Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

Assortative Matching of Exporters and Importers*

Yoichi Sugita† Kensuke Teshima‡ Enrique Seira§

July 2021

Abstract

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

JEL Classification: F1; **Keywords:** Firm heterogeneity, assortative matching, two-sided heterogeneity, trade liberalization

*We are grateful to comments from three anonymous referees and the editor Amit Khandelwal, especially their encouragement for many-to-many matching extensions. We thank Andrew Bernard, Bernardo Blum, Kerem Cosar, Don Davis, Swati Dhingra, Lukasz Drozd, Michael Gechter, Julia Cajal Grossi, Meixin Guo, Daniel Halvarsson, Keith Head, Wen-Tai Hsu, Mathias Iwanowsky, Hiroyuki Kasahara, Ben Li, Alberto Ortiz, Nina Pavcnik, James Rauch, Bob Rijkers, Esteban Rossi-Hansberg, Peter Schott, Yuta Suzuki, Heiwai Tang, Yong Tang, Catherine Thomas, Kosuke Uetake, Yasutora Watanabe, Yuta Watabe, David Weinstein, Shintaro Yamaguchi, Makoto Yano and participants at seminars and conferences for their comments. We thank Secretaria de Economia of Mexico and the Banco de Mexico for help with the data. Financial supports from the Private Enterprise Development in Low-Income Countries (PEDL), the Wallander Foundation, the Asociacion Mexicana de Cultura, and JSPS KAKENHI (Grant Numbers 22243023, 26220503, 15H05392, 17H00986, 18K19955 and 19H01477) are gratefully acknowledged. This research benefits from the IDE-JETRO project and the RIETI project. Francisco Carrera, Diego de la Fuente, Zheng Han, Carlos Segura, Yuri Sugiyama, Yuta Suzuki, Jumpei Takubo, Makoto Tanaka, and Stephanie Zonszein provided excellent research assistance.

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

‡Institute of Economic Research, Hitotsubashi University. 2-1 Naka Kunitachi, Tokyo 186-8601, Japan. (E-mail: kensuke-teshima@ier.hit-u.ac.jp)

§ITAM. Av. Santa Teresa # 930, Mexico, D. F. 10700 (E-mail: enrique.seira@itam.mx)

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

1 Introduction

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

This paper examines how exporters and importers match based on their capability by investigating the change in such exporter–importer matching during trade liberalization. From Mexico's customs administrative records, we construct a matched exporter–importer dataset for Mexican textile/apparel exports to the United States from 2004 to 2007. Mexico–US textile/apparel trade is particularly suitable for our purpose. First, since Mexico and the United States are large trading partners with each other, trade between them includes numerous heterogeneous exporters and importers.[1] Second, Mexico–US textile/apparel trade experienced large-scale liberalization. In 2005, the United States removed quotas on textile/apparel imports at the end of the Multi-Fibre Arrangement (MFA). Since Mexican products already had quota-free access to the US market under the North American Free Trade Agreement (NAFTA), the MFA's end effectively removed protection for Mexican products in the US market and forced them to compete with imports from third countries, principally China. The liberalization varied across products substantially and was arguably exogenous because the liberalization schedule was decided at the GATT Uruguay Round (1986–94) when China's export growth were not expected.

The MFA's end substantially changed the partnerships between Mexican exporters and US importers. Mexican exports to the United States decreased by the extensive margin (stopping exports)

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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

and intensive margin (reducing export values). The intensive margin adjustment involved substantial partner switching, often including the exporter's largest main partners. Main partner switching accounted for more than 50% of the intensive margin and caused a more than 230% excess reallocation of exports across US buyers beyond the intensive margin. As we explain in Section 2, this prevalence of main partner switching in trade liberalization was at odds with anonymous market models (e.g., neoclassical models, oligopoly models), love-of-variety models (the Krugman–Melitz model), and some recent exporter–importer matching models (e.g., Bernard, Moxnes, and Ulltveit-Moe, 2018) that combine the love-of-variety model and fixed costs of matching.

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

The model predicts that the MFA's end induced systematic partner switching that led to efficient buyer–supplier matching and improved consumer welfare. As empirically documented by Khandelwal, Schott, and Wei (2013), at the MFA's end, Chinese suppliers at various capability levels entered the US market. The entry of Chinese suppliers lowered the capability ranking of each Mexican supplier in the market. Therefore, to achieve PAM, Mexican exporters switched to US importers with lower capability, while US importers switched to Mexican exporters with

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

higher capability. We call these types of partner switching "partner downgrading" and "partner upgrading," respectively. Allowing capable Chinese suppliers to match with capable US final producers, this rematching achieved PAM in the global market, which improved aggregate capability and consumer welfare. By contrast, in an anonymous market in which matching is independent of capability, rematching should not occur in a systematic way or result in an efficiency gain.

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

To the best of our knowledge, detecting Beckerian PAM by capability in this way is a novel approach to addressing the endogeneity problem in the conventional approach. When matching matters for a firm's performance, most firm characteristics observable in typical production and customs data (e.g., inputs, outputs, and productivity measures) may reflect partners' unobserved capability as well as the firm's own capability. Therefore, the simple correlation of those characteristics across matches may suffer from endogeneity.[2] Instead, our approach utilizes the MFA's end as an exogenous negative shock on the capability ranking of Mexican exporters.

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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

As matched exporter-importer data become available to researchers, the last decade saw the burgeoning literature on buyer-supplier relationships in international trade.[3] Our paper contributes to a strand of this literature studying exporter-importer matching. Rauch (1996), Casella and Rauch (2002), and Rauch and Trindade (2003) pioneered the theoretical literature by using the assignment model of symmetric firms, while our model features firm heterogeneity in capability as in Melitz (2003). Antras, Garicano, and Rossi-Hansberg (2006) analyzed offshoring as the PAM of managers and workers across countries. The assignment model captures two distinctive features in exporter-importer relationships. First, trading with high capability firms improves a firm's performance, but the opportunity to trade with them is scarce and something that firms compete for. This view echoes with recent evidence that trading with high capability foreign firms improves local firm's performance through various channels.[4] Second, buyer–supplier matching is an allocation of scarce trading opportunities. Thus, trade liberalization induces partner switching to achieve a globally efficient matching. We provide the first evidence for this matching mechanism.

Bernard et al. (2018) recently developed another approach combining match-level fixed costs and the love-of-variety (CES) production function.[5] A buyer and a supplier are matched when the match surplus exceeds the match-level fixed costs. As the match surplus monotonically increases in the buyer's capability and the supplier's, all the matches are realized except those between low capability firms.[6] Thus, the model can predict the negative degree assortativity reported by Blum, Claro, and Horstmann (2010), Bernard et al. (2018), and others that a buyer's number of partners

[3]Domestic buyer-supplier matched data has recently become available for research on domestic production networks(e.g. Bernard, Moxnes, and Saito, 2019; Dhyne, Kikkawa, Mogstad, and Tintelnot, 2021).

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

[5]Bernard, Dhyne, Magerman, Manova, and Moxnes (2021) and Lim (2018) introduced idiosyncratic match-level fixed costs in the model of Bernard et al. (2018) and analyzed the formulation of domestic production networks. Carballo, Ottaviano, and Volpe Martincus (2018) applied the ideal variety approach instead of using the love-of-variety model, which incorporates the interaction between the buyer's taste for ideal varieties and the seller's productivity.

[6]In the assignment model, by contrast, the match surplus is a non-monotonic function. For a given firm, the match surplus is maximized at the capability of its equilibrium partner as we show in Section 3.1 (2).

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

is negatively correlated with the average number of firms to which the buyer's partners sell.

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

Another important strand of the literature studies the dynamics of an exporter's and importer's partner choice in a steady-state environment. Macchiavello (2010) introduced reputation building in an assignment model to explain an exporter's partner upgrading over time. Eaton, Eslava, Jinkins, Krizan, and Tybout (2014) and Eaton, Jinkins, Tybout, and Xu (2015) developed models incorporating search and learning frictions in partner acquisitions.[7] Eaton, Kortum, and Kramartz (2016) modeled random meeting and competition among multiple buyers and suppliers. Monarch (2021) estimated partner switching costs in a dynamic discrete choice model. Heise (2020) documented the dependence of exchange rate pass-through on the age of trade relationships.

Benguria (2021) and Dragusanu (2014) documented positive correlations between the size and productivity measures of exporters and importers in France–Colombia trade and India–US trade, respectively. Our model featuring Beckerian PAM also predicts these findings. Benguria (2021) and Dragusanu (2014) developed search effort models of the Stigler (1961) type to explain their findings by a different mechanism: a high productivity exporter spends greater search efforts finding a high productivity importer. Their models, however, do not explain Mexican exporters' partner

[7] Lu, Mariscal, and Mejia (2017) analyzed importer's switching intermediates in a search/learning model.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

downgrading at the MFA's end. In their models, search costs are sunk and importers are willing to trade with all exporters. Thus, Mexican exporters should continue to trade with pre-liberalization US partners instead of downgrading partners by paying additional search costs.

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

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

2 Mexico–US Textile/Apparel Trade

2.1 The End of the MFA

The MFA and its successor, the Agreement on Textiles and Clothing, are agreements about the quotas on textile/apparel imports among GATT/WTO countries. At the GATT Uruguay Round (1986–94), the United States (together with Canada, the European Union, and Norway) promised to abolish the quotas in four steps (in 1995, 1998, 2002, and 2005). The MFA's end in 2005 was the largest liberalization in which liberalized products constituted 49% of imports in 1990.

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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

motivate our analysis.

Fact 1: Surge in Chinese Exports to the United States According to Brambilla, Khandelwal, and Schott (2010), US imports from China disproportionally increased by 271% in 2005, while imports from most other countries decreased. Using Brambilla et al.'s (2010) US import quota data, we classify each HS six-digit textile/apparel product into two groups (see Appendix B.5 for details): the treatment group of products in which Chinese exports subject to the binding 2004 US import quota, and the control group of other textile/apparel products. We regress the HS six-digit product-year-level exports of China and Mexico on the annual year dummies with product fixed effects separately for the treatment group and control group. Figure 1 shows the coefficients of the annual year dummies with triangles for the treatment group and circles for the control group, separately for Chinese exports and Mexican exports. The difference in the coefficients between the two groups expresses the impacts of the MFA's end on Chinese and Mexican exports after controlling for product-specific effects. In the left panel for Chinese exports, while the coefficients before 2005 are stable and virtually identical between the two groups, after the 2005 quota removal, the coefficient for the treatment group increases much faster than that for the control group.[8]

<<Figure 1 is here >>

Fact 2: Mexican Exports Faced Competition from China By 2003, Mexico already had tariff- and quota-free access to the US market through NAFTA. With the MFA's end, Mexico lost its advantage over third-country exporters and faced increased competition from Chinese exporters in the US market, as the right panel of Figure 1 shows.[9] While the two groups were stable and almost

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

[9]In theory, Mexican firms can export products to the US that are produced from materials imported from China; however, the number of such cases is negligible because of NAFTA's restrictive rules of origin, which requires "yarn forward" (US CBP, 2014). The yarn must be made in Mexico to be qualified as NAFTA

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

identical before 2005, the exports in the treatment group significantly declined thereafter.

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

2.2 Partner Switching after the MFA's End

Data From Mexico's customs administrative records, we construct a matched exporter–importer dataset from June 2004 to December 2011 for Mexican textile/apparel exports (covering HS50 to HS63) to the United States. For each match of a Mexican exporter and a US importer, the dataset contains the following information: exporter ID, importer ID, HS six-digit product code, annual shipment value (USD), quantity and unit, an indicator of a duty-free processing reexport program (Maquiladora/IMMEX), and other information.

We assign the exporter ID and importer ID throughout the dataset. The exporter ID is the tax number unique to each firm in Mexico. Assigning importer IDs to US firms is challenging. Although the customs records report the name, address, and employment identification number (EIN) of the US importer for each transaction, none of these can uniquely identify a firm because it can use multiple names or change names, own multiple plants/establishments, or change tax numbers. Furthermore, a firm's name and address may be written in multiple ways and suffer from typographical errors. Therefore, simply counting combinations of names, addresses, and

products; therefore, only fibers can be imported from China. However, Mexico's fiber imports from China is 7 million USD in 2004 and accounts for only 0.08% of Mexico's textile/apparel exports to the US.

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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

EIN would wrongly assign more than one ID to one US importer.

We therefore assign the importer ID by applying a series of record linkage techniques.[11] First, we prepare a list of name variations such as fictitious names, previous names, and name abbreviations, a list of addresses of company branches/subsidiaries, and a list of EIN from Orbis by Bureau van Dijk, which covers 20 million company branches, subsidiaries, and headquarters in the United States. Second, the address format is standardized using software certified by the US Postal Office. Third, we match the lists from Orbis to each of the linking variables (name, address, EIN) in the customs data by fuzzy matching. Two types of errors can occur in fuzzy matching: "false matching" (matching records that should not be matched) and "false unmatching" (not matching records that should be matched). The criteria for fuzzy matching are chosen to minimize false unmatching because false matching is easier to identify by manual checks. Fourth, binary matched records are aggregated into clusters so that each record matches another record in that cluster. Then, we manually check each cluster and remove falsely matched records. A resulting cluster represents a firm and receives an importer ID. Appendix B explains the data construction process in detail.

Data cleansing drops some observations. First, since the dataset only covers observations from June to December in 2004, we drop the observations from January to May in other years to make the information in each year comparable. We obtain similar results when January–May observations are included. Second, while importer information is reported for most normal trade transactions, it is sometimes missing for processing trade transactions under the Maquiladora/IMMEX program in which exporters do not have to report an importer for each shipment.[12] We drop exporters that do not report the importer information for most transactions. To address the potential selection issues caused by this action, we distinguish normal trade and processing trade in the analyses below and conduct weighted regressions in Appendix B.4.

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

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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

Table 1 reports the summary statistics for the product-level and firm-level matching. A product-level match occurs if an importer and an exporter trade in a particular product, while a firm-level match occurs if an importer and an exporter trade in at least one product. Columns (a) and (b) in Table 1 report the mean and median of the product-level matching.[13] The first four rows show that 11–15 exporters and 15–20 importers exist in an average product market, but the majority of firms trade with only one partner.[14] Rows (5) and (6) show that even for firms that trade with multiple partners, more than 70% of their trade occurs with their single main partners.[15]

<< Table 1 is here.>>

Excess Partner Switching after the MFA's end Our new finding is that exporters and importers actively switch partners during liberalization. Panel A in Table 2 reports the changes in Mexican textile/apparel exports to the United States between 2004 and 2007 by incumbent exporters in 2004 separately for liberalized products (quota-bound) and other products (quota-free). The changes in total exports in Column (1) are decomposed into the *extensive margin* in Column (2) by exiters that stopped exporting by 2007 and *intensive margin* in Column (3) by continuing exporters in 2007.[16] The intensive margin in Column (3) is further decomposed into three margins of partner changes: *Partner Staying* in Column (4) expresses the changes in exports to continuing buyers that import from the exporter both in 2004 and 2007, *Partner Adding* in Column (5) expresses those to new buyers in 2007 that did not import from the exporter in 2004, and *Partner Dropping* in Column (6) expresses those to dropped partners that imported from the exporter in 2004 but not

[13]Table 1 removes products with only one exporter or one importer, which accounts for 3% of trade. Including them decreases the numbers in Columns (1) and (2), but barely changes those in the other columns.

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

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

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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

in 2007. The parentheses in Columns (5) and (6) report the share of export changes by *Partner Switchers* that simultaneously add and drop partners. These high shares imply that most partner changes are in fact partner switching. Column (7) reports the excess reallocation of partners, i.e., $|(5)| + |(6)| - |(5) + (6)|$.

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

<<Table 2 is here.>>

Table 2 shows that in liberalized industries, main partner switching [Columns (4)+(5)] accounted for 54% of the intensive margin [Column (1)] and caused a more than 230% excess reallocation of exports across US buyers beyond the intensive margin. This prevalence of main partner switching is at odds with anonymous market models (perfectly competitive and oligopoly models) and love-of-variety models (the Krugman–Melitz model) including some production networks models (e.g., Bernard et al., 2018). First, as we show in Section 3, in anonymous markets where firms are indifferent about partners, partner changes should be minimized to save partner switching costs. Exporters may either add or drop buyers, but should not switch among surviving buyers, that is, the excess reallocations in Panels A and C should be zero. Second, as Appendix D shows, in models combining the love-of-variety model and match-specific fixed costs, firms add and drop marginally important partners rather than main partners. Thus, the large main partner excess export reallocation in Panel C is puzzling to these models.

The decompositions in Panels A and C show the overall importance of partner switching. To examine the impact of liberalization at the disaggregated level, we regress each margin of the

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

HS six-digit product-level exports on the dummy variable of quota liberalization (the Binding dummy) with the HS two-digit fixed effects. Panel B and Panel D in Table 2 report the estimated coefficients. The large and statistically significant coefficients in Columns (5)–(7) in Panel B and Columns (4)–(6) in Panel D confirm the significant roles of partner switching.

3 The Model

This section develops an exporter–importer matching model in which partner switching is the principal margin of adjustment. Sections 3.1 sets up the model for the case of one-to-one matching and Section 3.2 derives the main insights about partner switching in trade liberalization. Section 3.3 introduces many-to-many matching and derive predictions that we take to the data.

3.1 Matching Model of Exporters and Importers

The model includes three types of a continuum of firms, namely, US final producers, Mexican suppliers, and Chinese suppliers.[17] US final producers may be retailers or wholesalers. The model has two stages. In Stage 1, a US final producer matches with a supplier from either Mexico or China to form a team that produces one variety of differentiated final goods. Suppliers tailor intermediate goods and transact them only within the team. Firms match under perfect information and each firm joins only one team. This one-to-one frictionless matching model is the simplest model predicting PAM. Introducing search frictions does not change the qualitative predictions that we take to the data.[18] In Stage 2, teams compete in the US final good market under monopolistic competition.

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

[18]The general conclusion of the theoretical literature on search frictions (e.g. see Smith (2011) for an excellent survey) is that as long as the complementarity within matches is large enough, PAM holds on average, as in the frictionless matching model that we consider.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

The US representative consumer maximizes the CES utility function:

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

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

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

Production technology is of the Leontief type. When a team with capability θ produces q units of final goods, the team supplier produces q units of intermediate goods at costs $c_y\theta^{\beta}q + f_y$; then, the final producer assembles these intermediate goods into final goods at costs $c_x\theta^{\beta}q + f_x$, where c_i and f_i are positive constants ($i = x, y$). The team's total costs are $c(\theta,q) = c\theta^{\beta}q + f$, where $c \equiv c_x + c_y$ and $f \equiv f_x + f_y$. The externalities within teams make firms' marginal costs dependent on both their partner's capability and their own capability.[20] For simplicity, we assume that the

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

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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

firm's marginal costs depend on the team's capability. The team's capability θ shifts both demand and marginal costs depending on α and β. Therefore, θ may represent productivity (e.g., Melitz, 2003) and/or quality (e.g., Baldwin and Harrigan, 2011; Verhoogen, 2008).

Stage 2 We obtain an equilibrium by backward induction. The team's optimal price is $p(\theta) = c\theta^{\beta}/\rho$. Hence, team revenue $R(\theta)$, total costs $C(\theta)$, and joint profits $\Pi(\theta)$ become:

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

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

Stage 1 Firms choose their partners and decide how to split team profits, taking A as given. Profit schedules, $\pi_x(x)$ and $\pi_y(y)$, and matching functions, $m_x(x)$ and $m_y(y)$, characterize equilibrium matching.[21] A final producer with capability x matches with a supplier having capability $m_x(x)$ and receives the residual profit $\pi_x(x)$ after paying profits $\pi_y(m_x(x))$ to the partner. $m_y(y)$ is the inverse function of $m_x(x)$, where $m_x(m_y(y)) = y$.

We focus on stable matching that satisfies the following two conditions: (i) *individual rationality*, wherein all firms earn non-negative profits, $\pi_x(x) \geq 0$ and $\pi_y(y) \geq 0$ for all x and y; and

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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

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

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

From the envelop theorem, we obtain[22]

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

Thus, profits increase in capability. The capability cutoffs x_L and y_L exist such that only final producers with $x \geq x_L$ and suppliers with $y \geq y_L$ engage in trade, which satisfy

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

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

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

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

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

[22] The use of differentiation is a convenient shortcut for deriving the sorting pattern, following Sattinger (1979). Lemma 5 in Appendix D presents a general proof of sorting that can be applied to finite agents.

[23] In Case C and Case S, θ is also called strict supermodular and strict submodular, respectively. An example for Case C is the quality complementarity of tasks in a production process (e.g., Kremer, 1993). For instance, a high-quality part may be more useful when combined with other high-quality parts. An

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

firms, whereas low capability firms match with low capability firms. In Case S, we have negative assortative matching ($m_x'(x) < 0$): high capability firms match with low capability firms. In Case I, we cannot determine a matching pattern (i.e., $m_x(x)$ cannot be defined as a function) because each firm is indifferent about partner capability. Therefore, we assume that matching is random and independent of capability in Case I.

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

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

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

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

<<Figure 2 is here.>>

Finally, we obtain the cutoff x_L as follows. In both Case C and Case I, the team with the capability cutoff θ_L comprises a final producer with x_L and a supplier with y_L. In Case C, $m_x(x)$ determines aggregate capability $\Theta\left(x_L\right) = M_U \int_{x_L}^{\infty} \theta\left(x, m_x(x)\right) dF(x)$ and the capability cutoff $\theta_L\left(x_L\right) = \theta\left(x, m_x(x_L)\right)$ as functions of x_L. In Case I, let $\theta(x, y) \equiv \theta^x(x) + \theta^y(y)$.

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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

Condition (4) determines $y_L(x_L)$ as a function of x_L. Then, $\Theta(x_L) = M_U \int_{x_L}^{\infty} \theta^x(x)\, dF(x) + (M_M + M_C)\int_{y_L(x_L)}^{\infty} \theta^y(y) dG(y)$ and $\theta_L(x_L) = \theta^x(x_L) + \theta^y(y_L(x_L))$ become functions of x_L. From (1), (4), and $A = \delta/\sigma\Theta$, the team with the capability cutoff earns zero profits:

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

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

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

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

Case C Figure 2 (B) shows how matching changes from $m_x^B(x)$ to $m_x^A(x)$ for the given capability x. Area A expresses US importers with capability higher than x. They initially match with suppliers in areas $B+C$ that have higher capability than $m_x^B(x)$. After the MFA's end, the original matches become unstable because some US importers are willing to switch to the new entrants. In the new matching, final producers in area A match with suppliers in areas $B+D$ that have higher capability than $m_x^A(x)$. A US final producer with capability x switches its main partner from one with capability $m_x^B(x)$ to one with higher capability, namely, $m_x^A(x)$. We call this change "partner upgrading" by US final producers. This in turn implies "partner downgrading" by Mexican suppliers. Mexican suppliers with capability $m_x^A(x)$ match with final producers with strictly higher capability than x before the MFA's end. Not all Mexican suppliers can match with new partners, however, and those with low capability exit the market, as proven in Appendix A.2.

Case I Figure 2 (C) shows that the MFA's end increases the supplier's cutoff from y_L^B to y_L^A, as proven in Appendix A.2. Since whether x_L increases or decreases is generally ambiguous, the figure depicts the case in which x_L unchanged. As low capability suppliers in Area C exit, US importers that matched with them switch to new Chinese suppliers in Area D. Other firms do not change their partners, although they change the price and quantity of goods traded. Firms are indifferent about their partners as long as those partners have a capability level above the cutoffs.

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

We show that the rematching effect in Case C is a new mechanism of gains from trade that did not exist in standard trade models nested in Case I (perfectly competitive models and Krugman–Melitz models with one-sided heterogeneity). We consider a hypothetical "no-rematching" equilibrium at which firms switch partners only if their current partners exit the market and denote variables in this equilibrium by "NR." The following proposition compares the price indices across the three cases (the proof is in Appendix A.2).

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

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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

pability increases as $\Theta^A > \Theta^{NR} > \Theta^B$.[24] In other words, trade liberalization improves consumer welfare by improving global buyer–supplier matching and aggregate capability.

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

3.3 Many-to-Many Matching

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

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

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

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

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

The production line k of supplier j with firm capability y_j has *line capability* $v_{jk} = y_j + \varepsilon_{jk}$,

[24] The intuition of the theorem follows from the definition of the supermodularity of θ such that for any $x > x'$ and $y > y'$, $\theta(x, y) + \theta(x', y') > \theta(x', y) + \theta(x, y')$. Applying the theorem to Proposition 1 is not trivial since A is endogenous in our setting.

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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

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

Matching occurs between a final product variety and a supplier production line. The conditions for stable variety-to-line matching are similar to those in Section 3.1. Stable matching consists of the matching function $\upsilon=m_\chi(\chi)$ and $\chi=m_\upsilon(\upsilon)$ between product capability χ and line capability υ, the variety's profit schedule $\pi_\chi(\chi)$, and the line's profit schedule $\pi_\upsilon(\upsilon)$. Following (1), we can obtain a match's joint profit as $\Pi\left(\chi,\upsilon\right)=A\theta\left(\chi,\upsilon\right)-f$, where f is the fixed cost per product. The stability conditions continue to be (2) and the sign of θ_{12} determines the sign of sorting. The matching market-clearing condition in Case C is similar to that in (6):

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

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

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

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

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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

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

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

Thus, the mean number of partners is increasing in firm capability and decreasing in the cutoffs.

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

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

Predictions of Main Partner Choices, Exit, and Number of Partners We derive the model's predictions of firm-to-firm matching that we take to the data. Our data on Mexico–US trade only record partner switching by firms engaging in Mexico–US trade both before and after the MFA's end. We call these firms *US continuing importers* and *Mexican continuing exporters.*

We examine a firm's main partner choice because of its importance in our dataset. First, consider Case C. Let $\chi_i^* \equiv x_i + \max_s \eta_{is}$ be the highest product capability of final producer i.

[28] Strictly speaking, the number of a final producer's partners could be fewer than the number of lines matching with the final producer. However, since production lines are heterogenous, the probability that one supplier provides multiple production lines to the same final producer is negligible when firms are of a continuum and small when they are finite.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

The mean firm capability of final producer i's main partner is $\bar{y}^t(\chi_i^*) \equiv E\left[y|\, y+\varepsilon = m_\chi^t(\chi_i^*)\right]$ for $t \in \{A, B\}$. Similarly, the mean firm capability of supplier j's main partner is $\bar{x}^t(\upsilon_j^*) \equiv E\left[x|\, x+\eta = m_\upsilon^t(\upsilon_j^*)\right]$ for $t \in \{A, B\}$, where $\upsilon_j^* \equiv y_j + \max_k \varepsilon_{jk}$. A final producer i upgrades its main partner if $\bar{y}^A(\chi_i^*) > \bar{y}^B(\chi_i^*)$, and downgrades if $\bar{y}^A(\chi_i^*) < \bar{y}^B(\chi_i^*)$. Similarly, a supplier j upgrades its main partner if $\bar{x}^A(\upsilon_j^*) > \bar{x}^B(\upsilon_j^*)$, and downgrades if $\bar{x}^A(\upsilon_j^*) < \bar{x}^B(\upsilon_j^*)$.

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

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

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

We derive the model's predictions of firm exit and the number of partners that holds in both Cases C and I. First, the firm capability cutoff for Mexican suppliers $y_L = \upsilon_L - \varepsilon_{max}$ increases. Second, from (9), the number of partners $N^M(x)$ and $n^S(y)$ decrease.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

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

4 Empirical Strategy

4.1 Proxy for Firm Capability Rankings

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

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

For each HS six-digit product, we rank all the US importer and all the Mexican exporters, using their imports and exports of the product from their main partner in 2004, respectively. We use these rankings using 2004 data throughout our sample period (2004–2007) during which the ranking is stable.[29] Section 5.4 presents the results using alternative rankings.

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

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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

equals one if $NewPartnerRank_{igs} < OldPartnerRank_{igs}$ and the partner downgrading dummy $Down^c_{igs}$ equals one if $NewPartnerRank_{igs} > OldPartnerRank_{igs}$.

4.2 Specifications

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

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

where c, i, g, and s represent the country (United States and Mexico), firm, HS six-digit product, and sector (HS two-digit level), respectively. The dummy variable $Binding_{gs}$ equals one if Chinese exports of product g to the United States faced a binding quota in 2004, which is constructed from Brambilla et al. (2010). λ_s represents the HS two-digit-level fixed effects.[30] ε^c_{Uigs} and ε^c_{Dijs} are the error terms. Appendix B.5 explains the construction of the binding dummy and other variables. The regression sample includes both continuing US importers and Mexican exporters.

The coefficients of interest β^c_U and β^c_D in (10) are identified by comparing the treatment and control groups within HS two-digit sectors. The treatment is the removal of binding quotas on Chinese exports to the US. The coefficients estimate its impact on the probability of partner upgrading and downgrading, respectively. The HS two-digit fixed effects control for basic product characteristics such as textile/apparel and knit/woven.

Prediction C1 for PAM states that at the MFA's end, all the continuing US importers upgrade their main partners, whereas all the continuing Mexican exporters downgrade. Although the fric-

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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

tionless matching model predicts that all the firms will change their partners, in reality, other factors such as transaction costs are likely to prevent some from making such a change, at least in the short run. Accordingly, we reformulate Prediction C1 as follows: US importers' partner upgrading and Mexican exporters' partner downgrading will occur more frequently in the treatment group than in the control group, which corresponds to $\beta_U^{US} > 0$, $\beta_D^{US} = \beta_U^{Mex} = 0$, and $\beta_D^{Mex} > 0$ in (10).

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

Our regression (10) does not suffer from the endogeneity problem that existed in the conventional correlation approach to detecting PAM that regresses an exporter's characteristics on those of an importer. For instance, the cross-sectional regression of an exporter's rank on an importer's rank could produce a mechanical positive correlation regardless of the sign of sorting.[31] We use firm characteristics (trade volume) only to construct the outcome variables on the left-hand side. Any discrepancy between the true capability ranking and trade ranking should appear in the error terms ε_{Uigs}^c and ε_{Digs}^c, which might reflect the capability of the firm and its partners, and other unobservable firm and product characteristics. However, as long as the binding dummy is uncorrelated with these unobservables, β_U^c and β_D^c are consistently estimated.[32]

Another advantage of (10) is controlling for the various unobservable determinants of a firm's partner rankings. First, idiosyncratic shocks to demand and cost may change firm capability and

[31]Suppose importers are homogeneous in capability (i.e., $\theta_1 = 0$), such as homogenous warehouses. This is a special case of Case I and there is no sorting. Then, the ranking of importer's trade equals that of unobserved exporter's capability, which yields a positive mechanical correlation of exporters' and importers' rankings. Oberfield (2018, Proposition 6) showed this point in a more general model.

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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

generate partner switching. As long as these shocks appearing as error terms in (10) are uncorrelated to the MFA liberalization, they should not bias our estimates. Second, the dependent variables are constructed from time differences in partner rankings. Time differencing controls for all the time-invariant firm-specific determinants of the *level* of partner rankings.

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

$$NewPartnerRank_{ig}^{c} = \alpha^{c} + \gamma^{c} OldPartnerRank_{ig}^{c} + \varepsilon_{ig}^{c} \tag{11}$$

$$\text{for firm } i \text{with } NewPartnerRank_{ig}^{c} \neq OldPartnerRank_{ig}^{c}.$$

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

Two additional points need to be mentioned. First, if we run (11) only for firms that do not change partners, then γ^{c} equals one by construction. To avoid this mechanical correlation, we estimate (11) only for firms that change partners. Second, the regression (11) combines both the treatment and the control groups since Prediction C2 should hold for both groups in Case C.[33]

Capability Cutoff Changes (E1) We test Prediction E1 using two models. First, we estimate a product-level difference-in-difference model of the export cutoffs for the pre-liberalization (2001–2004) and post-liberalization (2004–2007) periods:[34]

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

For surviving exporters in the final year of period r, the minimum of their exports of product g in the initial year of period r proxies for the capability cutoff, $ExportCutoff_{gsr}$. Since importer in-

[33]For instance, if an industry-wide shock induces a Mexican exporter's partner to downgrade in both the treatment and the control groups, the model with PAM should predict $\gamma^{c} > 0$ for both groups. In Appendix E.4, we present the regression (11) only for the treatment group.

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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

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

We use the difference-in-difference specification to test the predictions about the cutoff *changes*. In (12), the cutoff increase in Prediction E1 implies $\delta_2 > 0$ as the coefficient of interest. On the contrary, δ_1 estimates the difference in the *levels* of the cutoffs between the liberalized and non-liberalized products. We perform a placebo check of no difference in the prior trends in the cutoffs by estimating equation (12) for the two pre-liberalization periods (1998–2001 and 2001–2004).

The product-level regression (12) raises two potential concerns. First, it fails to control for firm heterogeneity within products. Second, a rise in the export cutoff may not imply more firm exits from the market. Therefore, we also estimate the following threshold model of a firm's exit. In each period r, Mexican supplier i receives a random i.i.d. shock ε_{ir} to its profit, which captures the idiosyncratic factors inducing firm exit in the absence of liberalization (e.g., Eaton et al., 2014). The firm chooses to exit if ε_{ir} is below the threshold $\bar{\varepsilon}_{ir}\left(y\right)$. Prediction E1 implies two predictions: (i) the MFA's end increases the threshold $\bar{\varepsilon}_{ir}(y)$ for the given capability y and (ii) the threshold $\bar{\varepsilon}_{ir}(y)$ is a decreasing function of the firm's capability y. Then, we estimate the following firm-level regression for Mexican firm i that exports product g to the United States in the initial year of period $r \in \{2001-04,\ 2004-07\}$:

$$\begin{aligned} Exit_{igsr} = {} & \delta_1 Binding_g + \delta_2 Binding_g \times After_r + \delta_3 After_r + \delta_4 \ln Exports_{igr} \\ & + \delta_5 After_r \times \ln Exports_{igr} + \lambda_s + u_{igsr}. \end{aligned} \tag{13}$$

The dummy variable $Exit_{igsr}$ equals one if the firm stops exporting during period r. $\ln Exports_{igr}$ is the log of the firm's total exports of product g in the initial year of period r, which proxies for firm capability. Regression (13) uses the *level* of exports instead of their *ranking* because the level

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

of capability determines the firm's exit, while the ranking of capability determines the matching. Predictions (i) and (ii) mentioned above are expressed as follows: (i) $\delta_2 > 0$, i.e., the end of the MFA increased the exit probability for a given capability level, and (ii) $\delta_4 < 0$ and $\delta_4 + \delta_5 < 0$, i.e., small low capability firms are more likely to exit.[35]

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

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

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

5 Results

5.1 Partner Changes

Panel A in Table 3 examines partner changes during 2004–2007 using linear probability models.[36] The columns with odd numbers report the estimates of β^c_d ($c = US, Mex$ and $d = U, D$) from the baseline regressions (10). 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 of β^c_d support Case C and reject Case I. The removal of

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

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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

binding quotas from Chinese exports increased the probability of US importers' partner upgrading by 5.2 percentage points and the probability of Mexican exporters' partner downgrading by 12.7 percentage points.[37] These effects are quantitatively large compared with the sample averages of Up_{igs}^{US} and $Down_{igs}^{Mex}$, which are 3 and 15 percentage points, respectively.[38]

<<Table 3 is here.>>

The columns with even numbers in Panel A in Table 3 add the firm's own ranking and its interaction with the binding dummy. Both large and small firms switch their partners as the model predicts. Figure 3 illustrates these results by drawing the kernel-weighted local mean regressions of the partner change dummies on the firm's own ranking for apparel products.[39] The dashed lines and areas represent the regression lines with 90% confidence bands for the treatment group, while the solid lines and areas represent those for the control group. A higher probability of US importers' upgrading and Mexican exporters' downgrading in the treatment group is found uniformly for all the capability rankings. By contrast, little difference between the two groups in the probability of US importers' downgrading and Mexican exporters' upgrading is found.

<<Figure 3 is here.>>

Panel B in Table 3 examines partner changes in the later periods of 2007–2011 and 2009–2011 to check our assumption that both the treatment and the control groups exhibit similar partner

[37] β_D^{Mex} is estimated to be larger than β_U^{US} because of the following partner changes within initial partners, which is consistent with the theoretical model. Suppose that a Mexican exporter had been exporting to two US importers in 2004 and that these two US importers buy only from that exporter. Then, in 2007, the exporter stopped exporting to its 2004 main partner and exported only to the second importer. This is counted as partner downgrading for the exporter but not as partner upgrading for the two importers. This causes β_D^{Mex} to be estimated as larger than β_U^{US}. Appendix E.3.5 shows the results are robust when distinguishing a firm's main partner change within and beyond initial partners.

[38] These numbers *do not* mean that 97% of US importers and 85% of Mexican exporters traded with the same main partner both in 2004 and in 2007. In the dataset, only 12% of US importers and 12% of Mexican exporters traded with the same main partner in both 2004 and 2007. The sample averages of Up_{igs}^{US} and $Down_{igs}^{Mex}$ are likely to underestimate the probabilities of partner changes in the population. Our data observe partner upgrading/downgrading only if the firm, new partner, and old partner are all continuing firms. Partner switching to firms in other countries and firms not existing in 2004 are excluded.

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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

change patterns if the treatment is absent.[40] For each period, we reconstruct the capability rankings based on trade in the new initial years and recreate the upgrading/downgrading dummies. If the transition from the old to the new equilibrium was largely completed by 2007, we should observe no difference in partner changes between the two groups. Small and insignificant estimates for β_U^{US} and β_D^{Mex} in 2007–11 and 2009–11 support our assumption.[41]

We conduct numerous robustness checks in Appendix E.3. First, we include as additional controls several product-level and firm-product-level characteristics that statistically differ between the treatment and control groups.[42] Second, we conduct three exercises to address potential within-firm interactions in firms trading multiple products and firms with multiple partners. We add the number of products that a firm trades and its interaction with the binding dummy, address the case that the main partner switching occurs within initial partners, and distinguishing firms that had a single partner and those that had multiple partners. Finally, we adopt alternative variable definitions. We define partner switching using rank bins, define quota binding under alternative criteria, and use alternative year windows. Our results are robust to all of these alternatives.[43]

5.2 New and Old Partners Ranks

Figure 4 reports regression (11), which tests Predictions C2 and I2, with the corresponding scatterplots. For those US importers that changed their main partners between 2004 and 2007, the

[40] Checking the assumption by examining partner changes before 2004 is not feasible since our data only contain partner information from June 2004 onward. At the aggregate level, Figure 1 demonstrates the absence of differential time trends in aggregate exports before the removal of the MFA quota in 2005.

[41] The 2008–11 result differs from those in the other periods. One reason may be that the global financial crisis of 2008 might have introduced noise into the rankings since Mexican exports declined markedly in the second half of 2008.

[42] These product-level characteristics are the number of exporters, number of importers, log product trade, and product type dummies on whether products are for men, women, or not specific to gender and those on whether products are made of cotton, wool, or synthetic textiles. These firm-product-level characteristics are the log of a firm's product trade with the main partner, share of Maquiladora/IMMEX trade in a firm's product trade, number of partners, and dummy of whether a US importer is an intermediary firm.

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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

left panel displays the rankings of their old partners on the horizontal axis and those of their new partners on the vertical axis. The right panel draws a similar plot for Mexican exporters. The lines represent OLS regression (11). Figure 4 and the regressions show significant positive relationships. Firms that matched with relatively high capability partners in 2004 switched to relatively high capability partners in 2007. This result again supports Case C and rejects Case I.

<<Figure 4 is here. >>

5.3 Capability Cutoff Changes and Number of Partners

Table 4 reports the tests of Prediction E1. Column (1) reports the baseline specification of product-level regression (12) and Column (2) includes as additional control variables the product characteristics for the initial year in each period and their interactions with the after dummy. These controls, when available, are the same as in footnote 42.[44] The estimates of the positive and significant δ_2 confirm the prediction that the MFA's end increased the capability cutoff for Mexican exporters. Column (5) reports the baseline specification of firm-level regression (13) and Column (6) includes the product characteristic variables and their interactions with the after dummy. The estimates of the positive and significant δ_2 confirm that the MFA's end increased their exit probability for a given capability level. In addition, the negative estimates of δ_4 and $\delta_4 + \delta_5$ confirm that small exporters are more likely to exit the market.

<<Table 4 is here. >>

Columns (3) and (7) show placebo checks that estimate regressions (12) and (13) using two periods before the MFA liberalization, 1998–2001 and 2001–2004, respectively.[45] Columns (4) and (8) include the control variables. In all the placebo checks, the estimated δ_2 is close to zero

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

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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

and statistically insignificant, or shows a negative sign. These results reject the concern that the estimate of δ_2 captures a prior difference in the trend between the two groups.

Panel B in Table 4 report regression (14). The negative and significant coefficients of the binding dummy in Columns (1) and (2) confirm Prediction E2 that both US importers and Mexican exporters reduce the number of partners in liberalized industries.

5.4 Does Capability Reflect Quality or Productivity?

We have studied exporter-importer matching by capability without specifying whether capability determining matching is quality or productivity. To shed a light on this question, we create rankings based on two alternative variables: a firm's unit price with the main partners in 2004 and a firm's quality estimated using the method of Khandelwal et al. (2013). If the exporter's capability mainly reflects quality rather than productivity, the two rankings may agree with the capability ranking. On the contrary, if the exporter's capability mainly reflects productivity, the unit price ranking may become the reverse of the capability ranking.

Appendix E.5 shows that the main results are robust to the price and quality rankings.[46] Therefore, exporter's quality determines whether it can match with high capability importers. This result is consistent with the literature's finding that quality is an important determinant of a firm's export participation (e.g., Kugler and Verhoogen, 2012).

5.5 Alternative Explanations

In Appendix C, we examine four alternative hypotheses for our findings. The first hypothesis is negative assortative matching under which trade rankings may not agree with true capability rankings. The second hypothesis is repeated random independent matching. Suppose random partner change occurs in every period and exhibits mean reversion. The exit of low capability Mexican exporters may create a positive correlation between the binding dummy and downgrading

[46] Appendix E.5 shows our results are robust with the ranking based on a firm's total product trade.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

by Mexican exporters. The third hypothesis is that Mexican exporters switch a product segment from large-scale production with small markups to small-scale production with large markups. The final hypothesis is that a US importer's partner switches from small to large suppliers to seek large production capacity. For these hypotheses, we conduct additional analyses and show that none of them fully explain our results.

6 Concluding Remarks

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

References

Antras, Pol, Luis Garicano, and Esteban Rossi-Hansberg. 2006. "Offshoring in a Knowledge Economy." *Quarterly Journal of Economics*, 121(1): 31–77.

Atkin, David, Amit Khandelwal, and Adam Osman. 2017. "Exporting and Firm Performance: Evidence from a Randomized Experiment." *Quarterly Journal of Economics*, 132(2): 551–615.

Baldwin, Richard, and James Harrigan. 2011. "Zeros, Quality and Space: Trade Theory and Trade Evidence." *American Economic Journal: Microeconomics,* 3(2): 60–88.

Becker, Gary S. 1973. "A Theory of Marriage: Part I." *Journal of Political Economy*, 81(4): 813–46.

Benguria, Felipe. 2021. "The Matching and Sorting of Exporting and Importing Firms: Theory and Evidence." forthcoming in *Journal of International Economics*.

Bernard, Andrew B., and Swati Dhingra. 2019. "Importers, Exporters and the Division of the Gains from Trade." mimeo.

Bernard, Andrew B., Emmanuel Dhyne, Glenn Magerman, Kalina Manova, and Andreas Moxnes. 2021. "The Origins of Firm Heterogeneity: A Production Network Approach." forthcoming in *Journal of Political Economy*.

Bernard, Andrew B., Andreas Moxnes, and Yukiko U. Saito. 2019. "Production Networks, Geography, and Firm Performance." *Journal of Political Economy* 127(2): 639-688.

Bernard, Andrew B., Andreas Moxnes, and Karen Helene Ulltveit-Moe. 2018. "Two-Sided Heterogeneity and Trade." *Review of Economics and Statistics*, 100(3): 424–439.

Bernard, Andrew B., Stephen J. Redding, and Peter K. Schott. 2011. "Multiproduct Firms and Trade Liberalization." *Quarterly Journal of Economics*, 126(3): 1271–318.

Blum, Bernardo S., Sebastian Claro, and Ignatius Horstmann. 2010. "Facts and Figures on Intermediated Trade." *American Economic Review Paper and Proceedings*, 100(2): 419–23.

Brambilla, Irene, Amit K. Khandelwal, and Peter K. Schott. 2010. "China's Experience under the Multi-fiber Arrangement (MFA) and the Agreement on Textiles and Clothing (ATC)." Robert C. Feenstra and Shang-Jin Wei eds., *China's Growing Role in World Trade.* University of Chicago Press: 345–87

Browning, Martin, Pierre-Andre Chiappori, and Yoram Weiss. 2014. *Economics of the Family.* Cambridge University Press.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

Carballo, Jeronimo, Gianmarco Ottaviano, and Christian Volpe Martincus. 2018. "The Buyer Margins of Firms' Exports." *Journal of International Economics,* 112: 33–49.

Cajal-Grossi, Julia, Rocco Macchiavello, and Guillermo Noguera. 2020. "Buyers' Sourcing Strategies and Suppliers' Markups in Bangladeshi Garments." mimeo.

Casella, Alessandra, and James E. Rauch. 2002 "Anonymous Market and Group Ties in International Trade." *Journal of International Economics,* 58(1): 19–47.

Dayaratna-Banda, O.G., and John Whalley. 2007. "After the Multifibre Arrangement, the China Containment Agreements." *Asia-Pacific Trade and Investment Review,* 3(1): 29–54.

De Loecker, Jan. 2007. "Do Exports Generate Higher Productivity? Evidence from Slovenia." *Journal of International Economics,* 73(1): 69–98.

Dragusanu, Raluca. 2014. "Firm-to-Firm Matching Along the Global Supply Chain." mimeo.

Dhyne, Emmanuel, Ayumu Ken Kikkawa, Magne Mogstad, Felix Tintelnot. 2021. "Trade and Domestic Production Networks." *Review of Economic Studies*, 88(2): 643–668,

Eaton, Jonathan, Marcela Eslava, David Jinkins, C. J. Krizan, and James Tybout. 2014. "A Search and Learning Model of Export Dynamics." mimeo.

Eaton, Jonathan, David Jinkins, James Tybout, and Daniel Yi Xu. 2015. "International Buyer Seller Matches." mimeo.

Eaton, Jonathan, Samuel Kortum, and Francis Kramartz. 2016. "Firm-to-Firm Trade: Imports, Exports, and the Labor Market." RIETI DP Series 16-E–048.

Gretsky, Neil E., Joseph M. Ostroy, and William R. Zame. 1992. "The Nonatomic Assignment Model." *Economic Theory*, 2(1): 103–27.

Grossman, Gene M., and Giovanni Maggi. 2000. "Diversity and Trade." *American Economic Review*, 90(5): 1255–1275.

Heise, Sebastian. 2020. "Firm-to-Firm Relationships and the Pass-Through of Shocks: Theory and Evidence." mimeo.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

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

Ignatenko, Anna. 2019. "Buyer Size, Price Discrimination, and Quality Differentiation in International Trade." mimeo.

Javorcik, Beata Smarzynska. 2004. "Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spillovers Through Backward Linkages." *American Economic Review*, 94(3): 605–27.

Khandelwal, Amit K., Peter K. Schott, and Shang-Jin Wei. 2013. "Trade Liberalization and Embedded Institutional Reform: Evidence from Chinese Exporters." *American Economic Review*, 103(6): 2169–95

Koopmans, Tjalling C., and Martin Beckmann. 1957. "Assignment Problems and the Location of Economic Activities." *Econometrica*, 25(1): 53–76.

Kremer, Michael. 1993. "The O-Ring Theory of Economic Development." *Quarterly Journal of Economics*, 108(3): 551–75.

Kugler, Maurice, and Eric Verhoogen. 2012. "Prices, Plant Size, and Product Quality." *Review of Economic Studies*, 79(1): 307–39.

Lim, Kevin. 2018. "Endogenous Production Networks and the Business Cycle." mimeo.

Lu, Dan, Asier Mariscal, and Luis-Fernando Mejia. 2017. "How Firms Accumulate Inputs: Evidence from Import Switching." mimeo.

Macchiavello, Rocco. 2010. "Development Uncorked: Reputation Acquisition in the New Market for Chilean Wines in the UK." mimeo.

Macchiavello, Rocco, and Ameet Morjaria. 2015. "The Value of Relationships: Evidence from a Supply Shock to Kenyan Rose Exports." *American Economic Review,* 105(9): 2911–45.

Melitz, Marc J. 2003. "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity." *Econometrica*, 71(6): 1695–725.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

Monarch, Ryan. 2021. "It's Not You, It's Me: Breakups in U.S.-China Trade Relationships." forthcoming in *Review of Economics and Statistics.*

Oberfield, Ezra. 2018. "A Theory of Input-Output Architecture." *Econometrica*, 86(2): 559–89.

Ornelas, Emanuel, John L. Turner, and Grant Bickwit. 2021. "Preferential Trade Agreements and Global Sourcing." *Journal of International Economics* 128: 103395.

Rauch, James E. 1996. "Trade and Search: Social Capital, Sogo Shosha, and Spillovers." NBER Working Paper 5618.

Rauch, James E., and Vitor Trindade. 2003. "Information, International Substitutability, and Globalization." *American Economic Review*, 93(3): 775–91.

Roth, Alvin E., and Marilda A. Oliveira Sotomayor. 1990. *Two-sided Matching: A Study in Game-theoretic Modeling and Analysis,* Cambridge University Press, Cambridge.

Sattinger, Michael. 1979. "Differential Rents and the Distribution of Earnings." *Oxford Economic Papers*, 31(1): 60–71.

Shapley, Lloyd S., and Martin Shubik. 1971. "The Assignment Game I: The Core." *International Journal of Game Theory,* 1(1): 111–30.

Smith, Lones. 2011. "Frictional Matching Models." *Annual Review of Economics*, 3(1): 319–38.

Stigler, George J. 1961. "The Economics of Information." *Journal of Political Economy*, 69(3): 213–25.

Sugita, Yoichi. 2015. "A Matching Theory of Global Supply Chains." mimeo.

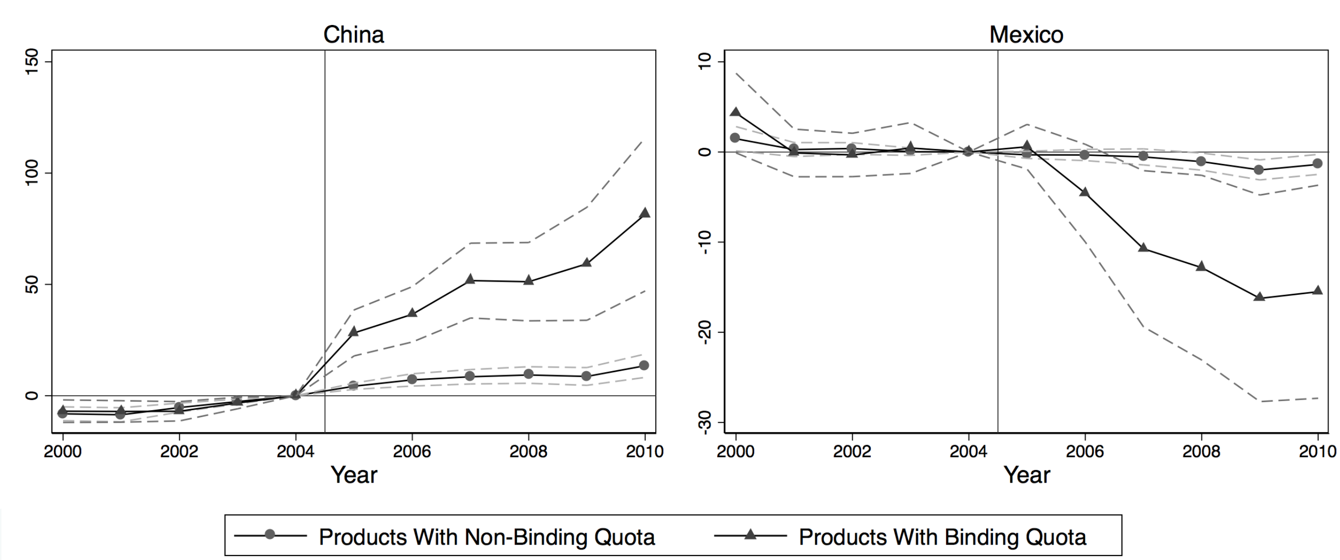
Tanaka, Mari. 2020. "Exporting Sweatshops? Evidence from Myanmar." *Review of Economics and Statistics*, 102(3): 442–56

US CBP. 2014. *NAFTA: A Guide to Customs Procedure.* U.S. Customs and Border Protection. https://www.cbp.gov/document/guides/nafta-guide-customs-procedures

Verhoogen, Eric A. 2008. "Trade, Quality Upgrading, and Wage Inequality in the Mexican Manufacturing Sector." *Quarterly Journal of Economics,* 123(2): 489–530.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

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

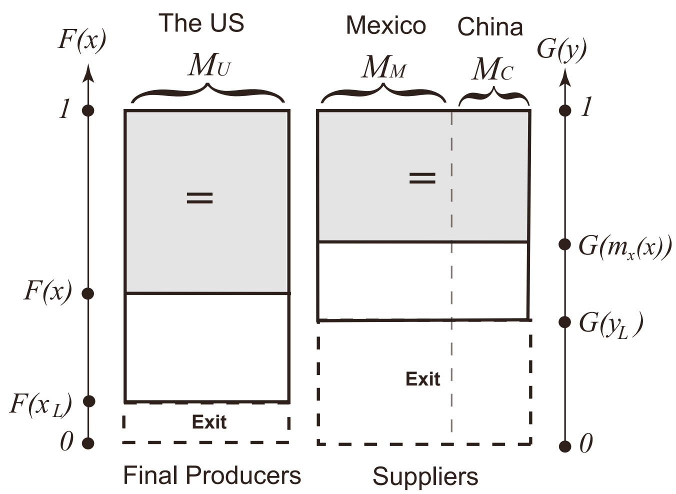


Note: The left panel plots the coefficients of the annual year dummies in the regression of the HS six-digit product-year-level exports of China on the annual year dummies and product fixed effects separately run for the products on which the United States had imposed binding quotas against China in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

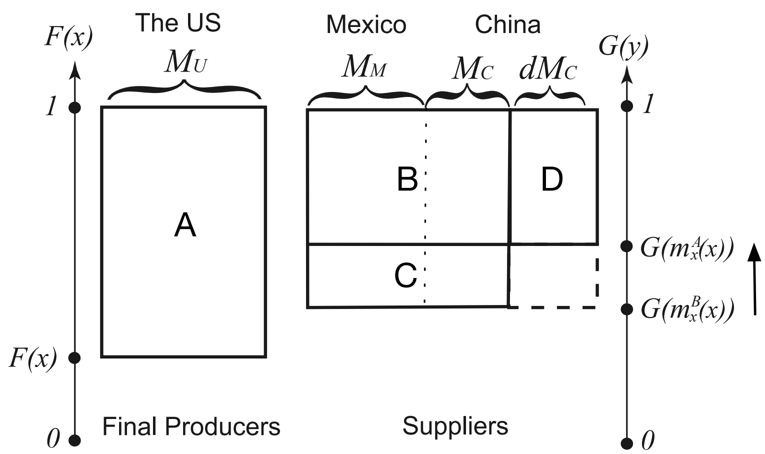
Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

Figure 2: Matching Model's Predictions

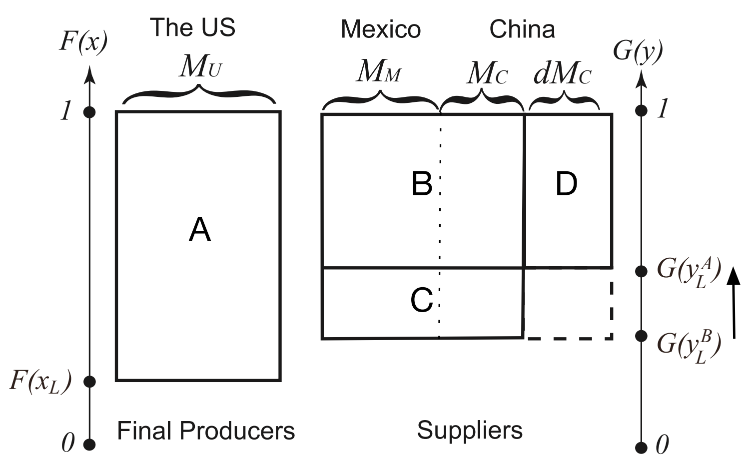
(A) Case C: Matching Market Clearing



(B) Case C: Rematching at the MFA's end

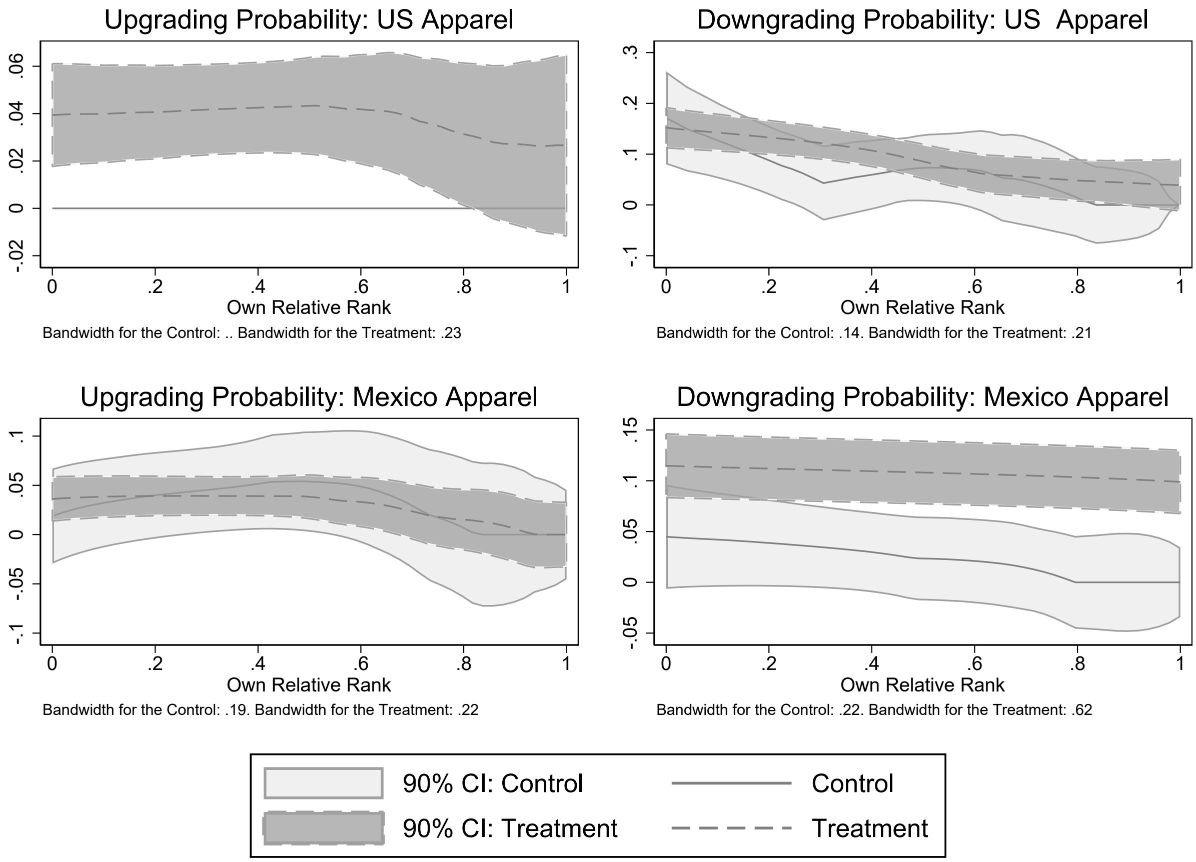


(C) Case I: Rematching at the MFA's end



Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

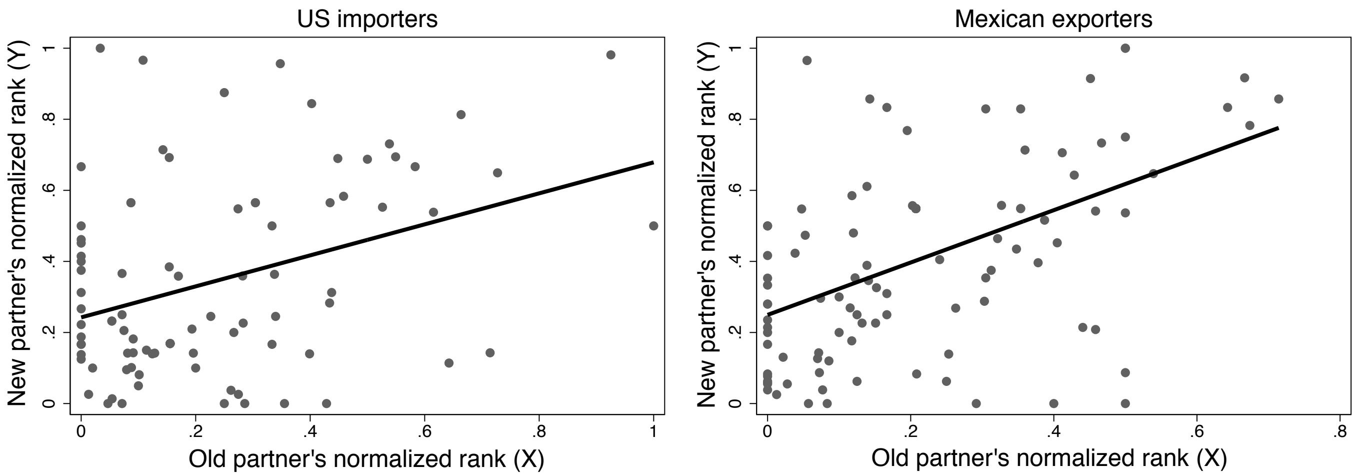
Figure 3: Partner Change during 2004–2007 and Initial Capability Rankings: Apparel Products



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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

Figure 4: Old and New Partner Ranks



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

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

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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

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

	Product-Level Match		Firm-Level Match	
	2004	2007	2004	2007
mean statistics (median)	(a)	(b)	(c)	(d)
(1) Number of Exporters	15.6 (8)	11.8 (6)	1,340	1,036
(2) Number of Importers	20.3 (11)	15.2 (8)	2,031	1,541
(3) Number of Exporters Selling to an Importer	1.1 (1)	1.1 (1)	1.4 (1)	1.3 (1)
(4) Number of Importers Buying from an Exporter	1.5 (1)	1.4 (1)	2.1 (1)	1.9 (1)
(5) Value Share of Main Exporter (Number of Exporters > 1)	0.76	0.77	0.75	0.78
(6) Value Share of Main Importer (Number of Importers > 1)	0.74	0.77	0.73	0.76

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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

Table 2: Changes in Mexican Textile/Apparel Incumbent Exports to the United States from 2004 to 2007 (Million USD)

Partner Margin Decomposition

	Total	Traditional Margins		Partner Margins			Excess
		Extensive	Intensive	Stay	Add	Drop	Reallocation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Aggregate decomposition							
Quota-bound	-950.9	-887.4	-63.4	-25.1	83.5	-121.9	167.1
% of (3)			100%	39.5%	-131.7%	192.2%	263.4%
Switcher share					(0.95)	(0.82)	
Quota-free	-223.0	-179.6	-43.4	-24.0	37.5	-56.9	75.1
% of (3)			100%	55.4%	-86.6%	131.2%	173.2%
Switcher share					(0.79)	(0.87)	
B. HS six-digit product-level regression coefficients							
Binding	-4.441**	-4.052**	-0.389	-0.132	0.388**	-0.645**	0.706**
(s.e.)	(2.046)	(1.883)	(0.306)	(0.230)	(0.165)	(0.274)	(0.296)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Main Partner Margin Decomposition

	Intensive	Non-Main	Main Partner Margins			Main Partner
	Margin	Partner	Stay	Add	Drop	Excess Reallocation
	(1)	(2)	(3)	(4)	(5)	(6)
C. Aggregate decomposition						
Quota-bound	-63.4	-15.2	-13.7	72.9	-107.4	145.8
% of (1)	100%	24.0%	21.6%	-114.9%	169.3%	229.8%
Quota-free	-43.4	-14.2	-10.9	38.7	-56.9	77.4
% of (1)	100%	32.8%	25.1%	-89.2%	131.3%	178.4%
D. HS six-digit product-level regression coefficients						
Binding	-0.389	-0.080	-0.095	0.332**	-0.545**	0.602**
(s.e.)	(0.306)	(0.082)	(0.205)	(0.141)	(0.238)	(0.240)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: In Panel A and Panel C, each column reports the changes in Mexican textile/apparel exports to the United States between 2004 and 2007 by incumbent exporters in 2004 for quota-bound products and other quota-free products. In Panel A, the changes in total exports in (1) are decomposed into the extensive margin by exiters in (2) and the intensive margin by survivors in (3). The intensive margin in (3) is decomposed into (4) exports to continuing partners, (5) exports to new partners, and (6) exports to dropped buyers. Column (7) is |(5)|+|(6)|- |(5)+(6)|. In Panel C, the intensive margin changes by survivors in (1) are decomposed into (2) exports to non-main partners, (3) exports to continuing main partners, (4) exports to new main partners, and (5) exports to dropped main partners. Column (6) is |(4)|+|(5)|- |(4)+(5)|. In Panel B and Panel D, each column reports the product-level regressions of each margin on the quota-bound product dummy (Binding) with the HS two-digit fixed effects. Standard errors are clustered at the HS six-digit product level. Significance: * 10%, ** 5%, *** 1%.

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

Table 3: Partner Change during 2004–07

A. Benchmark Regression

	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

B. Placebo Check: Partner Change in Different Periods

	Linear Probability Models					
	Up^{US}			$Down^{Mex}$		
	2007–11	2008–11	2009–11	2007–11	2008–11	2009–11
	(1)	(2)	(3)	(4)	(5)	(6)
Binding	-0.001	0.027**	-0.000	-0.007	0.047	0.005
	(0.018)	(0.011)	(0.006)	(0.036)	(0.031)	(0.020)
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	449	575	747	393	499	655

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

Review of Economics and Statistics Just Accepted MS.
https://doi.org/10.1162/rest_a_01114

Table 4: Capability Cutoff Changes and Number of Partners

A. Capability Cutoff Changes

	Product-Level Difference-in-Difference				Firm-Level Difference-in-Difference			
	$\ln ExportCutoff_{gsr}$				$Exit_{igsr}$			
Period 1	2001–04		1998–2001		2001–04		1998–2001	
Period 2	2004–07		2001–04		2004–07		2001–04	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Binding	-1.255***	-0.668***	-1.074***	-0.786***	-0.040***	-0.028**	-0.021	0.009
(δ_1)	(0.281)	(0.246)	(0.248)	(0.249)	(0.014)	(0.013)	(0.016)	(0.014)
Binding	1.031**	1.188**	0.106	0.324	0.076***	0.089***	-0.003	-0.034**
$\times$After (δ_2)	(0.479)	(0.490)	(0.178)	(0.244)	(0.017)	(0.021)	(0.013)	(0.015)
After	-3.402***	-0.863	-0.230	0.809	-0.361***	-0.345***	-0.119***	-0.212***
(δ_3)	(0.364)	(1.620)	(0.151)	(0.785)	(0.042)	(0.077)	(0.034)	(0.056)
$\ln Export$					-0.058***	-0.056***	-0.069***	-0.066***
(δ_4)					(0.002)	(0.003)	(0.003)	(0.003)
$\ln Export$					0.020***	0.020***	0.011***	0.008**
$\times$After (δ_5)					(0.003)	(0.003)	(0.003)	(0.003)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
HS2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	696	696	652	652	22,625	22,624	24,043	22,142

B. Number of Partners

	Change in Number of Partners	
	Mexico	US
	(9)	(10)
Binding	-0.65**	-0.12*
	(0.33)	(0.06)
HS2 FE	Yes	Yes
Obs.	601	718

Note: All the regressions include the HS two-digit (sector) fixed effects. Standard errors are shown in parentheses and clustered at the HS six-digit product level. Significance: * 10%, ** 5%, *** 1%.Panel A: $\ln ExportCutoff_{gsr}$ is the log of the minimum of firm-product-level exports in the initial year of period r. $Exit_{igsr}$ is a dummy variable indicating whether Mexican firm i stops exporting product g to the US in period r. $Binding_{gs}$ is a dummy variable indicating whether product g from China faced a binding US import quota in 2004. $After_r$ is a dummy variable indicating whether period r is after 2004. $lnExport_{igr}$ is the log of firm i's exports of product g in the initial year of period r. Columns (2), (4), (6), (8) include the product-level controls. Panel B: the dependent variables are the change in the number of partners during 2004–2007.