Assortative Matching of Exporters and Importers*

Yoichi Sugita† Hitotsubashi
Kensuke Teshima‡ ITAM
Enrique Seira§ ITAM

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Abstract

This paper studies the mechanism behind matching between exporters and importers in Mexican textile/apparel exports to the US. A surge in Chinese exports to the US after the end of the Multi-Fibre Arrangement in 2005 caused re-matching of incumbent US importers and Mexican exporters according to their pre-liberalization trade volume. We show that the re-matching pattern is consistent with a model combining Becker-type positive assortative matching of exporters and importers by their capability with the standard Melitz-type model. The combined model suggests the observed re-matching brings new gains from trade: trade liberalization improves buyer-supplier matching within industries.

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

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†Graduate School of Economics, Hitotsubashi University. 2-1 Naka Kunitachi, Tokyo 186-8601, Japan. (E-mail: yoichi.sugita@r.hit-u.ac.jp)

‡Centro de Investigación Económica, Instituto Tecnológico Autónomo de México Av. Santa Teresa # 930, México, D. F. 10700 (E-mail: kensuke.teshima@itam.mx)

§Centro de Investigación Económica, Instituto Tecnológico Autónomo de México Av. Santa Teresa # 930, México, D. F. 10700 (E-mail: enrique.seira@itam.mx)

1 Introduction

Over the past decade, a growing body of research has focused on firms and trade. A robust finding that only firms with high capability in areas such as productivity and quality engage in exporting and importing has spurred new theories emphasizing new gains from trade (e.g., Bernard and Jensen, 1995; Melitz, 2003; Bernard, Eaton, Jensen, and Kortum, 2003), i.e., that trade liberalization shifts resources to more capable firms within industries (e.g., Pavcnik, 2002; Trefler, 2004).[1]

In contrast to our knowledge regarding who exports and imports, we have little knowledge about who trades with whom, i.e. how exporters and importers match in a product market. Do exporters and importers match based on their respective capabilities? Does trade liberalization change matching in any systematic way? Does matching matter for aggregate gains from trade liberalization? This paper is one of the first attempts to answer these questions empirically.

We study matching between Mexican exporters and US importers in textile/apparel product markets. The Mexico–US textile/apparel trade is particularly suitable for our purpose. First, Mexican exporters and US importers mainly find their foreign trading partners in the other of these two countries. In 2004, the US was the largest market of textile and apparel for Mexico, while Mexico was the second largest source for the US.[2] Second, the Mexico–US textile/apparel trade experienced a large trade liberalization due to the end of the Multi-Fibre Arrangement (MFA). Following the schedule decided at the GATT Uruguay round, the US removed import quotas against non-NAFTA countries for some textile/apparel products in 2005, which induced the massive entry of Chinese exporters to the US. This arguably exogenous product-level shock to matching of Mexican exporters and US importers

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

[2] 91.9 % of Mexican exports are shipped to the US and 9.5% of US imports are from Mexico.

helps us identify the mechanism behind their matching. Finally, at the disaggregate product (HS 6-digit) level, matching of Mexican exporters and US importers in a given year is approximately one-to-one.[3] "Main-to-main" matches, in which both the exporter and the importer are the main partner of each other, account for 80% of the aggregate trade volume. This allows us to analyze firm's choice of their main partners in a simple one-to-one matching model.

Our theoretical framework is a model combining a canonical matching model of Becker (1973) with a Melitz-type model of heterogeneous firms. The model has final producers (importers) in the US and suppliers (exporters) in Mexico and China, all of whom are heterogeneous in capability. A final producer and a supplier form a team under perfect information. These teams compete in the US final good market in a monopolistically competitive way. Team member capabilities exhibit complementarity within teams, so stable matching becomes positively assortative matching (PAM) by capability: high capability exporters match with high capability importers, while low capability exporters match with low capability importers.

Using this model, we analyze the end of the MFA, which led to the massive entry of Chinese suppliers at various capability levels. This new entry makes the original matching unstable and induces existing firms to change partners so that the resulting new matching becomes PAM under the new environment. Final producers switch to partners with higher capability, while suppliers switch to partners with lower capability. Suppliers with the lowest capability exit. This rematching toward PAM leads to an efficient use of technology exhibiting complementarity and lowers the consumer price index. This is a new mechanism of gains from trade: trade liberalization improves buyer-supplier matching within industries.

Then, we empirically analyze the end of the MFA and test the model's predictions regarding rematching toward PAM. Using firms' pre-liberalization trade vol-

[3] We will explain this in detail in Section 2.2.

umes in 2004 as a proxy for capability, we obtain three results. First, US importers switched their Mexican main partner to one with higher capability, whereas Mexican suppliers switched their US main partner to one with lower capability. Partner changes in the other direction did not occur. Second, Mexican exporters with low capability stopped exporting. We identify these results by comparing firms trading products subject to US binding quotas on imports from China in 2004 (treatment group) and those in other textile/apparel products (control group) within HS 2-digit industry categories. The treatment group exhibits the above rematching and exit patterns more frequently than the control group. Finally, among firms who switched their main partners, the capability ranks of the new partners are positively correlated with those of the old partners. These three findings support Becker-type PAM. We present numerous additional analyses that support the robustness of our results and reject alternative explanations.

Our finding supports the matching approach to modeling international trade pioneered by James Rauch and his coauthors. Workhorse trade models such as Ricardian, Heckscher-Ohlin and the love of variety models consider types of trade wherein exporter-importer matching does not play an important role.[4] Rauch (1996), Casella and Rauch (2002), and Rauch and Trindade (2003) developed Becker-type matching models of exporters and importers to emphasize the importance of having the right matches for firms and the role of frictions against matching in non-anonymous markets.[5] Our finding provides the first evidence for this approach based on actual data on exporter-importer matching. Furthermore, while in these models firms match based on horizontally differentiated characteristics, we find

[4] In perfectly competitive models such as the Ricardian and Heckscher-Ohlin models, the market is anonymous in the sense that exporters and importers are indifferent regarding who they trade with. The love of variety model also avoids positing any specific matching mechanism, instead predicting that all exporters will trade with all importers.

[5] Chaney (2014) and Eaton, Jinkins, Tybout and Xu (2015) present buyer-supplier matching models emphasizing informational frictions.

instead firms match based on vertically differentiated capability (e.g., Antras, Garicano and Rossi-Hansberg, 2006; Sugita 2015). That is, every exporter prefers to trade with high capability importers, but only high capability exporters can in fact trade with them.

Our paper is also related to recent empirical literature on exporter-importer matching. As pioneering studies, Blum, Claro, and Horstmann (2010, 2011) and Eaton, Eslava, Jinkins, Krizan, and Tybout (2012) document characteristics of matching in Chile–Colombia trade, Argentina–Chile trade, and Colombia–US trade, respectively. Bernard, Moxnes, and Ulltveit-Moe (2016), Carballo, Ottaviano, and Volpe Martincus (2013), Eaton, Kortum and Kramatz (2016) analyze customs data from Norway, from Costa Rica, Ecuador, and Uruguay, and from France, respectively, to examine exports from one country to multiple destinations. Benguria (2014) and Dragusanu (2014) find positive correlations for firm-level variables (employment, revenue, etc.) of exporters and importers for France–Colombia trade and India–US trade, respectively. Eaton et al. (2012) and Machiavello (2010) are pioneering studies about exporter partner changes in Colombian exports to the US and in Chilean wine exports to the UK, respectively. Monarch (2015) analyzes partner changes in Chinese exports to the US. While these studies consider partner changes in steady state dynamics, we study partner changes caused by trade liberalization. The above-mentioned studies propose different theories to explain their findings, but none of them proposes Becker-type PAM.[6]

The rest of the paper is organized as follows. Section 2 discusses our data and the Mexico–US textile/apparel trade. Section 3 presents our model and derives predictions. Section 4 explains our empirical strategies. Section 5 presents the main empirical results and robustness checks. Section 6 discusses results using

[6]Note that our treatment–control group comparison is silent about whether other mechanisms exist or not. Thus, our finding should be regarded as complementary to these studies.

alternative measures and additional results rejecting alternative explanations for our results. Section 7 concludes the paper. There is an online Appendix that provides calculations, proofs, data construction, summary statistics, and additional analyses.

2 Mexico–US Textile Apparel Trade

This section explains two features of the Mexico–US textile/apparel trade that motivate our theoretical analysis: the end of the Multi-Fibre Arrangement and approximately one-to-one matching of exporters and importers at the product level.

2.1 End of the Multi-Fibre Arrangement

The Mexico–US textile/apparel trade experienced large-scale trade liberalization in 2005, the end of the Multi-Fibre Arrangement (MFA). The MFA and its successor, the Agreement on Textile and Clothing, are agreements on quota restrictions regarding textile/apparel imports among GATT/WTO member countries. At the GATT Uruguay round, the US (together with Canada, the EU, and Norway) promised to abolish their quotas in four steps (1995, 1998, 2002, and 2005). At each removal, liberalized products constituted 16, 17, 18, and 49% of imports in 1990, respectively. The end of the MFA in 2005 is the largest liberalization.

Several studies have investigated the impact of the 2005 quota removal. We highlight three facts from previous studies that motives our analysis.

Surge in Chinese Exports to the US According to Brambilla, Khandelwal, and Schott (2010), US imports from China disproportionally increased by 271% in 2005, whereas imports from almost all other countries decreased. Using data by Brambilla et al. (2010) on US import quotas, we classify each HS 6-digit textile/apparel product into one of two groups [see Appendix for details]. The first treatment group consists of products for which Chinese exports to the US are subject to a binding quota in 2004, while the second control group consists of other textile/apparel products. The left panel in Figure 1 displays Chinese exports to the US from 2000 to 2010 for the treatment group with a dashed line and the control group with a solid line. After the 2005 quota removal, Chinese exports of the treatment group increased much faster than those of the control group.[7]

Exports by New Chinese Entrants with Various Capability Levels Using Chinese customs transaction data, Khandelwal, Schott, and Wei (2013) decompose the increases in Chinese exports to US, Canada, and the EU after the quota removal into intensive and extensive margins. They find that increases in Chinese exports belonging to the treatment group were mostly driven by the entry of Chinese exporters who had not previously exported these products. Furthermore, these new exporters are much more heterogeneous in capability than incumbent exporters, with many new exporters being more capable than incumbent exporters.[8]

Mexican Exports Face Competition from China Mexico already had tariff- and quota-free access to the US market through the North American Free Trade Agreement (NAFTA).[9] With the MFA's end, Mexico lost its advantage over third-country exporters, thus facing increased competition from Chinese exporters in the US mar-

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

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

[9]NAFTA liberalized the US market for Mexican exports in 1994, 1999, and 2003.

ket. The right panel in Figure 1 shows Mexican exports to the US from 2000 to 2010 for the treatment group (dashed line) and control group (solid line). The two series had moved in parallel before 2005, whereas the treatment group significantly declined after 2005. The parallel movement of the two series before 2005 suggests that the choice of products subject to quota removal in 2005 was exogenous to Mexican exports to the US.

2.2 Approximately One-to-One Matching

Matched Exporter Importer Data Using the Mexican customs data, we construct matched exporter–importer data from June 2004 to December 2011 for Mexican textile/apparel exports (covering HS50 to HS63) to the US. For each match between a Mexican exporter and a US importer, the dataset contains: (1) exporter-ID; (2) importer-ID; (3) year; (4) 6-digit HS product code; (5) value of annual shipment (in US dollars); (6) quantity and unit; and (7) an indicator of involvement with a duty free processing reexport program (Maquiladora/IMMEX program); and other information. The Appendix explains the construction of the dataset.

Data cleaning drops some information. First, since the dataset covers only June to December for 2004, we drop observations from January to May for other years to make each year's information comparable. Similar results are obtained with January–May data. Second, we drop exporters who do not report importer information for most transactions. These exporters use the Maquiladora/IMMEX program where exporters do not have to report an importer for each shipment.[10] Luckily, a substantial number of Maquiladora/IMMEX exporters do report importer informa-

[10]The Maquiladoras program started in 1986 and was replaced by the IMMEX (Industria Manufacturera, Maquiladora y de Servicios de Exportation) program in 2006. In the Maquiladoras/IMMEX programs, firms in Mexico can import materials and equipment duty free if they export products assembled using them. To be eligible for the program, exporters must register the foreign buyers' information in advance but do not need to report it for each shipment.

tion. To address potential selection issues, we compare these Maquiladora/IMMEX exporters and other normal exporters in almost all empirical analyses below.

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

Furthermore, product-level matching between Mexican exporters and US importers is approximately one-to-one. To show this, we develop a new measure "main-to-main share," which expresses the extent to which overall transactions in one product market are quantitatively close to one-to-one matching. We define a "main-to-main match" as a match in which the exporter is the main partner of the importer while simultaneously, the importer is the main partner of the exporter. Then, we define "main-to-main share" as the share of trade volume by main-to-main matches out of the total aggregate trade volume. If matching is exactly one-to-one in each product market, this share takes the maximum value, which is one. We say that matching is approximately one-to-one if the main-to-main share is close to one.

Column (1) in Table 2 reports the main-to-main share for Mexico's overall textile/apparel exports to the US, which is approximately 80% and stable across years.[12] This means that a one-to-one matching model is a fair approximation

[11] Numbers in Rows (1) to (4) in Table 1 appear smaller than those in other studies such as Blum et al. (2010, 2011), Bernard et al. (2013), and Carballo et al. (2013). This is probably because they report matches at the country level in their main tables, while we report matches at the product–country level, which identifies fewer partners for firms trading in multiple products. When a match is defined at the country level, the numbers in Rows (1) to (4) in Table 1 increase and become similar to those reported by other studies.

[12] In the Appendix, we investigate the distribution of main-to-main shares across product-year

of product-level matching in the Mexico–US textile/apparel trade.[13] Furthermore, Columns (2) and (3) show that main-to-main share remains stable regardless of whether products are liberalized at the MFA end or not. This allows us to analyze the impact of trade liberalization on matching in a one-to-one matching model.[14]

3 The Model

3.1 Matching Model of Exporters and Importers

Based on discussion in Section 2, we develop a matching model of importers and exporters. The model includes three types of continuum of firms, namely, US final producers, Mexican suppliers, and Chinese suppliers.[15] A US final producer matches with a supplier from either Mexico or China to form a team that produces one variety of differentiated final goods. Once teams are formed, suppliers tailor intermediate goods for their teams; therefore, firms transact intermediate goods only within their team. Each firm joins only one team.

Firms' capabilities are heterogeneous. Capability reflects either productivity or quality. Let x and y be the capability of final producers and suppliers, respectively. There exist a fixed mass M_U of final producers in the US, M_M of suppliers in Mexico, and M_C of suppliers in China. The cumulative distribution function (c.d.f.) for the capability of US final producers is $F(x)$ with continuous support $[x_{min}, x_{max}]$.

combinations. The median main-to-main share is 0.97 and the 25th percentile is 0.86. Furthermore, we find high main-to-main share is not related with the number of firms in each product.

[13]One potential reason for one-to-one matching is exclusive dealing. A firm might not allow the partner to trade with other rivals to prevent information leakage or to raise rival's costs through vertical foreclosure.

[14]Columns (4) and (5) show that high main-to-main share is common in both the Maquiladora/IMMEX program for processing reexports and other normal trade.

[15]Our model is a partial equilibrium version of Sugita (2015) wherein firm entry is endogenous and international matching arises from Ricardian comparative advantage in a two-country general equilibrium model.

The capability of Mexican and Chinese suppliers follows an identical distribution, and the c.d.f. is $G(y)$ with continuous support $[y_{min}, y_{max}]$.[16] For simplicity, a Chinese supplier is a perfect substitute for a Mexican supplier of the same capability.

Teams' capabilities are heterogeneous. Team capability $\theta(x, y)$ increases members' capability, $\theta_1 \equiv \partial\theta(x, y)/\partial x > 0$ and $\theta_2 \equiv \partial\theta(x, y)/\partial y > 0$. The model has two stages. In Stage 1, teams are formed under perfect information. Matching endogenously determines the distribution of θ. In Stage 2, teams compete in the US final-good market in a monopolistically competitive fashion.

The US representative consumer maximizes the following utility function:

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

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

Production technology is of Leontief type. When a team produces q units of final goods, the team supplier produces q units of intermediate goods with costs $c_y\theta^{\beta}q + f_y$; then, the final producer assembles these intermediate goods into final goods with costs $c_x\theta^{\beta}q + f_x$, where c_i and f_i are positive constants ($i = x, y$). The total costs for a team with capability θ producing q units of final goods are $c(\theta, q) = c\theta^{\beta}q + f$, where $c \equiv c_x + c_y$ and $f \equiv f_x + f_y$. Externalities within teams

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

makes firms' marginal costs dependent on both their partner's capability and their own capability.[17] For simplicity, we assume firm's marginal costs depend on the team's capability.

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

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

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

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

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

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

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

We focus on stable matching that satisfies the following two conditions: (i) *individual rationality*, wherein all firms earn non-negative profit, $\pi_x(x) \geq 0$ and $\pi_y(y) \geq 0$ for all x and y; (ii) *pair-wise stability*, wherein each firm is the optimal partner for the other team member:[18]

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

The first order conditions for the maximization in (2) are

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

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

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

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

[18] Roth and Sotomayor (1990) provide an excellent background on matching models.

Differentiating the first order condition (3) by x, we obtain

$$m_x'(x) = \frac{A\theta_{12}}{\pi_y'' - A\theta_{22}}, \text{ where } \theta_{12} \equiv \frac{\partial^2\theta}{\partial x \partial y} \text{ and } \theta_{22} \equiv \frac{\partial^2\theta}{\partial y^2}.$$

Since the denominator is positive from the second order condition, the sign of cross derivatives θ_{12} is the same as the sign of $m_x'(x)$, i.e. the sign of sorting in stable matching (e.g., Becker, 1973). For simplicity, we consider three cases where the sign of θ_{12} is constant for all x and y: (1) Case C (Complement) $\theta_{12} > 0$; (2) Case I (Independent) $\theta_{12} = 0$; (3) Case S (Substitute) $\theta_{12} < 0$.[19] In Case C, we have positive assortative matching (PAM) ($m_x'(x) > 0$): high capability firms match with high capability firms whereas low capability firms match low capability firms. In Case S, we have negative assortative matching (NAM) ($m_x'(x) < 0$): high capability firms match low capability firms. In Case I, we cannot determine a matching pattern [i.e., $m_x(x)$ cannot be defined as a function] because each firm is indifferent about partner capability. Therefore, we assume matching is random in Case I. Case I is a useful benchmark because it nests traditional models where firm heterogeneity exists only for one side of the market, i.e., either among exporters ($\theta_1 = \theta_{12} = 0$) or among importers ($\theta_2 = \theta_{12} = 0$). We focus on Case C and Case I in the main text of the paper and discuss Case S in Section 6 and the Appendix.

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

$$M_U\left[1 - F(x)\right] = \left(M_M + M_C\right)\left[1 - G\left(m_x(x)\right)\right] \text{ for all } x \geq x_L. \tag{5}$$

[19]In Case C and Case S, θ is also called strict supermodular and strict submodular, respectively. An example for Case C is the complementarity of quality of tasks in a production process (e.g., Kremer, 1993). For instance, a high-quality car part is more useful when combined with other high-quality car parts. An example for Case S is technological spillovers through learning and teaching. Gains from learning from high capable partners might be greater for low capability firms. See e.g., Grossman and Maggi (2000) for further examples on Case C and Case S.

The left hand side of (5) is the mass of final producers with higher capability than x and the right hand side is the mass of suppliers who match with them, i.e., suppliers with higher capability than $m_x(x)$. Figure 2 describes how matching function $m_x(x)$ is determined for a given $x \geq x_L$. The width of the left rectangle equals the mass of US final producers, whereas the width of the right rectangle equals the mass of Mexican and Chinese suppliers. The left vertical axis expresses the value of $F(x)$ and the right vertical axis indicates the value of $G(y)$. The left gray area is the mass of final producers with higher capability than x, while the right gray area is the mass of suppliers with higher capability than $m_x(x)$. Matching function $m_x(x)$ is determined so that the two areas are the same size for all $x \geq x_L$.

An equilibrium is obtained as follows. In both Case C and Case I, the team with the lowest capability θ_L comprises a final producer with x_L and a supplier with y_L. From (1), (4) and $A = \delta/\sigma\Theta$, the team earns zero profits:

$$A\theta_L = \frac{\delta\theta_L}{\sigma\Theta} = f. \tag{6}$$

In Case C, matching function $m_x(x)$ determines $\Theta(x_L) = M_U \int_{x_L}^{\infty} \theta(x, m_x(x))\, dF(x)$ and $\theta_L(x_L) = \theta(x, m_x(x_L))$ as functions of x_L. In Case I, Condition (4) determines $y_L(x_L)$ as a function of x_L. Let $\theta(x,y) \equiv \theta^x(x) + \theta^y(y)$. Then, $\Theta(x_L) = M_U \int_{x_L}^{\infty} \theta^x(x)\, dF(x) + (M_M + M_C) \int_{y_L(x_L)}^{\infty} \theta^y(y) dG(y)$ and $\theta_L(x_L) = \theta^x(x_L) + \theta^y(y_L(x_L))$ become functions of x_L. Finally, equation (6) determines a unique 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

We analyze the impact of Chinese entries at the end of the MFA on matching between US importers and Mexican exporters. As discussed in Section 2.3, new entrants are heterogeneous in capability. Thus, we model this event as an exogenous increase in the mass of Chinese suppliers ($dM_C > 0$) in the US market. We assume positive but negligible costs for switching partners so that a firm changes its partner only if it strictly prefers the new match over the current match.

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

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

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

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

C3: Mexican exporters with low capability exit the US market.

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

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

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

I3: Mexican exporters with low capability exit the US market.

Rematching Gain from Trade The entry of Chinese exporters causes two adjustments. First, new Chinese suppliers with high capability replace Mexican suppliers with low capability (replacement effect). Second, in Case C, continuing firms rematch (rematching effect). We show each of these two adjustments lowers the price index and benefits the consumer.

To see each adjustment, we consider a hypothetical "no-rematching" equilibrium where no rematching occurs among continuing firms and firms switch partners only if their current partner exits the market. Denote variables in this no-rematching equilibrium by "NR," variables before the MFA's end by "B," and variables after the MFA's end by "A." Then, the change in the price index $P^B - P^A$ can be decomposed into the replacement effect $P^B - P^{NR}$ and the rematching effect $P^{NR} - P^A$. The following lemma compares the price index across these three environments.

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

The proof is given in the Appendix. In Case C, the rematching effect is positive, that is, the rematching creates an additional consumer gain. From $P = c/\left(\rho\Theta^{1/(\sigma-1)}\right)$, these falls in the price index reflect increases in the aggregate capability, i.e. $\Theta^A > \Theta^{NR} > \Theta^B$. The aggregate capability gains arises from a classic theorem in the matching theory that a stable matching (i.e., PAM) maximizes participants' aggregate payoffs (i.e. $A\Theta - Mf$ for a given A) (Koopmans and Beckmann, 1957; Shapley and Shubik, 1972; Gretsky, Ostroy and Zame, 1992). In Case I, the rematching effect is zero because matching is irrelevant. The rest of the paper identifies this rematching process in the data.

4 Empirical Strategies

4.1 Proxy for Capability Rankings

Testing predictions C1-C3 and I1-I3 requires data on firm capability. Estimating capability measures such as total factor productivity at the firm-product level is one strategy, but it is extremely difficult. Instead, we use firm trade volumes as a proxy for firm capability, using a property of the model in Case C and Case I.

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

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

The proof is in the Appendix. Lemma 2 is derived from the fact that within team trade $T(x, y)$ is increasing in importer's capability x and exporter's capability y.

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

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

Then, we create variables of partner changes as follows. Partner upgrading dummy Up^c_{igs} equals one if $NewPartnerRank_{igs} < OldPartnerRank_{igs}$, i.e. the firm switched to a partner with higher capability. Partner downgrading dummy $Down^c_{igs}$ equals one if $NewPartnerRank_{igs} > OldPartnerRank_{igs}$.

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

4.2 Specifications

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

$$
\begin{aligned}
Up^c_{igs} &= \beta^c_U Binding_{gs} + \lambda_s + \varepsilon^c_{Uigs} \\
Down^c_{igs} &= \beta^c_D Binding_{gs} + \lambda_s + \varepsilon^c_{Digs},
\end{aligned} \tag{7}
$$

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

The coefficients of interest in (7) are β^c_U and β^c_D. With HS 2-digit product fixed effects, these coefficients are identified by comparing treatment and control groups within the same HS 2-digit sectors. The treatment is the removal of binding quotas on Chinese exports to the US [$Binding_{gs} = 1$]. The coefficients β^c_U and β^c_D estimate its impact on the probability that firms will switch from their initial main partner to one with higher and lower capabilities, respectively.

Prediction I1 for random matching states that in response to the MFA's end, continuing US importers and Mexican exporters would not change their partners at all. In reality, other shocks that could induce partner changes may exist. A virtue of our treatment–control group comparison is that it enables us to distinguish the effect of the MFA's end from the effects of these other shocks if the latter symmetrically affected both groups. Considering this point, we reformulate Pre-

[21] We drop HS 2-digit sectors (HS 50, 51, 53, 56, 57, and 59) in which no variation of the binding dummy at HS 2-digit level occurs.

diction I1: no difference should exist in the probability of partner changes in any direction between treatment and control groups. This prediction corresponds to $\beta_U^{US} = \beta_D^{US} = \beta_U^{Mex} = \beta_D^{Mex} = 0$ in (7).

Prediction C1 for PAM states that in response to the MFA's end, all continuing US importers upgrade whereas all continuing Mexican exporters downgrade their main partners. Though the frictionless matching model predicts all firms will change their partners, in reality, other factors such as transaction costs are likely to prevent some firms from making such a change, at least in the short run. Again, our treatment–control group comparison can control for these other factors as long as they symmetrically affect both groups. Accordingly, we reformulate Prediction C1 as follows: US importers' partner upgrading and Mexican exporters' partner downgrading will occur more frequently in the treatment group than in the control group, which corresponds to $\beta_U^{US} > 0$, $\beta_D^{US} = \beta_U^{Mex} = 0$, and $\beta_D^{Mex} > 0$ in (7).

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

$$NewPartnerRank_{ig}^c = \alpha^c + \gamma^c OldPartnerRank_{ig}^c + \varepsilon_{ig}^c \quad (8)$$
$$\text{for firms with } NewPartnerRank_{ig}^c \neq OldPartnerRank_{ig}^c.$$

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

Two additional points need to be mentioned. First, if we run (8) only for firms that do not change partners, then γ^c equals to one by construction. To avoid this mechanical correlation, we estimate (8) only for firms who change partners. Second, the regression (8) combines both the treatment and control groups since PAM should hold for both groups in Case C. For instance, an industry-wide shock occurs that induces Mexican exporter's partner to downgrade in both treatment and control groups, the model with PAM should predict $\gamma^c > 0$ for both groups.

Small Exporter's Exit (C3 and I3) Finally, we test predictions C3 and I3 about Mexican exporters' exit to check whether trade volume actually reflects firm capability. While the MFA's end is the only shock existing in the model, other shocks might exist that induce exit from the market. To address this possibility, we consider a simple threshold model of exit behavior. In each period r, Mexican supplier i receives a random i.i.d. shock ε_{ir} to its profits, which captures idiosyncratic factors inducing firm exit. The firm chooses to exit if ε_{ir} is below a threshold $\bar{\varepsilon}_{ir}(y)$, that is, firm i's exit probability is $\Pr[\varepsilon < \bar{\varepsilon}_{ir}(y)]$. Case C and Case I have two predictions: (i) threshold $\bar{\varepsilon}_{ir}(y)$ is a decreasing function in the firm's capability y; and (ii) the MFA's end increases threshold $\bar{\varepsilon}_{ir}(y)$ for a given capability.

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

$$Exit_{igsr} = \delta_1 Binding_g + \delta_2 Binding_g * After_r + \delta_3 After_r + \delta_4 \ln Exports_{igr} + \delta_5 After_r * \ln Exports_{igr} + \lambda_s + u_{igsr}. \quad (9)$$

Dummy variable $Exit_{igsr}$ equals one if the firm stops exporting during period r. Dummy variable $After_r$ equals one if period r is 2004–07 (after the end of the MFA). $\ln Exports_{igr}$ is the log of the firm's total export volume of product g in the initial year of period r, which proxies firm capability.[22] λ_s represents HS 2-digit level fixed effects and u^c_{igs} are error terms.

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

5 Results

5.1 Partner Changes

Table 3 reports regressions for partner changes during 2004–07 using linear probability models.[23] Columns with odd numbers report estimates of β^c_d ($c = US, Mex$ and $d = U, D$) from baseline regressions (7). We find that β^{US}_U in Column (1) and β^{Mex}_D in Column (7) are positive and statistically significant, while β^{US}_D in Column (3) and β^{Mex}_U in Column (5) are close to and not statistically different from zero. These signs on β^c_d support Case C and reject Case I. The removal of binding quotas from Chinese exports increased the probability that US importers upgrade partners by 5.2 percentage points and the probability that Mexican exporters downgrade partners by 12.7 percentage points. These effects are quantitatively large when compared with the sample averages of Up^{US}_{igs} and $Down^{Mex}_{igs}$, which are 3

[22] Regression (9) includes (the log of) export volumes instead of the rank of export volumes used in regressions (7) and (8). This is because in the model the rank of capability determines matching, while the level of capability determines firm's exit.

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

percentage points and 15 percentage points, respectively.[24]

In Table 3, columns with even numbers report regressions adding the firm's own rank and its interaction with the binding dummy. The coefficients on the interaction terms are estimated to be small and statistically insignificant, while the coefficients on the binding dummy remain similar to the baseline estimates. This means that both large and small firms switch their partners as in the model.

Panel A in Table 4 reports estimates of β_U^{US} and β_D^{Mex} after changing the end year to 2006, 2007, or 2008. First, β_D^{US} and β_U^{Mex} remain positive and statistically significant, showing that our findings are not sensitive to choice of end year. Second, estimates of β_U^{US} and β_D^{Mex} in later periods such as 2004–07 and 2004–08 are larger than those in the early period 2004–06. This suggests that partner changes occur gradually over time, probably due to certain partner switching costs.

Panel B in Table 4 examines partner changes in later periods of 2007–11 and 2009–11 in order to check our assumption that both treatment and control groups exhibit similar partner change patterns if the treatment was absent.[25] For each period, we re-construct capability rankings based on trade volume in the new initial years and re-create the upgrading/downgrading dummies. If the transition from old to new equilibrium was largely completed by 2007, we should not observe any difference in partner changes between the two groups. Panel B in Table 4 reports very small and insignificant estimates for β_U^{US} and β_D^{Mex} in 2007–11 [Columns (7) and

[24]These numbers do not mean that 97% of US importers and 85% of Mexican exporters traded with the same main partner both in 2004 and 2007. In the data, only XX% of US importers and YY% of Mexican exporters traded with the same main partner both in 2004 and 2007. Note that 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 data partner upgrading/downgrading are observed only if the firm, new partner, and old partner are all continuing firms. Partner switching to firms in other countries and to firms that did not exist in 2004 are not included.

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

(10)] and 2009–11 [Columns (9) and (12)]. These results support our assumption.[26]

Finally, Table 5 controls for product and firm characteristics in 2004. In the Appendix, we choose several characteristics that might affect partner changes and examine whether they significantly differ between the treatment and control groups. Table 5 includes characteristics that are statistically different between the two groups within HS 2-digit product categories.[27] Even with additional controls, estimates of β_U^{US} and β_D^{Mex} remain statistically significant and similar in magnitude.

5.2 New and Old Partners Ranks

Figure 4 reports regression (8) testing predictions C2 and I2 with corresponding scatter plots. For those US importers who change their main partners between 2004 and 2007, the left panel displays the ranks of old partners in the horizontal axis and those of new partners in the vertical axis. The right panel draws a similar plot for Mexican exporters. The lines represent OLS regression (8). Figure 4 and regressions show significant positive relationships. Firms who match with relatively high capablity partners in 2004 switch to relatively high capablity partners in 2007. This result again supports Case C PAM and rejects Case I random matching.

[26]The period 2008–11 [Columns (8) and (11)] shows a very different pattern from other two periods. One possible reason is the effect of the Lehman crisis and the Great Trade Collapse of 2008. As exports from other countries, Mexican exports declined by a huge amount in the second half of 2008. This shock might introduce noise into the rankings.

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

5.3 Small Exporter Exit

Table 6 reports the results of using regressions (9) to test predictions C3 and I3. Columns (1), (3), and (5) report baseline regressions using three different lengths of the two periods, respectively. Columns (2), (4), and (6) include additional control variables of product and firm characteristics in the initial year of each period and their interactions with the After dummy. We choose the same control variables as used in Table 5.[28]

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

6 Discussion

6.1 Alternative Capability Rankings

We create two alternative rankings using firm's total product trade volume in 2004 and firm's unit price of the product's trade with the main partners in 2004, respectively. Then, we estimate partner change regression (7) and new and old partner ranks regression (8) using these two rankings.[29] We use the total trade ranking as a robustness check and the price ranking for investigating the source of exporter's capability. If exporter's capability mainly reflects quality rather than productivity, the

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

[29]Note that the baseline exit regression (9) uses firm's total product trade volume as capability. Since price data before 2004 are very noisy, we do not estimate the exit regression using price data.

unit price ranking may agree with the true capability ranking. On the other hand, if capability mainly reflects productivity, the unit price ranking may become the exact reversal of the true capability ranking.

Table 7 reports partner change regressions in Panel A and regressions of new and old partner ranks in Panel B. Columns labeled “Baseline”, “Total Trade”, and “Price” report estimates using our baseline rankings, total volume rankings, and price rankings, respectively. All three rankings support the main results. The results from price rankings also imply that exporter’s capability mainly reflects its quality. Previous studies on export data find that quality is an important determinant of firm’s export participation.[30] Table 7 shows one further aspect: quality also determines a firm’s export partner.[31]

6.2 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) The Appendix shows that Case S is different from Case C and Case I in two aspects. First, firm’s trade volume may not be monotonically increasing in capability. The import volume of US importers with capability x, $I(x)$, and export volume of Mexican exporters with capability y, $X(y)$, satisfy $X(m_x(x)) = I(x)$. Since $X'(m_x(x))m'_x(x) = I'(x)$ and $m'_x(x) < 0$, then $I'(x)$ and $X'(y = m_x(x))$ must have the opposite signs. Thus, it is impossible that the trade ranking agrees with true capability ranking both for exporters

[30] See e.g., Kugler and Verhoogen (2012) and Manova and Zhang (2012) for studies using firm-level data and Baldwin and Harrigan (2011), Bernard et al. (2007), and Johnson (2012) for studies using product-level data.

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

and importers. Second, if the MFA's end increases the mass of suppliers in the US, then the direction of partner change depends on the firm's capability. A threshold capability $\tilde{x}$ exists such that US importers with $x > \tilde{x}$ upgrade their partners, while those with $x < \tilde{x}$ downgrade their partners. With these two complications, it is theoretically possible yet unlikely that NAM explains the observed systematic relationships between rematching and trade ranking.

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

If this hypothesis mainly explains our findings, small firms and large firms should respond to the end of the MFA in heterogeneous ways. As small "custom" US importers should become more attractive to Mexican exporters and able to match to more capable Mexican exporters, small US importers should upgrade partners more frequently than large US importers. However, Table 3 shows that both small and large US importers upgrade partners in a similar way.[32]

[32] In Appendix A.7, we also examine whether imports by initially small "custom" US importers show higher growth rates than those by large "standardized" US importers. We actually find import growth by small US importers, but this pattern holds more strongly in the control group rather than in the treatment group, which is inconsistent with the hypothesis.

Production Capacity Another hypothesis posits that firm's trade volume mainly reflects the size of Mexican supplier's production capacity instead of productivity and quality. Since production capacity can be regarded as an element of firm's capability, this hypothesis is still consistent with PAM by capability. However, the mere demand for production capacity is unlikely to be the main reason for the observed partner upgrading. If this is the case, US importers in the treatment group who upgrade partners should increase their imports more than other firms. However, Appendix A.7 reports that the import growth rate of US importers during 2004–07 is not correlated with either a dummy on whether firms belong to the treatment group or a dummy on whether firms upgrade Mexican partners.

7 Conclusion

This paper has empirically identified a simple mechanism determining exporter and importer matching at the product level: Becker-type positive assortative matching by capability. When the end of the MFA enabled Chinese suppliers to enter the US market, existing US importers and Mexican exporters changed partners so that the resulting matching becomes positively assortative under the new environment. Our model, which combines Becker (1973) and Melitz (2003) models, shows that this rematching brings additional gains from trade. Thus, it can be said that trade liberalization improves buyer–supplier matching within industries.

We believe the proposed assortative matching model will provide new insights on firms and trade. For instance, policy discussions often encourage domestic suppliers to export, particularly to highly capable foreign buyers. However, the implications of importer capability for exporters cannot be analyzed using conventional anonymous market models where exporters are indifferent about importer's capability in equilibrium. In contrast, the assortative matching model explains why exporters prefer to trade with highly capable importers but often fail to do so. Suppliers must develop a high capability themselves in order to trade with highly capable foreign buyers.

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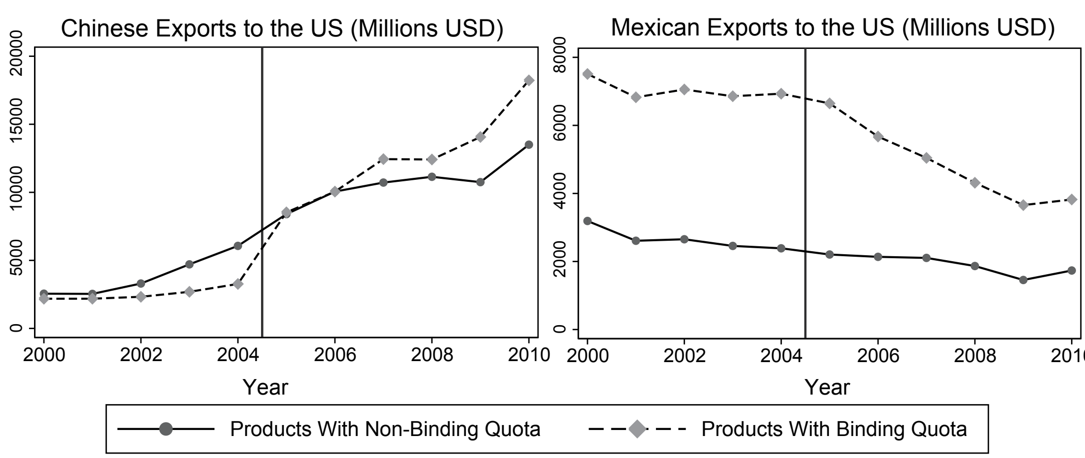
Figure 1: Chinese and Mexican Textile/Apparel Exports to the US



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

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

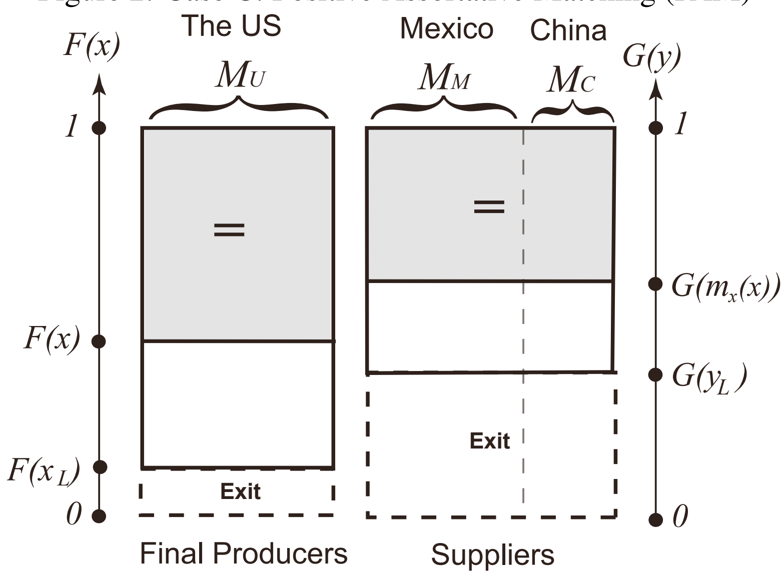


Figure 3: Case C: Response of Matching to the MFA's End

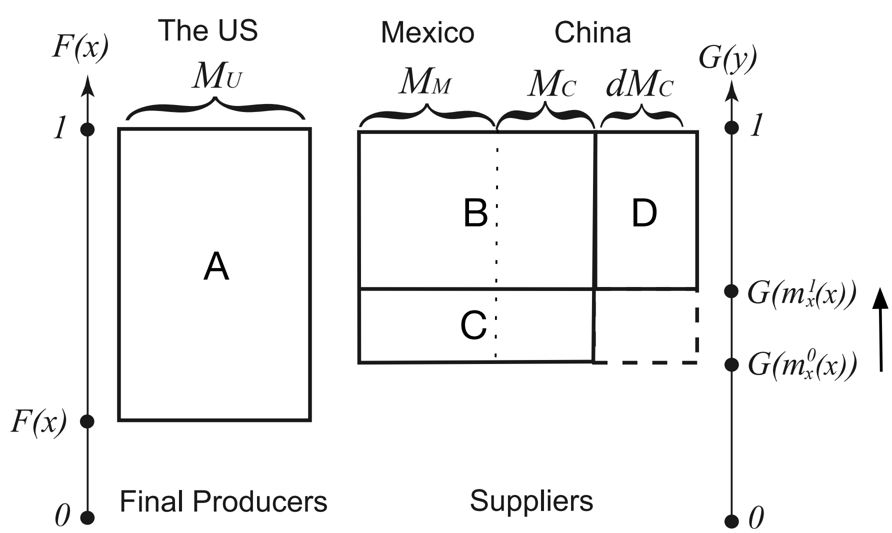
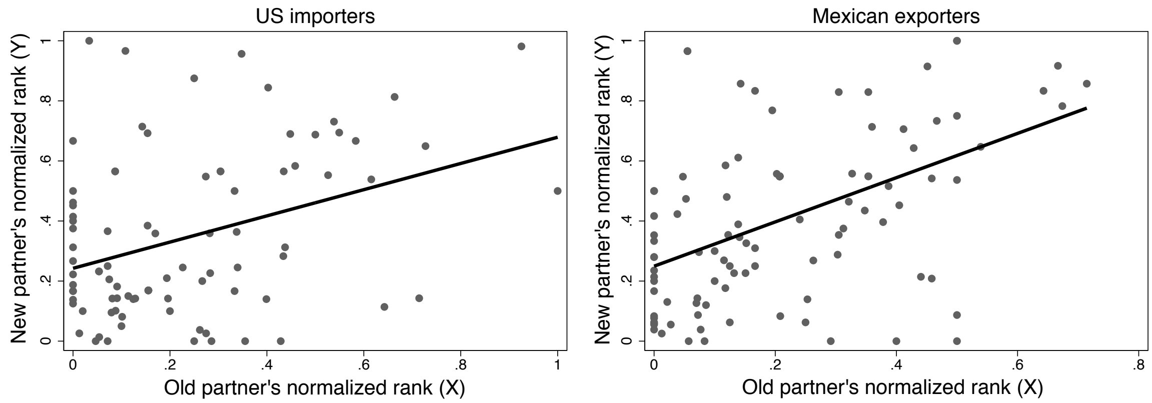


Figure 4: Old and New Partner Ranks



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

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

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

Table 1: Summary Statics for Product-Level Matching

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

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

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

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

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

Table 3: Partner Change during 2004–07

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

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

Table 4: Partner Change in Different Periods

A: Gradual Partner Changes

	Partner Change in Different Periods: Linear Probability Models					
	Up^{US}			$Down^{Mex}$		
	2004–06	2004–07	2004–08	2004–06	2004–07	2004–08
	(1)	(2)	(3)	(4)	(5)	(6)
Binding	0.036**	0.052**	0.066**	0.056*	0.127***	0.121***
	(0.015)	(0.021)	(0.027)	(0.031)	(0.035)	(0.032)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	964	718	515	767	601	442

B: Placebo Checks

	Partner Change in Different Periods: Linear Probability Models					
	Up^{US}			$Down^{Mex}$		
	2007–11	2008–11	2009–11	2007–11	2008–11	2009–11
	(7)	(8)	(9)	(10)	(11)	(12)
Binding	-0.001	0.027**	-0.000	-0.008	0.047	0.005
	(0.018)	(0.011)	(0.006)	(0.036)	(0.031)	(0.020)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	449	575	747	393	499	655

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

Table 5: Partner Change during 2004–07 with Additional Controls

A: HS 6-digit Product Level Controls: Linear Probability Models

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

B: Firm-Product Level Controls: Linear Probability Models

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

Note: Dependent variables Up^{c}_{igs} and $Down^{c}_{igs}$ are dummy variables indicating whether during 2004-07 firm i in country c switched its main partner of HS 6-digit product g in country c' to one with a higher capability rank or lower capability rank, respectively. $Binding_{gs}$ is a dummy variable indicating whether product g from China faced a binding US import quota in 2004. $\#Exporters_g$ and $\#Importers_g$ are numbers of exporters and importers of product g in 2004, respectively. $LnTotalTrade_g$ is the log of trade volume for product g in 2004. Product Types are a collection of dummy variables indicating whether products are men's, women's, cotton, wool, or synthetic (man-made). $LnTrade_{ig}$ is the log of firm i's trade volume of product g in 2004. $Maquiladora_{ig}$ is the share of Maquiladora/IMMEX trade in firm i's trade of product g in 2004. $\#Partners_{ig}$ is the number of firm i's partner in product g in 2004. $US\,Intermediary_{ig}$ is a dummy variable indicating whether US firm i or firm i's US main partner is an intermediary firm. All regressions include HS 2-digit (sector) fixed effects. Standard errors are shown in parentheses and clustered at the HS 6-digit product level. Significance: * 10 percent, ** 5 percent, *** 1 percent.

Table 6: Mexican Exporter's Exit from the US market

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

Note: Dependent variable $Exit_{igsr}$ is a dummy variables indicating whether Mexican firm i stops exporting product g to the US in period r. $Binding_{gs}$ is a dummy variable indicating whether product g from China faced a binding US import quota in 2004. $After_r$ is a dummy variable indicating whether period r is after 2004. $lnExport_{igr}$ is the log of firm i's export of product g in the initial year of period r. Columns (2), (4) and (6) include the following control variables of the initial year and their interactions with $After_r$: share of Maquiladora/IMMEX trade in firm i's trade of product g in the initial year; log of trade volume for product g; number of exporters of product g; a collection of dummy variables indicating products types: whether products are men's, women's, cotton, wool, or synthetic (man-made). All regressions include HS 2-digit (sector) fixed effects. Standard errors are shown in parentheses and clustered at the HS 6-digit product level. Significance: * 10 percent, ** 5 percent, *** 1 percent.

Table 7: Alternative Capability Rankings

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

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

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

B: Old and New Partners 2004–07: OLS

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

Note: Rankings are based on firm's product trade with the main partner in 2004 in "Baseline", firm's product total trade in 2004 in "Total Trade", and firm's unit price of product in 2004 in "Price". Significance: * 10 percent, ** 5 percent, *** 1 percent. (Panel A) Dependent variables Up^c_{igs} and $Down^c_{igs}$ are dummy variables indicating whether during 2004–07 firm i in country c switched its main partner of HS 6-digit product g in country c' to one with a higher capability rank or lower capability rank, respectively. $Binding_{gs}$ is a dummy variable indicating whether product g from China faced a binding US import quota in 2004. All regressions include HS 2-digit (sector) fixed effects. Standard errors are shown in parentheses and clustered at the HS 6-digit product level. (Panel B) Regressions are run for firm i in country c who switched their main partners of product g during 2004-07. The dependent variable $NewPartnerRank^c_{ig}$ is the normalized rank of firm i's new main partner of product g in 2007. $OldPartnerRank^c_{ig}$ is the normalized rank of firm i's old main partner of product g in 2004.

Appendix (Not for Publication)

A1. Solving the Model

Consumer Maximization

The consumer maximization problem is equivalent to maximizing

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

The first order conditions are

$$\frac{\delta\theta\left(\omega\right)^{\alpha}q\left(\omega\right)^{\rho-1}}{\int_{\omega'\in\Omega}\theta(\omega')^{\alpha}q(\omega')^{\rho}d\omega'} = p\left(\omega\right)\text{ for all }\omega\in\Omega. \tag{10}$$

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

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

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

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

where $P \equiv \left[\int_{\omega\in\Omega} p(\omega)^{1-\sigma}\theta\left(\omega\right)^{\alpha\sigma} d\omega\right]^{1/(1-\sigma)}$ is the price index. Substituting this into (10), we obtain the demand function:

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

$$\delta\theta\left(\omega\right)^{\alpha} q\left(\omega\right)^{\rho-1}\left(\frac{\theta(\omega)^{\alpha(\sigma-1)} p\left(\omega\right)^{1-\sigma}}{q(\omega)^{\rho} P^{1-\sigma}}\right) = p\left(\omega\right)$$

$$q(\omega) = \frac{\delta\theta\left(\omega\right)^{\alpha\sigma}}{P^{1-\sigma}} p(\omega)^{-\sigma}. \tag{11}$$

Stage 2: Team profit maximization

Facing the demand function (11), 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

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

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

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

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

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

Stage 1

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

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

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,

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

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

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

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

Proof for Lemma 2

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

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

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

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

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

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

Theorem 1 was developed by Koopmans and Beckmann (1957) and Shapley and Shubik (1972) for the case with finite agents and by Gretsky, Ostroy and Zame (1992) for the case with a continuum of agents.

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 Corollary 1:

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.*

Then, 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, $A^I\Theta^I - M^I f \geq A^I\Theta^J - M^J f$ from Corollary 1. Since $M^I > M^J$, this implies $\Theta^I > \Theta^J$. (ii) Since equilibrium matching of environment J is feasible and not stable in environment I, $A^I\Theta^I - M^I f > A^I\Theta^J - M^J f$ 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* and the environment before the MFA's end as *B-environment*. 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 $y_L^A \leq y_L^B$. 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 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 (6), we have $\Theta^A < \Theta^B$. This contradiction implies $y_L^A \geq y_L^B$. □

Proof for Lemma 1

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

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

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

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

Proof. Suppose $y_L^{NR} \leq y_L^B$. This means $x_L^{NR} < x_L^B$ and $M^{NR} > M^B$. Since $\theta_L = \theta(x_L, y_L)$ holds in Case C and Case I, $y_L^{NR} < y_L^B$ and $x_L^{NR} < x_L^B$ imply that $\theta_L^{NR} < \theta_L^B$. From $\theta_L = \frac{\sigma f}{\delta}\Theta$ in (6), 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 $\theta_L^A \leq \theta_L^{NR}$ and $\Theta^A < \Theta^{NR}$. Since equilibrium matching of the NR-environment is feasible and not stable in the A-environment, Lemma 3 and $M^A \geq M^{NR}$ imply $\Theta^A > \Theta^{NR}$. This contradiction implies $y_L^A > y_L^{NR}$. □

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

Proof. Suppose $\Theta^{NR} \leq \Theta^B$, which implies that $\theta^{NR} \leq \theta^B$ from (6). 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 $\Theta^{NR} > \Theta^B$, .

Suppose $\Theta^A \leq \Theta^{NR}$, which implies $\theta^A \leq \theta^{NR}$ from (6). Since equilibrium matching in the NR-environment is feasible and not stable in the A-environment, Lemma 3 implies $M^A < M^{NR}$. From $M = M_U[1 - F(x_L)]$, this means $x_L^A > x_L^{NR}$. In Case C, $\theta_L = \theta(x_L, y_L)$, $y_L^A > y_L^{NR}$ from Claim 3, and $\theta_L^A \leq \theta_L^{NR}$ imply $x_L^A < x_L^{NR}$. This contradiction implies $\Theta^A > \Theta^{NR}$. □

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

A.3 Negative Assortative Matching

Solving the Model

In Case S, the market clearing condition becomes

$$M_U[1-F(x)] = (M_M + M_C)\left[G\left(m_x\left(x\right)\right) - G(y_L)\right] \text{ for all } x \geq x_L. \tag{12}$$

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 (12) 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

$$A\theta\left(x_L, y_{max}\right) - f = A\int_{m_x(x_{max})}^{y_{max}} \theta_2(m_y(t), t)dt$$

$$\frac{\delta}{\sigma\Theta(x_L)}\left[\theta\left(x_L, y_{max}\right) - \int_{m_x(x_{max})}^{y_{max}} \theta_2(m_y(t), t)dt\right] = f. \tag{13}$$

The above equation uniquely determines x_L since the left hand side is monotonically increasing in x_L.

Supplier Exit after the MFA's End

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

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

Proof. Suppose $y_L^A \le y_L^B$. 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 (13) 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

$$\begin{aligned}\int_{y_{L^B}}^{y_{max}} \int_{m_y^A(t)}^{m_y^B(t)} \theta_{12}(z,t)dzdt &= \int_{y_{L^B}}^{y_{max}} \left[\theta_2(m_y^B(t),t) - \theta_2(m_y^A(t),t)\right] dt \\ &= \int_{y_{L^B}}^{y_{max}} \theta_2(m_y^B(t),t)dt - \int_{y_L^B}^{y_{max}} \theta_2(m_y^A(t),t)dt \\ &\geq \int_{y_{L^B}}^{y_{max}} \theta_2(m_y^B(t),t)dt - \int_{y_L^A}^{y_{max}} \theta_2(m_y^A(t),t)dt \\ &> 0. \end{aligned} \tag{14}$$

On the other hands, the matching market clearing condition implies for $y \geq y_L^B$, 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 $y \geq y_L^B$,

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

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

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

which contradicts with (14). $\square$

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 (12), we obtain the partner change of importers with capability x:

$$dm_x(x) = \frac{\Gamma(x)}{g(m_x(x))}, \Gamma(x) \equiv g(y_L)dy_L - \frac{G(m_x(x)) - G(y_L)}{(M_M + M_C)} dM_C. \tag{15}$$

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 $x < \tilde{x}$. □

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

A.4 Data Construction

Customs transaction data Our primary data set is a Mexican customs transaction data set for Mexican textile/apparel exports to the US. The data set is created from the administrative records held on every transaction crossing the Mexico–US border from June 2004 to December 2011. The Mexican customs agency requires both individuals and firms who ship goods across the border to submit a customs form (pedimento aduanal in Spanish) that must be prepared by an authorized agent. The form contains information on (1) date of clearing customs; (2) total value of shipment (in US dollars); (3) 8-digit HS product code (we use from HS50 to HS63); (4) quantity and unit; (5) name, address, and tax identification number of the Mexican exporter; (6) name, address, and tax identification number (employment identification number, EIN) of the US importer; (7) an indicator of a duty free processing reexport program (the Maquiladora/IMMEX program); and other information.

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

We therefore used a series of methods developed in record-linkage research for data cleaning to assign importer-ID.[33] First, as the focus of our study is firm-to-firm matching, we dropped transactions for which exporters were individuals and courier companies (e.g., FedEx, UPS, etc.). Second, we standardized the format of addresses using the software, ZP4, which received a quality certification of address cleaning (CASS certification) from the United States Postal Services. Third, we remove generic words in company names that did not help identify a particular company such as legal terms (e.g., Co., Ltd., etc.). Fourth, we prepared lists of fictitious names, previous names and name abbreviations, a list of addresses of company branches, and a list of EINs from data on company information, using Orbis by Bureau van Dijk, which covers 20 millions company branches, subsidiaries, and headquarters in the US.[34] Fifth, for each HS 2-digit industry, we matched names within customs data and names between customs data and name lists from Orbis mentioned above. In conducting our matching, we used fuzzy matching techniques allowing small typographical errors and abbreviations.[35] To increase the accuracy

[33] An excellent textbook for record linkage is Herzog, Scheuren, and Winkler (2007). In additon, 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.

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

[35] The two names compared are "fuzzy matched" if one of the followings is satisfied: (1) they are close to each other in terms of the Jaro-Winkler metric, which is available in the Record Linkage package of R; (2) they agree on the number of the first n letters; (3) the longer of the two names includes the shorter one.

of fuzzy matching, we removed words commonly appearing in the industry (e.g., "apparel") from the two names compared if the word appears in both names. Also we do not apply fuzzy matching techniques to very short names. Sixth, we conducted similar matches for addresses and EINs. For addresses, we also use fuzzy matching techniques for street and city name matching.

From these operations, we obtain matched pairs of names, addresses and EINs. Then, using these matched relations and the network theory software (the igraph package of R), we created clusters of information (names, addresses, and EINs) in which one cluster identifies one firm. We identified a cluster utilizing the following general rule. Each entry in a cluster matches with some other entries in the cluster either by EIN or by both names and addresses. After automatically creating clusters, we manually checked them and separated entries that should not have been matched. Finally, we assigned importer-IDs to each cluster.

Data Cleaning Some information was dropped from the dataset. First, we dropped exporters who are individuals or courier companies (e.g., FedEx, UPS, etc.) because we focus on firm to firm matching. Second, as the dataset contains information only from June to December for 2004, we dropped observations from January to May for other years to make each year's information comparable.[36] Third, we dropped one product (HS570210) where the number of importers unreasonably fluctuates, suggesting low data quality.[37] 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%

[36]We conducted our main analysis (Tables 2 and 3) without conducting the latter two operations and obtained similar results.

[37]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.

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.

A5. Variable Construction

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

$$Binding_g = I\left\{\frac{\sum_{j\in J(g)} x^m_{j2004} I\{\text{quota on } j \text{ was binding in 2004}\}}{\sum_{j\in J(g)} x^m_{j2004}} \geq 0.5\right\}, \tag{16}$$

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 clasification includes the words “men”, “women”, “wool”, “cotton”, or “manmade”, respectively. $\#Exporters_{gs}$ is the number of exporters of product g in 2004, $\#Importers_{gs}$ is the number of importers of product g in 2004, and $TotalTrade_{gs}$ is the total trade volume of product g in 2004 .

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

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

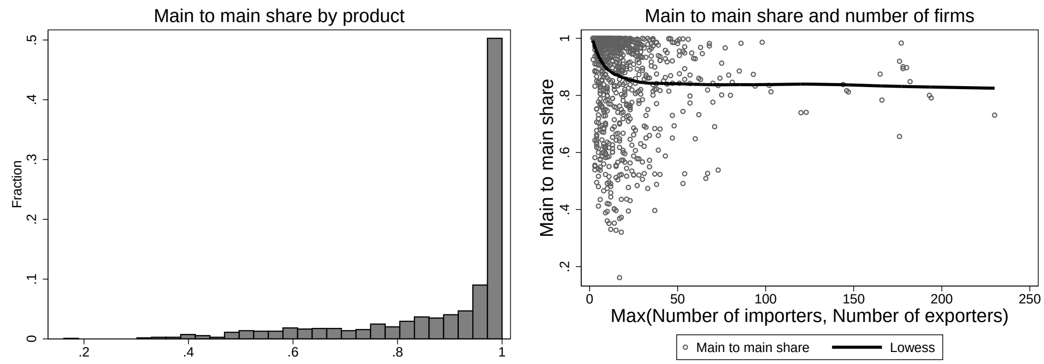
Dummy variable $US\,Intermediary_{igs}$ equals one either if firm i is a US intermediary firm or if firm i is a Mexican exporter and its US main partner is an intermediary firm. US intermediary firms are identified as follows. One US importer is typically matched with several records of US firms in Orbis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

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

A6. Main-to-Main Share at Product Level

Two panels in Figure 5 draw the distribution of main-to-main shares across product-year combinations. A histogram in the left panel strikingly shows that main-to-main shares exceed 0.9 for most combinations with the median 0.97 and 25th percentile 0.86. The right panel in Figure 5 plots main-to-main shares against the maximum of the number of importers (n_m) and exporters (n_x), $\max\{n_m, n_x\}$. This exercise is motivated by the love of variety model with symmetric firms that predicts main-to-main share will equal $1/\max\{n_m, n_x\}$. An estimated Lowess curve is above 0.80 and almost horizontal, which implies that main-to-main share is not related with the total number of firms. Figure 5 remains very similar when the horizontal axis expresses either n_m or n_x.

Figure 5: Main-to-Main Shares for HS 6-Digit Textile/Apparel Products



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

A7. Summary Statistics and Treatment Control Group Comparison

Table 8 provides summary statics of product-level characteristics. Column (1) reports means and standard deviations of each product level characteristics for the control group, with the number of observations in Column (2). Columns (3) and (4) report the difference in each characteristic between treatment and control groups. We regress each characteristic of product g on the treatment dummy $Binding_{gs}$ and report the OLS coefficient b of the dummy in Column (3). Column (4) reports the OLS coefficient b of the dummy from a similar regression with HS 2-digit fixed effects, which captures the difference between the two groups within the same HS 2-digit sector. Column (5) reports the number of observations for the regressions for Columns (3) and (4). Though a simple comparison in Column (3) shows that the two groups differ in many characteristics, with HS 2-digit fixed effects the difference becomes smaller and even insignificant for many characteristics, as shown in Column (4).

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

Table 9 reports similar summary statistics for importer-product level characteristics. Even with HS 2-digit fixed effects, the treatment group shows more trade volume and a higher share of processing trade (Maquiladora/IMMEX).

Table 10 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 8: Product-Level Characteristics in 2004

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

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

Table 9: Importer-Product Level Characteristics in 2004

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

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

Table 10: Exporter-Product Level Characteristics in 2004

Exporter-Product Level Characteristics in 2004					
Own Characteristics					
	Control group		Treatment-Control Difference		
	Mean	Obs.	b	b (w. HS2 FE)	Obs.
	(1)	(2)	(3)	(4)	(5)
Maquiladora	0.33	1818	0.122***	0.093***	4131
[s.d.](s.e.)	[0.46]		(0.015)	(0.019)	
Northern State	0.24	1818	-0.103***	0.002	4131
Dummies	[0.43]		(0.012)	(0.015)	
LnTrade	7.60	1818	1.562***	0.963***	4131
	[3.52]		(0.109)	(0.139)	
N of Partners	1.5	1818	-0.036	0.213***	4131
	[2.01]		(0.056)	(0.072)	
Main Partner Share	0.73	296	0.018	-0.014	724
	[0.21]		(0.016)	(0.022)	
Main Partner's Characteristics					
	Control group		Treatment-Control Difference		
	Mean	Obs.	b	b (w. HS2 FE)	Obs.
US Intermediary	0.31	1219	0.020	-0.053**	2833
[s.d.](s.e.)	[0.46]		(0.018)	(-0.024)	

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

A.8. Import Growth of US Importers

Table 11 presents the analyses of import growth rate of US importers that were mentioned in Section 6.2 to reject alternative explanations. Columns (1) and (2) concern the segment-switching hypothesis. The hypothesis predicts small-sized US importers in a "custom" segment should grow more than large-sized US importers in a "standardized" segment. This 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.

Columns (3) and (4) concern 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 11: Import Growth of US Importers during 2004-2007

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

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

References

Herzog, Thomas N., Fritz J. Scheuren, and William E. Winkler. *Data quality and record linkage techniques*. Springer, 2007.