^*)$ be the density of $\varepsilon^*(y)$. Let $H_{\upsilon^*|y}(\upsilon|y) \equiv \Pr(\varepsilon^* \leq \upsilon - y | \varepsilon^* \geq \upsilon_L - y)$ be the CDF of $\upsilon^*(y)$ conditional on y. The export by a supplier with firm capability y to the mean main partner is

$$X(y) = \int T(m_\upsilon(s), s) dH_{\upsilon^*|y}(s|y).$$

Claim 4. For $y_1 > y_0$, $H_{\upsilon^*|y}(\cdot|y_1)$ first order stochastically dominates $H_{\upsilon^*|y}(\cdot|y_0)$.

Proof. The CDF $H_{\upsilon^*|y}(s|y)$ is given by

$$\begin{aligned} H_{\upsilon^*|y}(s|y) &= \Pr(\varepsilon^* \leq s - y | \varepsilon^* \geq \upsilon_L - y) \\ &= \frac{G_{\varepsilon^*(y)}(s - y) - G_{\varepsilon^*(y)}(\upsilon_L - y)}{1 - G_{\varepsilon^*(y)}(\upsilon_L - y)}. \end{aligned}$$

Its derivative with respect to y is

$$\begin{aligned}\frac{dH_{\upsilon^*|y}(s|y)}{dy} &= -\frac{g_{\varepsilon^*(y)}(s-y)\left[1-G_{\varepsilon^*(y)}(\upsilon_L-y)\right]-g_{\varepsilon^*(y)}(\upsilon_L-y)\left[1-G_{\varepsilon^*(y)}(s-y)\right]}{\left[1-G_{\varepsilon^*(y)}(\upsilon_L-y)\right]^2}\\ &= -\frac{\left[1-G_{\varepsilon^*(y)}(s-y)\right]}{\left[1-G_{\varepsilon^*(y)}(\upsilon_L-y)\right]}\left[\frac{g_{\varepsilon^*(y)}(s-y)}{1-G_{\varepsilon^*(y)}(s-y)}-\frac{g_{\varepsilon^*(y)}(\upsilon_L-y)}{1-G_{\varepsilon^*(y)}(\upsilon_L-y)}\right]. \end{aligned} \tag{A8}$$

Since $G_{\varepsilon^*(y)}(\varepsilon) = G_\varepsilon(\varepsilon)^{n(y)}$ and $g_{\varepsilon^*(y)}(\varepsilon) = n(y)G_\varepsilon(\varepsilon)^{n(y)-1}g_\varepsilon(\varepsilon)$,

$$\ln g_{\varepsilon^*(y)}(\varepsilon) = n(y) + (n(y)-1)\ln G_\varepsilon(\varepsilon) + \ln g_\varepsilon(\varepsilon). \tag{A9}$$

Since $g_\varepsilon(\cdot)$ is logconcave, $G_\varepsilon(\cdot)$ is also logconcave (see An, 1995, Lemma 3). Therefore, from (A9), $g_{\varepsilon^*(y)}(\cdot)$ is also logconcave.

Since $g_{\varepsilon^*(y)}(\cdot)$ is logconcave, the hazard rate $\frac{g_{\varepsilon^*(y)}(\cdot)}{1-G_{\varepsilon^*(y)}(\cdot)}$ is monotonically increasing (see An, 1995, Proposition 1). Therefore, from (A8), $H_{\upsilon^*|y}(s|y)$ is decreasing in y for all $s \geq \upsilon_L$. $\square$

Since $T(m_\upsilon(\upsilon),\upsilon)$ is increasing in υ, Claim 4 implies $X(y_1) \geq X(y_0)$ for $y_1 \geq y_0$. The monotonicity of $I(x)$ can be proved by similar steps.

Case I Consider a supplier with firm capability y. Denote the supplier's exports to a partner k by $T(\chi_k, y+\varepsilon_k)$ and that to the main parter by $T^*(y) = \max_{k=1,\ldots,n(y)} T(\chi_k, y+\varepsilon_k)$.

Let $H_{\upsilon|y}(s|y) \equiv \Pr(\varepsilon \leq s-y|\varepsilon \geq \upsilon_L - y)$ be the CDF of an active production line's capability at a supplier with firm capability y and $h_{\upsilon|y}(s|y)$ be its density. Similar steps in Claim 4 proves the following claim.

Claim 5. For $y_1 > y_0$, $H_{\upsilon|y}(\cdot|y_1)$ first order stochastically dominates $H_{\upsilon|y}(\cdot|y_0)$.

Let $K_{T^*}(t|y) = \Pr(T^*(y) \leq t|y, \upsilon \geq \upsilon_L)$ be the CDF of $T^*(y)$ conditional on y. Then, the mean export to the main partner by the supplier is expressed as

$$\begin{aligned} X(y) &= E\left[T^*(y)|y, \upsilon \geq \upsilon_L\right] \\ &= \int t dK_{T^*}(t|y). \end{aligned}$$

Claim 6. For $y_1 > y_0$, $K_{T^*}(\cdot|y_1)$ first order stochastically dominates $K_{T^*}(\cdot|y_0)$.

Proof. Let $K_T(t|y) \equiv \Pr\left(T(\chi, \upsilon) \leq t|y, \upsilon \geq \upsilon_L\right)$ be the CDF of $T(\chi_k, y + \varepsilon_k)$ conditional on y and active production lines, which is given by

$$\begin{aligned} K_T(t|y) &\equiv \Pr\left(T(\chi, \upsilon) \leq t|y, \upsilon \geq \upsilon_L\right) \\ &= \int\int I\{T(\chi, \upsilon) \leq t\} f_\chi(\chi) h_{\upsilon|y}(\upsilon|y, \upsilon \geq \upsilon_L) d\chi d\upsilon \\ &= \int \left[\int I\{T(\chi, \upsilon) \leq t\} f_\chi(\chi) d\chi\right] h_{\upsilon|y}(\upsilon|y, \upsilon \geq \upsilon_L) d\upsilon \\ &= \int \bar{T}(\upsilon, t) h_{\upsilon|y}(\upsilon|y, \upsilon \geq \upsilon_L) d\upsilon \end{aligned} \tag{A10}$$

where $I\{\cdot\}$ is an indicator function and $\bar{T}(\upsilon, t) \equiv \int I\{T(\chi, \upsilon) \leq t\} f_\chi(\chi) d\chi$. Consider $y_1 > y_0$. Since $\bar{T}(\upsilon, t)$ is non-increasing in υ for given t, Claim 5 implies $\int \bar{T}(\upsilon, t) h_{\upsilon|y}(\upsilon|y_1, \upsilon \geq \upsilon_L) d\upsilon \leq \int \bar{T}(\upsilon, t) h_{\upsilon|y}(\upsilon|y_0, \upsilon \geq \upsilon_L) d\upsilon$. Therefore, $K_T(t|y_1) \leq K_T(t|y_0)$.

Since

$$\begin{aligned} K_{T^*}(t|y) &= \prod_{k=1}^{n(y)} \Pr\left(T(\chi_k, y + \varepsilon_k) \leq t|y, \upsilon \geq \upsilon_L\right) \\ &= K_T(t|y)^{n(y)}, \end{aligned}$$

$K_{T^*}(t|y_1) \leq K_{T^*}(t|y_0)$ holds for all t. That is, $K_{T^*}(t|y_1)$ first order stochastically dominates $K_{T^*}(t|y_0)$. □

For $y_1 > y_0$, Claim 6 implies $X(y_1) \geq X(y_0)$. Therefore, $X(y)$ is increasing in y. The monotonicity of $I(x)$ can be proved by similar steps. QED.

A.3 Negative Assortative Matching

A.3.1 Solving the Model

In Case S, the market clearing condition becomes

$$M_U[1-F(x)] = (M_M + M_C)\left[G\left(m_x\left(x\right)\right) - G(y_L)\right] \text{ for all } x \geq x_L. \tag{A11}$$

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 (A11) 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

$$
\begin{aligned}
A\theta\left(x_L, y_{max}\right) - f &= A\int_{m_x(x_{max})}^{y_{max}} \theta_2(m_y(t), t)dt \\
\frac{\delta}{\sigma\Theta(x_L)}\left[\theta\left(x_L, y_{max}\right) - \int_{m_x(x_{max})}^{y_{max}} \theta_2(m_y(t), t)dt\right] &= f.
\end{aligned}
\tag{A12}
$$

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 1. 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), (A11) and (A12).

A.3.2 Supplier Exit after the MFA's End

Following section A.2.1, 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 (A12) 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

$$\begin{aligned}
\int_{y_L^B}^{y_{max}} \int_{m_y^A(t)}^{m_y^B(t)} \theta_{12}(z,t)dzdt &= \int_{y_L^B}^{y_{max}} \left[\theta_2(m_y^B(t), t) - \theta_2(m_y^A(t), t)\right] dt \\
&= \int_{y_L^B}^{y_{max}} \theta_2(m_y^B(t), t)dt - \int_{y_L^B}^{y_{max}} \theta_2(m_y^A(t), t)dt \\
&\geq \int_{y_L^B}^{y_{max}} \theta_2(m_y^B(t), t)dt - \int_{y_L^A}^{y_{max}} \theta_2(m_y^A(t), t)dt \\
&> 0. \qquad \text{(A13)}
\end{aligned}$$

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

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

which contradicts with (A13). $\square$

A.3.3 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 (A11), we obtain the partner change of importers with capability x:

$$dm_x(x) = \frac{\Gamma(x)}{g(m_x(x))}, \Gamma(x) \equiv g(y_L)dy_L - \frac{G(m_x(x)) - G(y_L)}{(M_M + M_C)} dM_C. \tag{A14}$$

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.

B Data Construction

B.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.

In addition to the dataset described in the previous paragraph, we also use the Mexican customs transaction record from 1998 January to 2004 May in our analysis in Section 5.3. The customs transaction dataset for 2000 January -2004 May does not contain variable (6) mentioned in the previous paragraph. The customs transaction dataset for 1998-1999 does not contain variables (6) or (7). Thus, these datasets cannot be used for our analysis of partner switching and are used to conduct placebo checks in Section 5.3. Next sections explain the cleaning and construction of variables from our primary dataset.

B.2 Assign Importer IDs

We used a series of methods developed in record-linkage research to assign importer-ID.[48]

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.[49] 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

[48] 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.

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

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 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.

B.3 Data Cleaning

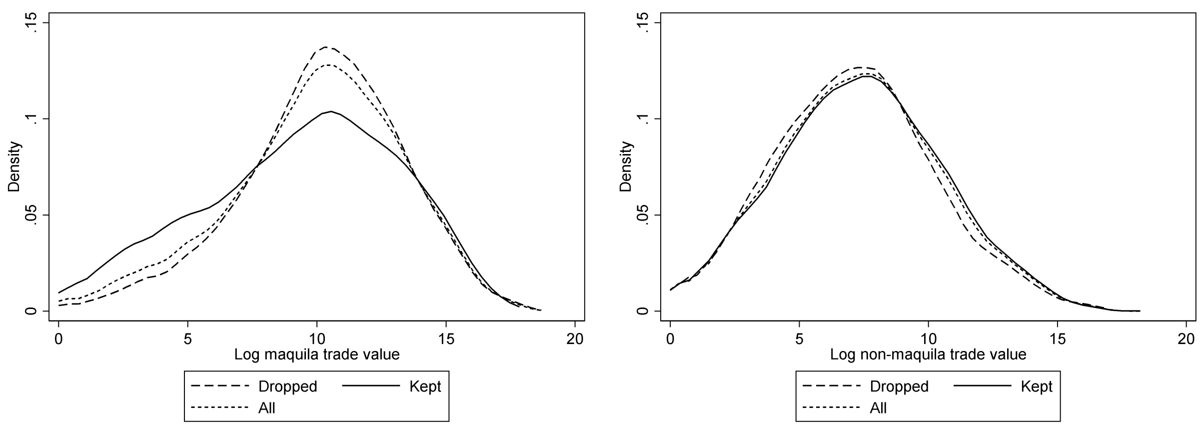
Some information was dropped from the dataset. First, we dropped exporters who are individuals or courier companies (e.g., FedEx, UPS, etc.) because we focus on firm to firm matching. Second, as the dataset contains information only from June to December for 2004, we dropped observations from January to May for other years to make each year's information comparable. We conducted our main analysis (Table 4) 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.[50] 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 densi-

[50] 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.

ties 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

Figure A.1: Sample Selection



Note: 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").

B.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.[51] Then, we run weighted least squares of the main specification in Table 4, using the inverse of estimated selection probability as weight. The results shown in Table A.1 are very similar to those in Table 4. Thus, our results are

[51]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.

not driven by sample selection due to the data cleaning.

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
$\times$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.

B.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:

$$Binding_g = I\left\{\frac{\sum_{j\in J(g)} x^m_{j2004} I\{\text{quota on } j \text{ was binding in 2004}\}}{\sum_{j\in J(g)} x^m_{j2004}} \geq 0.5\right\}, \tag{A15}$$

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.

C 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 independent random matching" where firms are forced to change partners randomly and independently of capability 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, we should also observe that 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 (10). However, columns (5) and (6) in Table 4 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 4 shows that both small and large US importers upgrade partners in a similar way.

Furthermore, Table A.2 examines whether imports by initially small US importers ("custom") show higher growth rates than those by large US importers ("standardized"). 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_{igs}^{US}				-0.191
				(1.062)
Up_{igs}^{US}×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_{igs}^{US} 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.

D A Two-Tier Exporter-Importer Matching Model

D.1 Replication of Firm-Level Negative Degree Assortativity

Table A.3 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.3 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.3 shows that the negative degree assortativity holds at firm-level but almost disappears at 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.3: Negative Degree Assortativity under Different Match Definitions

Definition of Match	Log average number of sellers per buyer					
	Firm-Level		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)	(0.020)	(0.017)
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.

D.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:

$$q = x\left(\sum_{k=1}^{K}\left(y_k^\beta d_k\right)^{\frac{\eta-1}{\eta}}\right)^{a\eta/(\eta-1)}\left(l - n_m f_x - f\right)^{1-a}, \tag{A16}$$

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 $c_y \left(y_k\right)^\gamma q + f_y$ 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

$$M_S^1 > M_S^2 > ... > M_S^K. \tag{A17}$$

The CDFs of Mexican supplier's capability and Chinese supplier's capability are the same and given by $y_k \sim G\left(y\right)$ 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

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

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.[52]

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

Assumption 2. *θ is symmetric with respect to $(y_1, ..., y_K)$, increasing, 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 $\partial^2\theta(z)/\partial y_j \partial y_k > 0$ 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 $\pi_i(0) \equiv 0$, and $I\{y'_i \neq 0\}$ indicates whether the team includes intermediate i supplier or not. Vector y_{-k} is a $K-1$ dimensional vector that represents the capability of all suppliers in the team except k-th supplier.

As in the case of one-to-one matching, stable matching is PAM. The proof is given at the end

η.

of this section.

Lemma 7. *Stable matching is PAM.*

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

$$M_U[1 - F(x)] = M_S^k [1 - G(m_k(x))]. \tag{A18}$$

From (A17) and (A18), the order of product capability across intermediates within a team is

$$m_1(x) > m_2(x) > ... > m_K(x). \tag{A19}$$

Final producers with low x may prefer to match with fewer than K partners to save fixed costs of matching. From (A19), 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

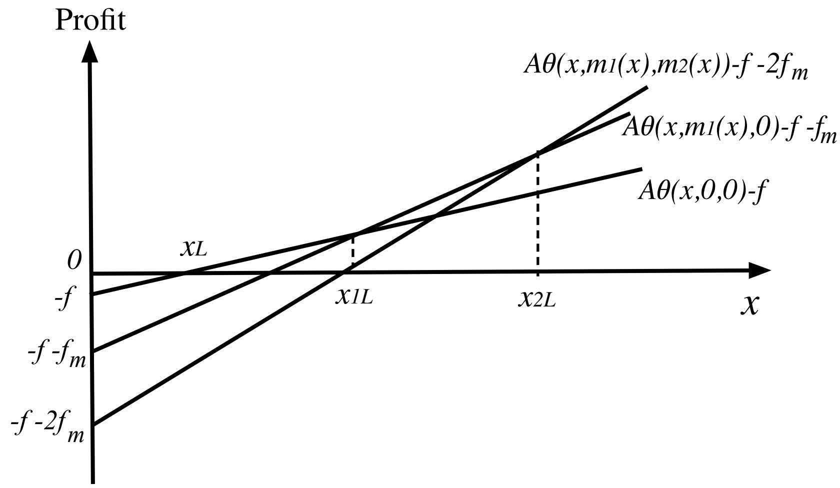
$$\begin{aligned} &A\theta\left(x_{kL}, m_1(x_{kL}), ..., m_{k-1}(x_{kL}), m_k(x_{kL}), 0, .., 0\right) \\ &\qquad - A\theta\left(x_{kL}, m_1(x_{kL}), ..., m_{k-1}(x_{kL}), 0, 0, .., 0\right) = f_m. \end{aligned} \tag{A20}$$

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 (A20) for x_{kL} and x_{k-1L} can be rewritten as:

$$
\begin{aligned}
A\int_0^{y_{kL}} \frac{\partial\theta\left(x_{kL}, m_1(x_{kL}), ..., m_k(x_{kL}), t, 0, .., 0\right)}{\partial y_k} dt &= f_m \\
A\int_0^{y_{k-1L}} \frac{\partial\theta\left(x_{k-1L}, m_1(x_{k-1L}), ..., m_{k-1}(x_{k-1L}), t, 0, .., 0\right)}{\partial y_k} dt &= f_m.
\end{aligned} \tag{A21}
$$

Second, Assumption 2 and PAM imply

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

Therefore, from (A21), $y_{kL} < y_{k-1L}$. The cutoff capabilities of final producers and suppliers are summarized as follows.

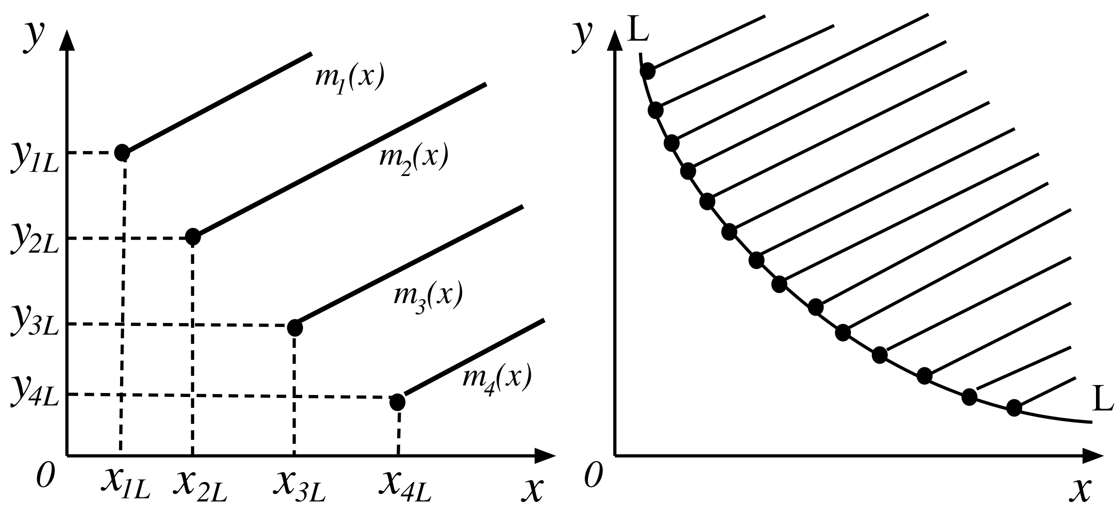
Lemma 8. *x_{kL} is increasing in k and y_{kL} is decreasing in k.*

Lemma 8 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 (A19). 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 (A19). 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 2. 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 4. *(1) The negative degree assortativity holds when a match is defined at the firm level, but not when it is defined at the product level. (2) PAM holds when a match is defined at the product level.*

The results in Table A.3 supports Proposition 4 as we explained above.

Proof for Lemma 7 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

$$\theta\left(z \vee z'\right) + \theta(z \wedge z') > \theta(z) + \theta(z'). \tag{A22}$$

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 (A22),

$$
\begin{aligned}
A\theta\left(z \vee z'\right)+A\theta\left(z \wedge z'\right)-\left(n+n'\right) f_m-2f &> A\theta\left(z\right)+A\theta\left(z'\right)-\left(n+n'\right) f_m-2f \\
&= \pi_x(x)+\sum_{i=1}^{K} \pi_i(y_i)+\pi_x(x')+\sum_{i=1}^{K} \pi_i(y_i') \\
&= \pi_x(x)+\pi_x(x')+\sum_{i=1}^{K} \pi_i(y_i \vee y_i')+\sum_{i=1}^{K} \pi_i(y \wedge y_i').
\end{aligned} \tag{A23}
$$

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

$$
\begin{aligned}
\pi_x(x) &\geq A\theta\left(z \vee z'\right)-n' f_m-f-\sum_{i=1}^{K} \pi_i(y_i \vee y_i'). \\
\Rightarrow \pi_x(x)+\sum_{i=1}^{K} \pi_i(y_i \vee y_i') &\geq A\theta\left(z \vee z'\right)-n' f_m-f
\end{aligned} \tag{A24}
$$

(A23) and (A24) imply

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

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.

E Additional Figures and Tables

E.1 Table 1 for Alternative Samples

Table 1 for 2005 and 2006 Table A.4 reports statistics in Table 1 for 2005 and 2006. They show very similar patterns as Table 1.

Table A.4: Summary Statics

	HS 6 Product-Level match		Firm-Level match	
mean statistics (median)	2005	2006	2005	2006
(1) N of Exporters	14.9(8)	12.2 (6)	1,275	1,136
(2) N of Importers	19.4 (10)	16.0 (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)	0.76	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.5 and Table A.6 report statistics in Table 1 for the regression sample. They show very similar patterns as Table 1.

Table A.5: Summary Statics for Product-Level Matching: Regression Samples

Product-Level Matching	2004	2005	2006	2007
(1) Number of Exporters*	19.9	18.4	18.4	17.0
(2) Number of Importers‡	20.0	17.9	17.4	17.5
(3) Number of Exporters Selling to an Importer*	1.3 (1)	1.4 (1)	1.3 (1)	1.2 (1)
(4) Number of Importers Buying from an Exporter‡	2.2 (1)	2.3 (1)	2.1(1)	1.8 (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.6: Summary Statics for Firm-Level Matching: Regression Samples

Firm-Level Matching	2004	2005	2006	2007
(1) Number of Exporters*	397	378	328	355
(2) Number of Importers‡	681	627	559	550
(3) Number of Exporters Selling to an Importer*	1.6 (1)	1.6 (1)	1.5(1)	1.5 (1)
(4) Number of Importers Buying from an Exporter‡	2.7 (1)	2.7 (1)	2.5 (1)	2.3 (1)
(5) Value Share of the Main Exporter* (Number of Exporters > 1)	0.73	0.76	0.74	0.77
(6) Value Share of the Main Importer‡ (Number of Importers > 1)	0.73	0.75	0.76	0.78

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.

E.2 Further decomposition of the extensive margin

Table A.7 decomposes the changes in the extensive margin in Column (1), which is the same as Column 2 in Table 2, into 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.

Table A.7: 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.

E.3 Partner Switching Regressions

E.3.1 Probit Regression Result

Table A.8 replicates Table 4 by using the Probit model instead of the linear probability model. The results are robust. The observations for which there is no variation in the dependent variable within HS2 are dropped, which makes the number of the observations change depending on the dependent variables in Mexican analysis.

E.3.2 Figure 5 for Non-Apparel Products

Figure A.4 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

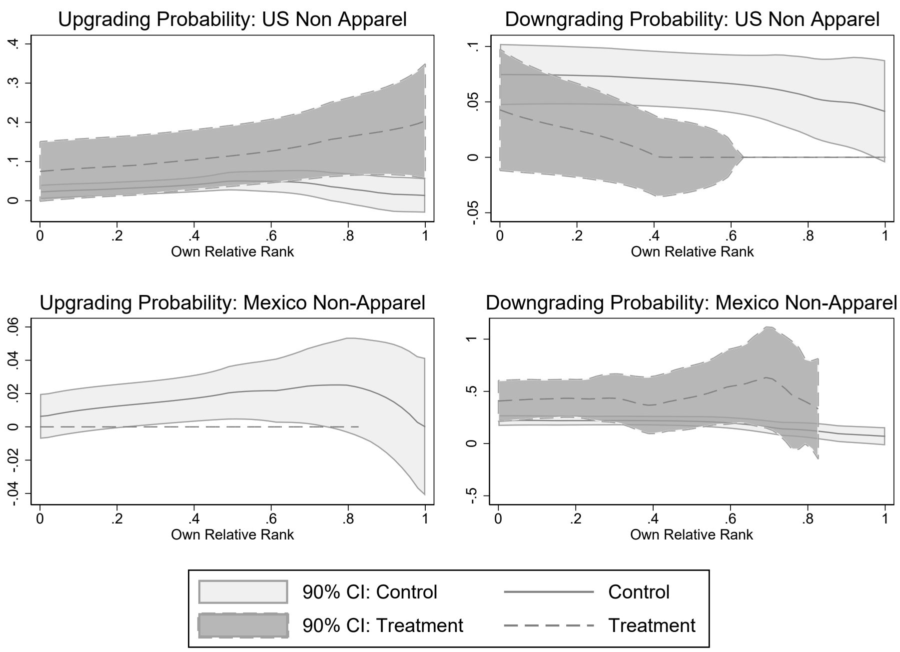
Table A.8: Partner Change during 2004–07

	Probit Models							
	Up^{US}		$Down^{US}$		Up^{Mex}		$Down^{Mex}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Binding	0.055**	0.049*	-0.017	-0.003	-0.003	0.001	0.151***	0.156***
	(0.022)	(0.026)	(0.024)	(0.035)	(0.020)	(0.020)	(0.045)	(0.055)
OwnRank		0.004		-0.085*		0.008		-0.085*
		(0.032)		(0.050)		(0.021)		(0.051)
Binding		0.016		-0.053		-0.010		-0.033
×OwnRank		(0.042)		(0.081)		(0.029)		(0.094)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	707	707	707	707	522	522	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.

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 4 and the predictions of PAM.

Figure A.4: 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.

E.3.3 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 than 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

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
	[15.53]		(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)	
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. 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	1579	-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)	(0.023)	

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.

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
	(0.021)	(0.022)	(0.021)	(0.021)	(0.021)	(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		-0.002
							(0.004)		(0.005)
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.	601	601	601	601	601	601	601	601	601

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.

E.3.4 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.

E.3.5 Main Partner Changes Beyond and Within Initial Partners

In data, some firms trade with multiple firms other than main partners. Main partner switching may occurs with initial partners in 2004. It may appear that main partner switching within initial partners contradicts with our theory, but it does not. The model in Section 3.3 allows main partner switching (US importer's main partner upgrading and Mexican main exporter's partner downgrading) to be either within or beyond initial partners. This prediction justifies our approach in the main text where we do not distinguish main partner switching beyond and within initial partners.

Table A.15 also shows partner switching regressions that distinguishes main partner switching beyond and within initial partners. E.g., the indicator of main partner upgrading in Columns labeled with "Beyond" is one if and only if partner upgrading occurs beyond initial partners. The table confirms prediction C1 of US importer's upgrading and Mexican exporter's downgrading even when main partner switching initial partners are removed.

Table A.15: Main Partner Changes Beyond and Within Initial Partners

	Liner Probability Models							
	Up^{US}		$Down^{US}$		Up^{Mex}		$Down^{Mex}$	
	Beyond	Within	Beyond	Within	Beyond	Within	Beyond	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.

E.3.6 Single Partner Firms and Multiple Partner Firms

In Table A.16, we distinguish US firms that had single partners in 2004 and those that had multiple partners. Columns (1) and (4) are the baseline results from Table 4 for reference. Columns (2) and (5) add the multi-partner firm dummy and its interaction term with the Binding dummy. Columns (3) and (6) further include the interaction of the multi-partner firm dummy with HS2 fixed effects, which would produce the results from running separately the regressions of Columns (1) and (4) each separately for single-partner firms and multi-partner firms.

Column (2) shows that the coefficient on Binding columns is similar to the one in Column (1) and the coefficient on the interaction term is close to zero. In Column (3), the coefficient on Binding columns becomes somewhat smaller and marginally statistically significant. The coefficient on the interaction term now becomes bigger though it is not statistically significant. These suggest that whether the response is similar between single partner firms and multi partner firms depends on the specifications, but the effect can be detected for single partner firms. We do not see much response going on downgrading for US firms.

Table A.16: Single Partner Firms and Multiple Partner Firms: US

	Partner Change in Different Periods: Linear Probability Models					
	Up^{US}			$Down^{US}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Binding	0.052**	0.047**	0.025*	-0.017	-0.038*	-0.014
	(0.021)	(0.018)	(0.014)	(0.027)	(0.022)	(0.019)
Multi-Partner		0.060	0.094		0.403***	0.239**
		(0.044)	(0.080)		(0.072)	(0.101)
Multi-Partner×Binding		-0.001	0.191		-0.094	-0.373***
		(0.058)	(0.131)		(0.097)	(0.133)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes
HS2 FE×Multi-Partner	No	No	Yes	No	No	Yes
Obs.	718	718	718	718	718	718

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

Table A.17 shows the results for Mexican firms. We see a similar pattern for Mexican firm's partner downgrading to the one we documented for the US firms' partner upgrading. We do not see much response going on upgrading for Mexican firms.

Table A.17: Single Partner Firms and Multiple Partner Firms: Mexico

	Partner Change in Different Periods: Linear Probability Models					
	Up^{Mex}			$Down^{Mex}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Binding	-0.003	-0.017	-0.020	0.127***	0.096***	0.042*
	(0.020)	(0.019)	(0.023)	(0.035)	(0.028)	(0.022)
Multi-Partner		0.012	0.018		0.332***	0.431***
		(0.017)	(0.023)		(0.042)	(0.106)
Multi-Partner×Binding		0.037	0.043		-0.001	0.195*
		(0.034)	(0.033)		(0.070)	(0.100)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes
HS2 FE×Multi-Partner	No	No	Yes	No	No	Yes
Obs.	601	601	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.

E.3.7 Using Bins instead of Ranks

As the supplier/buyer ranks may potentially suffer from the measurement errors, we used five bins, ten bins and twenty bins to rank firms. The results in Table A.18 are robust. These suggest that when firms upgrade/downgrade their trade partners, the ranks of their new main partners are sufficiently far away from those of the old partners.

Table A.18: Partner Change during 2004–07

	Linear Probability Models: Five Bins							
	Up^{US}		$Down^{US}$		Up^{Mex}		$Down^{Mex}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Binding	0.034*	0.034*	-0.022	-0.023	0.001	0.001	0.102***	0.113***
	(0.019)	(0.019)	(0.022)	(0.024)	(0.013)	(0.013)	(0.032)	(0.034)
OwnRank		0.002		0.001		-0.001		0.000
		(0.002)		(0.003)		(0.000)		(0.001)
Binding		-0.000		0.000		0.000		-0.005**
×OwnRank		(0.003)		(0.004)		(0.001)		(0.002)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	718	718	718	718	601	601	601	601
	Linear Probability Models: Ten Bins							
	Up^{US}		$Down^{US}$		Up^{Mex}		$Down^{Mex}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Binding	0.041**	0.037*	-0.029	-0.036	0.001	0.001	0.110***	0.126***
	(0.020)	(0.020)	(0.025)	(0.027)	(0.015)	(0.016)	(0.035)	(0.037)
OwnRank		0.003		-0.001		-0.002		0.000
		(0.005)		(0.005)		(0.001)		(0.003)
Binding		0.001		0.005		0.000		-0.012**
×OwnRank		(0.006)		(0.008)		(0.003)		(0.005)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	718	718	718	718	601	601	601	601
	Linear Probability Models: Twenty Bins							
	Up^{US}		$Down^{US}$		Up^{Mex}		$Down^{Mex}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Binding	0.046**	0.039*	-0.034	-0.040	-0.005	-0.002	0.115***	0.132***
	(0.021)	(0.022)	(0.026)	(0.028)	(0.020)	(0.022)	(0.034)	(0.037)
OwnRank		0.005		-0.003		-0.002		0.002
		(0.011)		(0.010)		(0.002)		(0.006)
Binding		0.006		0.009		-0.003		-0.028***
×OwnRank		(0.012)		(0.017)		(0.007)		(0.010)
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.

E.3.8 Alternative Binding Measure

We have used an indicator of quota binding defined for each HS6 product g as follows:

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

where $I\{\cdot\}$ is the indicator function and $J(g)$ is the set of HS 10 digit products in the HS 6 product g.

Continuous Binding Measure We extend this measure as a continuous measure without setting any threshold:

$$Binding^{cont}_g = \frac{\Sigma_{j \in J(g)} x^m_{j2004} I\left\{quota\ on\ j\ was\ binding\ in\ 2004\right\}}{\Sigma_{j \in J(g)} x^m_{j2004}}$$

that falls between 0 and 1. Table A.19 and Table A.20 replicate Table 4 and Table 6 by using this continuous binding measure. The results remain robust.

Table A.19: Partner Change during 2004–07: Continuous Binding Measure

	Linear Probability Models							
	Up^{US}		$Down^{US}$		Up^{Mex}		$Down^{Mex}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Binding	0.055***	0.045*	-0.012	0.013	-0.003	0.000	0.138***	0.149***
	(0.021)	(0.024)	(0.027)	(0.043)	(0.021)	(0.020)	(0.034)	(0.049)
OwnRank		-0.000		-0.069		0.005		-0.078
		(0.026)		(0.045)		(0.014)		(0.054)
Binding		0.030		-0.078		-0.008		-0.039
×OwnRank		(0.051)		(0.078)		(0.027)		(0.089)
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.

Table A.20: Mexican Exporter's Exit from the US market: Continuous Binding Measure

	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)	(8)
Binding	-1.323***	-0.750***	-1.068***	-0.767***	-0.041***	-0.032**	-0.021	0.012
(δ_1)	(0.294)	(0.266)	(0.254)	(0.257)	(0.015)	(0.014)	(0.016)	(0.015)
Binding	1.172**	1.432***	0.067	0.287	0.079***	0.098***	-0.005	-0.042***
$\times$After (δ_2)	(0.496)	(0.499)	(0.182)	(0.261)	(0.017)	(0.022)	(0.013)	(0.016)
After	-3.499***	-0.907	-0.203	0.814	-0.362***	-0.341***	-0.118***	-0.211***
(δ_3)	(0.368)	(1.621)	(0.152)	(0.787)	(0.042)	(0.077)	(0.034)	(0.055)
$\ln Export$					-0.058***	-0.056***	-0.069***	-0.066***
(δ_4)					(0.002)	(0.003)	(0.003)	(0.003)
$\ln Export$					0.020***	0.020***	0.011***	0.008**
$\times$After (δ_5)					(0.003)	(0.003)	(0.003)	(0.003)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	696	696	652	652	22,617	22,617	24,035	22,142

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), (4), (6), (8) include the product-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.

Different Trade Weights We consider an alternative measure by using Chinese exports x^{cn}_{j2004} to the US as the weight:

$$Binding_g^{CN} = \left\{ \frac{\Sigma_{j\in J(g)} x^{cn}_{j2004} I\left\{quota\ on\ j\ was\ binding\ in\ 2004\right\}}{\Sigma_{j\in J(g)} x^{cn}_{j2004}} \geq 0.5 \right\}.$$

Table A.21 and Table A.22 replicate Table 4 and Table 6 by using $Binding_g^{CN}$. The results remain robust.

Table A.21: Partner Change during 2004–07: Alternative Binding Measure

	Linear Probability Models							
	Up^{US}		$Down^{US}$		Up^{Mex}		$Down^{Mex}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Binding	0.054***	0.047**	-0.004	0.030	0.005	0.009	0.110***	0.119**
	(0.019)	(0.022)	(0.024)	(0.041)	(0.017)	(0.016)	(0.033)	(0.051)
OwnRank		0.001		-0.060		0.006		-0.088
		(0.026)		(0.043)		(0.014)		(0.055)
Binding		0.021		-0.096		-0.010		-0.028
$\times$OwnRank		(0.049)		(0.075)		(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.

Table A.22: Mexican Exporter's Exit from the US market: Alternative Binding Measure

	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)	(8)
Binding	-1.133***	-0.510**	-0.802***	-0.475*	-0.038***	-0.036**	-0.014	0.005
(δ_1)	(0.297)	(0.232)	(0.236)	(0.250)	(0.014)	(0.014)	(0.014)	(0.014)
Binding	0.922*	0.999*	-0.076	0.037	0.068***	0.079***	-0.009	-0.047**
$\times$After (δ_2)	(0.471)	(0.520)	(0.168)	(0.233)	(0.016)	(0.020)	(0.014)	(0.019)
After	-3.271***	-0.365	-0.107	0.853	-0.354***	-0.352***	-0.117***	-0.206***
(δ_3)	(0.332)	(1.663)	(0.135)	(0.783)	(0.041)	(0.079)	(0.034)	(0.054)
$\ln Export$					-0.058***	-0.056***	-0.069***	-0.066***
(δ_4)					(0.002)	(0.003)	(0.003)	(0.003)
$\ln Export$					0.020***	0.020***	0.011***	0.008**
$\times$After (δ_5)					(0.003)	(0.003)	(0.003)	(0.003)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	696	696	652	652	22,625	22,624	24,043	22,142

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), (4), (6), (8) include the product-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.

E.3.9 Different Time Windows

Table A.23 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.23: Gradual Partner Changes

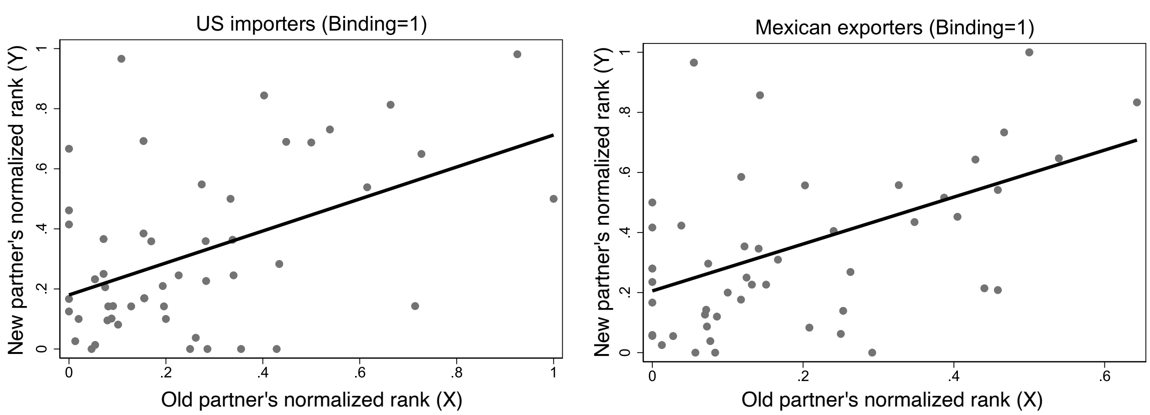
	Partner Change in Different Periods: Linear Probability Models					
	Up^{US}			$Down^{Mex}$		
	2004–06	2004–07	2004–08	2004–06	2004–07	2004–08
	(1)	(2)	(3)	(4)	(5)	(6)
Binding	0.036**	0.052**	0.066**	0.056*	0.127***	0.121***
	(0.015)	(0.021)	(0.027)	(0.031)	(0.035)	(0.032)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	963	718	515	768	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.

E.4 New and Old Partner Rank Regressions

Figure A.5 replicates Figure 6 for a sample only including the treatment group. The results are very similar to those in Figure 6.

Figure A.5: Old and New Partner Ranks



$Y = 0.18 + 0.53\,X$, R^2=0.22, Obs.=54.
(s.e. 0.05) (0.17)

$Y = 0.21 + 0.78\,X$, R^2=0.23, Obs.=51
(s.e. 0.06) (0.21)

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.

E.5 Alternative Capability Ranking

E.5.1 Construction of Price and Quality Rankings

One complication of creating the ranking of unit prices is that different observations may use different units and not be comparable. In the textile sectors, more than 90 % of the transactions use the units "kg" and "m^2". Therefore, we drop transactions use other units such as "piece", "dozen", or "hundreds" from the textile sectors.

We estimated product quality following Khandelwal et al. (2013, p 2187). Let q_{fhct} and p_{fhct} be the price and the quantity of firm f's exports in product h to destination country c at time t. Khandelwal et al. (2013) estimated the following equation:

$$\ln q_{fhct} + \sigma \ln p_{fhct} = \alpha_h + \alpha_{ct} + \eta_{fhct} \tag{A25}$$

where σ is the demand elasticity set as $\sigma = 4$, α_h is product fixed effects and α_{ct} is country-time fixed effects. From the estimated residual $\hat{\eta}_{fhct}$, the authors use $\hat{\eta}_{fhct}/(\sigma - 1)$ as the quality estimate. In our setting, we create the ranking of Mexican firm's quality within HS6 product only for one year 2004 and one destination (US). Therefore, the ranking of quality estimated by the Khandelwal et al. (2013) approach is equivalent with the ranking of $\ln q_{fhct} + \sigma \ln p_{fhct}$ in the left hand side in (A25) within each HS 6 product. To address the heterogeneity in the unit of quantity, we create the ranking separately for each HS 6 product-unit combination. We create the ranking of Mexican exporters by their price and quality, and the ranking of US importers by their main partners' price and quality.

E.5.2 Results using Alternative Rankings

We estimate partner change regression (10) and new and old partner ranks regression (11) using these three rankings. The baseline exit regression (13) 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 and quality data.

Table A.24 reports partner change regressions in Panel A and regressions of new and old partner ranks in Panel B. Columns labeled “Total”, “Price” and “Quality” report estimates using total trade, price and quality rankings, respectively. The main results are robust to alternative rankings. The results from price and quality 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.

Table A.24: Alternative Capability Rankings

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

	Up^{US}			$Down^{US}$		
	Total	Price	Quality	Total	Price	Quality
	(1)	(2)	(3)	(4)	(5)	(6)
Binding	0.052**	0.050***	0.064**	-0.017	-0.012	-0.026
	(0.021)	(0.018)	(0.025)	(0.027)	(0.028)	(0.027)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	718	677	677	718	677	677

	Up^{Mex}			$Down^{Mex}$		
	Total	Price	Quality	Total	Price	Quality
	(7)	(8)	(9)	(10)	(11)	(12)
Binding	0.001	0.022	0.000	0.123***	0.073***	0.094***
	(0.019)	(0.030)	(0.020)	(0.035)	(0.027)	(0.031)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	601	576	576	601	576	576

B: Old and New Partners 2004–07: OLS

	New Partner Rank					
	US Importers			Mexican Exporters		
	Total	Price	Quality	Total	Price	Quality
	(13)	(14)	(15)	(16)	(17)	(18)
Old Partner	0.46***	0.21*	0.33*	0.68***	0.38***	0.47**
Rank	(0.13)	(0.11)	(0.19)	(0.14)	(0.14)	(0.22)
Constant	0.24***	0.44***	0.28***	0.25***	0.36***	0.31***
	(0.04)	(0.07)	(0.07)	(0.04)	(0.07)	(0.05)
R^2	0.148	0.059	0.080	0.207	0.091	0.115
Obs.	88	79	79	104	96	96

Note: Rankings are based on firm's product total trade in 2004 in "Total", on firm's unit price of product in 2004 in "Price" and on firm's quality estimate in 2004 in "Price". . (Panel A) and (Panel B) replicate regressions in Table 4 and Figure 6, respectively. Significance: * 10 percent, ** 5 percent, *** 1 percent.

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