"It's Not You, It's Me": Breakups in U.S.-China Trade Relationships*†

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PRELIMINARY AND INCOMPLETE

Abstract

Any international trade transaction is a mutual agreement between firms in two separate countries for a particular product to be exchanged; however, the factors that determine the formation and length of the relationships between importing firms and exporting firms are still essentially unknown. This paper uses U.S. Customs and Border Protection data between the U.S. and China to document a number of empirical results related to these relationships: breakups occur with very high frequency- 45% of U.S. firms importing from China switched their importing partner between 2002 and 2003. There is also a strong geographic component connected to the decision of which exporting partner to use: almost one-quarter of all year-to-year switching occurs within the original partner's city, and firms importing from China are very unlikely to switch to a firm outside of China. Both of these trends become more pronounced as the time from the base year increases. Furthermore, higher exporter prices are correlated with a higher probability of breakup, and switching importers move to younger, smaller exporting firms. Guided by these facts, I design a dynamic discrete choice model of exporter choice embedded within a heterogeneous firm model of international trade. The model produces industry-specific estimates of exporter-specific and geographic switching costs that are consistent with a number of underlying industry trends, including geographic concentration, elasticity of substitution, market slackness, supplier firm size, and labor productivity. Model estimates predict that a decrease in switching frictions substantially lowers observed prices. Exchange rate pass-through into import prices is increased by accounting for switching behavior that accompanied the 2005 *renminbi* appreciation dramatically. Any policy meant to encourage 5% of U.S. imports from China to arrive from domestic suppliers instead will require extreme reductions in prices compared to the existing market prices.

JEL Codes: F23, F14, L14, D21;
Keywords: International Trade, International Business, Import Price, Transactional Relationships, Firm Behavior

*Author's Note: Blank tables have been officially submitted for disclosure, and will be approved within a few weeks. Qualitative description of the results are correct, but a version with all tables included will be available by August 12, 2013.

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1 Introduction

Any international trade transaction is, fundamentally, a two-sided contract between an exporting firm in one country and an importing firm in another country, where the particular value and quantity of product to be exchanged is agreed upon. But what determines why importing firms match with a particular exporting firm, and vice versa? This question is important for a number of results in international trade, particularly the idea that the sluggish response of trade flows to short-run price changes (known in the literature as the *short-run / long-run elasticity puzzle*[1]) stems from the difficulty of firms adjusting their trading partners. Drozd and Nosal (2012) offer a model of "customers as capital", where in the short run, adjustment costs to market expansion retard responses to short-run productivity shocks. Thus, trade flows are highly path-dependent, and the short-run / long-run elasticity puzzle appears naturally. Conversely, however, preliminary empirical results on relationship formation between importers and exporters emphasize a high degree of volatility in trade relationships, with any single trade relationship unlikely to last most than a few years (Kamal and Krizan (2012), Eaton, Eslava, Jinkins, Krizan, Kugler and Tybout (2012)). Such results imply that while indeed the quantity of trade may be slow to adjust, the short-run decision that is flexible appears to be the choice of one's importing partner. This distinction has significant implications for the effect of exchange rate changes on prices and aggregate trade flows that differ from the costy adjustment model described above.

Furthermore, the model of firm heterogeneity that has accounted for important trends in international trade tends to place agency on the exporting firm, with import demand subsumed within a broad aggregate preference framework. But there is less understanding of the factors that influence importing firms. In this paper, using firm-to-firm data on U.S. imports from China and a model of two-sided participation in international trade, I catalogue the patterns of supplier "switching" behavior at the firm, city, province, and country level, and qualitatively measure the frictions involved in importer-exporter relationships. I then use these estimates to illustrate the effects of switching behavior on prices, trade flows, the "re-shoring" of U.S. industry, and exchange rate pass-through.

Based on data from U.S. Customs and Border Protection, I demonstrate four main empirical results in this paper: (1) Switching suppliers from one year to the next is very common. Among U.S. importers from China in 2002, 45% of those who continued importing (from anywhere) in 2003 used a different exporting partner in 2003[2] [3]. (2) There is a strong geographic component to switching. Close to 10% of importers

[1] Ruhl (2008) surveys the literature surrounding this elasticity puzzle.

[2] The term "importer" here refers to a U.S. firm in a particular HS10 industry, i.e. a firm importing two different products appears as two different importers. The percentage figures cited here and throughout this section have minimal changes if one uses "firms" instead of "importers" as the unit of analysis.

[3] Many importers make use of multiple exporters. The cited statistics here and throughout this section make use of the most conservative definition of a "partner switch": if an importer "stayed" with at least one exporter, then that importer is a "stayer". Eaton et. al. (2012) show that 80% of importer-exporter matches are monogamous, and the average number of exporters for any multiple-partnered U.S. importer is 4.

switched to another supplier in the same city as their previous supplier from 2002 to 2003, accouting for almost one-quarter of all switching. Firms importing from China are far less likely to switch to a firm outside of China. (3) Over time, each of these trends becomes more pronounced within the same importing cohort-switching from one's original partner is more frequent, and more likely to be in the same city. Only 20% of continuing importers stay with their partner from 2002 to 2007, while 30% have switched within-city. 90% of all continuing importers stayed within China. (4) Prices are a major determinant of switching behavior, in addition to supplier characteristics. Higher received prices are correlated with a high probability of switching, and importers tend to switch to suppliers that are younger and smaller. These results guide the structural model I design, in which I measure frictions via implicit "switching costs" at the firm and city level and quantify their importance. My results are consistent with economic intuition for a number of underlying industry factors, including geographic concentration, elasticity of substitution, supplier firm size, and labor productivity.

The main quantitative results can be summarized as follows. First, the impact of relationship frictions are sizable. A reduction of switching costs by half would lead to more productive matches and a significantly smaller import price index. Using price elasticities from Broda and Weinstein (2005) together with these changes in prices, a change in switching costs translates into a large effect on trade flows between the U.S. and China. Secondly, I assess the possibility of "re-shoring" U.S. industries. I augment the model to determine how low a price a hypothetical U.S. supplier must provide in order to induce a "re-shoring" of 5% of U.S. potential imports back to the U.S. Such a supplier would have to provide prices in the range of x% lower than prevailing prices charged by U.S. suppliers in order to overcome the incentive for U.S. importers to use Chinese suppliers.

Finally, I compare the estimated effects of exchange rate pass-through (the change in import prices resulting from a change in exchange rates) in my model of volatile import-export relationships to those of more costly adjustment. I find that exchange rate appreciation between the U.S. and China induces more switching, and thus smaller effects of exchange rate changes on import prices. However, if firms were not allowed to switch out of China, then exchange-rate pass-through onto import prices would be substantially higher, a partial explanation of the very low levels of pass-through in studies of firm-to-firm exchange pass-through such as Gopinath and Rigobon (2008).

The paradigm I use for studying these issues is a dynamic discrete choice model of supplier choice based on final good producer profit maximization, embedded in a heterogeneous firm model that features exporters choosing price and quality. A dynamic discrete choice model is especially appealing in this context, as the computed estimates are applicable to out-of-sample applications, allowing the simulation of the counter-factual experiments described above. The baseline model estimates structural parameters capturing the frictions involved in switching suppliers and from using a supplier in another city, as well as the sensitivity of switching to different expected prices.

The rest of the paper is organized as follows. Section 2 describes the related literature on relationship-specificity and relationship length, both within the industrial organzation and international trade fields. Section 3 describes the data sources used in this paper and summarizes the empirical results. Section 4 presents the dynamic discrete choice model. Section 5 describes the implementation of the model and summarizes the quanitative results. Section 6 describes the counterfactuals. Section 7 concludes.

2 Related Literature

Although the field of international trade has focused on numerous aspects of firm-level participation in international activity, including especially the decision to export, import, enage in FDI, or use intermediaries, the study of individual exporter-importer relationships remains relatively sparse. One of the main contributions thus far is the work of Eaton et al (2012), who look explicitly at Colombian exporters and how many U.S. importers they partner with over time. The authors investigate the high amount of churning in importer-exporter relationships with a model that consists of synergies between exporters and importers. Costly searching behavior is undertaken by the exporter. They thus calibrate a search and matching model to match exporter decisions, including sales, number of clients, and transition probabilities. I also use transaction-level data, but account for firm behavior on *both* sides of a transaction, in particular, an exporter's pricing/quality decision together with an importer's choice of exporter based on these traits. Kamal and Krizan (2012) use U.S. Census trade transaction data to document trends in importer-exporter relationship formation. Similar to the trends discussed above, they too find great volatility in the length of importer-exporter relationships, a volatility that far exceeds entrance into international trade on either the (foreign) exporting side or (U.S.) importing side.

I estimate a structural model to better understand the factors underpinning importer-exporter switching behavior, including geographic components, and quantify the importance of this switching for international trade flows. To do this, I use a model of dynamic discrete choice, the type of which was pioneered by Rust (1987) in his study of bus engine replacement. Such techniques are refined in the random coefficients discrete choice model of the Berry, Levinsohn, and Pakes (1995) demand estimation problem, and in the implementation of the Mathematical Programming with Equilibrium Constraint (MPEC) methodology for solving discrete choice problems found in Su and Judd (2012) and Dube, Fox, and Su (2012) . As in those studies, my model uses implicitly defined costs entering into a firm's profit function, where in my case, the costs are supplier switching costs at both the partner and city level. Estimates are retrieved through maximizing a likelihood function based on observed outcomes for importer-exporter switching. The model I estimate is most similar to the model of firm choice utilized by Fox (2010) in his study of Swedish engineers switching between different employers. Similar to the use of wages as a driving force behind employee switching behavior, in my context, one of the main components of the "stay or switch" decisions is the price offered to U.S. importers by a Chinese supplier.

Specifically related to the supplier choice decision of firms, there are a number of papers that estimate the effects of relationship networks on partner search and contract length. Joskow (1985) studies contract length among coal suppliers and power plants, while Atalay, Hortacsu, and Syverson (2012) measure the extent to which firms rely on subsidiaries versus outside firms for intermediate input purchase. Egan and Mody (1992), and Kranton and Mineheart (2001) present models on the formation of buyer-seller networks and how the properties of these networks affect economic outcomes. The study of such networks has also taken place in the context of international trade. Rauch (2001) surveys the potential for transnational cultural networks to help smooth international trade and reduce barriers to entry, while Rauch and Watson (2004) present a general equilibrium model through which economic agents can use their supply of networks to either produce/export more efficiently or to become an intermediary. Their results provide an explanation for the growing importance of trading intermediaries, whose usage by firms on either side of a trade transaction has been modeled by Ahn, Khandewal, and Wei (2011) and Tang and Zhang (2012). Although I cannot observe the nature of interaction between an exporting and importing firm- other than the particulars of the transaction recorded by U.S. Customs and Border Protection- the ability to link firms on both sides of a transaction over time lets me examine the importance of relationship-specificity in exporter choice.

3 Data and Stylized Facts

3.1 Importer-Exporter Data

The main database I work with in this paper is the Longitudinal Foreign Trade Transaction Database (LFTTD), which contains confidential information on all international trade transactions by U.S. firms. It is maintained by the U.S. Census. The LFTTD consists of all the information included in customs documents provided by U.S. firms engaging in international trade, including quantity and value exchanged for each transaction, HS 10 product classification, date of import and export, port information, country of origin, and foreign partner information. The import data in particular contains identifiers for both the U.S. importing firm and the foreign exporting partner. Known as the *manufacturing ID*, or *MID*, the foreign partner identifier contains limited information on the name, address, and city of the foreign supplier[4]. Through a variety of checks outlined in Appendix A, I find substantial support for the use of the MID as a reliable, unique identifier, both over time and in cross-section. I use this variable to provide stylized facts for the amount of churning in U.S.-China trade relationships and the geographic elements of switching behavior[5].

At this stage, I perform an initial cleaning of the LFTTD, using methods outlined in Bernard, Jensen, and Schott (2009) as well as some specific cleaning operations related to the relationship variable I use. I drop all transactions with imputed quantities or values (which are typically very low-value transactions) or converted quantities or values. I also eliminate all related-party transactions, as exporters who are importing from separate branches of the same firm will likely have very different relationship dynamics than arm's-length exporters. In addition, I clean up unreasonable values for the MID specifically related to U.S.-China trade. I restrict the sample to importers with a firm country identifier of China (meaning the producing firm is located in China). Due primarily to the entrepot nature of Hong Kong's international trade flows, I concentrate solely on Mainland China- deleting any observation that has any appearance of coming from Hong Kong, Macau, or Taiwan. For example, a city code of "HON", even with a country code for mainland China, is likely referring to Hong Kong and thus dropped[6]. Finally, I drop any firm that has a three-letter city code that is not in the top 300 cities of China by population.

3.2 Stylized Facts

The starting point of my analysis is to use the exporting partner MID to catalog the prevalence of partner-switching. To do so, I keep track of U.S. firms importing from China in 2002, and determine whether they (a) continued importing in later years, and if so, (b) whether they continued to import from the same exporting partner or geographic location as in 2002. My unit of observation is a *firm-HS10 product* combination, and I use the most conservative definition of an importer staying with an exporter: if an importer stayed with any one of its (potentially many) exporting partners, then they are counted as an importer "staying" with its partner. I classify an importer as a city, province, or country "stayer" in the same way. Table 1 illustrates the results.

The first column of Table 1 contains the number of firm-product pairs from the 2002 importing-from-

[4]Specifically, the MID contains the ISO2 code for the country's name, the first three letters of the producer's city, six characters taken from the producer's name and up to four numeric characters taken from its address.

[5]The results below depend on the validity of the MID as both a cross-sectional unique identifier and as a panel variable tracking foreign exporters over time. Separately, one may also be concerned that the MID coming from such customs records is unreliable for a variety of reasons, including miscoding, unclear rules for construction, or the possibility of capturing intermediaries rather than firms actually producing the traded product. For this reason, I undertake an in-depth exploration of this variable, including its construction, the relevant laws surrounding information provided in trade transactions, and a number of checks for external validity of the MID. These issues are explored in Appendix A.

[6]Other dropped city codes: "KOW" for Kowloon, Hong Kong; "MAC" for Macau; "AOM" for the Chinese Pinyin spelling of Macau, "Aomen"; "KAO" for Kaohsiung, Taiwan.

China cohort still importing, while the later columns contain counts of "staying" importers, defined at different levels of aggregation. The data in Table 1 are converted to percentages (relative to the number of continuing importers) and shown in Figure 1. Table 1 and Figure 1 illustrate three key trends in the data: (1) Exporter partner switching is commonplace. (2) Partner switching has considerable geographic inertia. (3) Over time, switching among firms in the same cohort becomes both more common and more geographically concentrated.

It is clear from Table 1 and Figure 1 that even over a one-year time period, there is considerable exporter partner switching: only 55% of continuing importers (approximately 59,000 out of 105,000) stay with their original Chinese supplier from 2002 to 2003. This figure is in line with other studies of U.S. importers such as Eaton, et al (2012). But we can also tell from the geographic portion of the identifier that there are strong ties to an importer's previous city, with close to 10% of all continuing importers (approximately 10,000 out of 105,000) switching to another supplier in the same city as their previous partner from 2002 to 2003. This accounts for almost 25% of all total switching. There are many potential explanations for such a finding, including local network formation, efficient distribution channels focusing attention on a particular geographic location, or economic agglomeration caused by clustering on the export side. We can see similar patterns by looking at larger geographic areas, as well: over half of all switching importers stay within China from 2002 to 2003 (approximately 25,000 out of 45,000 switching importers). In sum, the year-to-year figures show that supplier choices are neither fixed in the short term, nor are decisions of whom to switch to free of geographic considerations.

Examining the data in Table 1 and Figure 1 over a longer time horizon, it is apparent that the two trends discussed above grow stronger over time. A smaller and smaller fraction of continuing importers remain with their partner, with only 20% of continuing importers (approximately 11,000 out of 54,000) remaining with the same Chinese exporting partner from 2002 to 2007. But even though more importers are switching, a greater and greater percentage of switchers have switched within the same city. Compared with the 20% of importers that have stayed with their importing partner, nearly 30% (approximately 17,000 out of 54,000) of continuing importers have switched to another supplier in the same city as their original partner, accounting for fully 42% of all switching. Remaining within China is also a key consideration for many importers, with nearly 90% of importers from China in 2002 that imported at all in 2007 remaining in China in 2007. It is these stylized facts related to switching, both geographically and over time, that govern the dynamic discrete choice model I lay out in Section 4.

The stylized facts about importer-exporter relationships described above are robust to a number of alternative specifications and checks. First, based on my definition of an importer as a *firm-HS10 product* combination, it is possible for one firm to appear multiple times in Table 1. In particular, if one firm imports multiple products, then the counts in Table 1 may exaggerate or understate the effects of firm switching behavior. I thus perform the same decomposition considering a *firm* as the unit of analysis, rather than a *firm-HS10 product* combination. Again, I use the most conservative definition possible for a "staying" importer- if a firm stayed with any of its trading partners (even potentially using that partner to import different products!), then I classify that firm as a "staying" importer. Even with this much more sparse assignment of switching firms, Table 2 Panel A shows that the results remain very similar: almost one-third of continuing importers (approximately 8,000 out of 24,000) switch partners from 2002 to 2003, with considerable geographic stickiness. The table also demonstrates that switching within-city becomes more common over time.

Another concern may be that with China's entry into the WTO in late 2001, the probability for name and address changes among exporters given rapidly changing macroeconomic conditions is high, potentially fouling up the ability of the MID to serve as a panel identifier. Though I address concerns about the reliability of the MID in Appendix A, a separate robustness check is to recreate Table 1 measuring only those switches that occur where the previously used supplier is found, but not used by the same importer, in the later year. This measure clearly will clearly understate the degree of switching, as the sample of Chinese suppliers found in U.S. trade is certainly not the entire population of Chinese exporters, and some switching must occur as a result of exporters leaving the U.S. or folding. But even with this bias, Table 2 Panel B shows that the same three stylized facts carry through even when using this alternate specification: importer-exporter relationships are highly volatile, geography matters, and these two trends intensify as a cohort ages[7]. The same results come through if I analyze only U.S. manufacturing firms (as identified in the 2002 Census of Manufacturers) as in Table 2 Panel C, or if I use firm-HS6 product as the unit of analysis, as shown in Table 2 Panel D. Ultimately, it is clear that the three stylized facts described above are consistent across a variety of specifications: there is non-negligible amount of switching among U.S. importers, there are strong geographic factors involved in the switching decision, and each of these trends strengthens over time.

3.3 Reduced Form Regression Results

Determining what factors govern the relationship formation and dissolution that is so common in the data is of great interest in predicting the response of trade flows to price changes, as the ability to search on the supplier level is generally not modeled in studies of international trade. I investigate a number of potential explanations for this switching behavior. These empirical findings guide the modelling and estimation procedure described below.

[7]Since all exporters not found in both 2002 and the later year are dropped from the overall sample, the counts of importing firms in 2002 change depending on which year is being analyzed.

I use a linear probability model to estimate the relationship between the decision of a U.S. importer to switch Chinese exporting partners and a variety of potential explanatory variables, including price, size and age of the Chinese partner, U.S. importer size, and the date of entry into importing.

Unlike the above tables of importer counts, I need to assign particular traits to a Chinese exporting firm, meaning I must take more care on the definition of who exactly is an importer "staying" with and/or "switching" from. This is because there are numerous importers who use more than one exporter- I must address this issue to claim a relationship between exporter characteristics and switching behavior[8]. My preferred specification is to use trade value information to determine which exporter had the highest percentage of an importer's total imports with in any HS10 code in any year (an importer is again a firm-HS10 product combination). This "main" exporter is calculated for every importer, and if an importer had the same main exporter across two years, then importer "stayed" with its partner (I will call this dummy variable *StayVal*)[9]. For this definition of staying, exporter covariates are simply those of the main exporter. I also use the definition from the previous section, meaning if a U.S. importer stayed with any one of its partners, it is a "staying" importer (I call this dummy variable *StayMax*)[10]. However, exporter covariates must therefore be assigned in a more creative way; if an importer has ($StayMax = 1$), then I use the average across the covariates of all exporters it stayed with, while if it has ($StayMax = 0$), I use the average across the covariates of all exporters it switched away from (i.e. all exporters it used in the previous period). Due to this less than appealing summary measure of exporter covariates, my preferred specification is to use $StayVal$, though I present results for both.

Price is an intuitive explanatory variable for why importers might switch their trading partner. Given a high price from one's current export partner, all else equal, we would expect movement to other competitors to be more likely. In the LFTTD, using value and quantity information from each transaction, I can construct the price ("unit value") paid simply by dividng value by quantity. I then define the price an importer paid to any one exporter by taking the average of unit values across all transactions between that importer and exporter. Due to the high possibility of outliers in price due to misreported quantity information, I use the log price as a covariate in the linear probability model. I also calculate the size of a Chinese exporter to the extent possible by summing together its total exports to the US, and similarly calculate the age of a Chinese exporter by calculating the first year a MID appears in the trade data. On the importer side, I constuct importer size by summing together total imports from China, the first year of its entry into the Chinese import market by calculating its first appearance in the Chinese import data, and employment from the Longitudinal Business Database, the U.S. domestic firm operations database. I use data from 2005, using

[8]In the above section, I defined a "staying" firm as a firm who stayed with any one of their potentially numerous partners.

[9]Importers with the same plurality share from more than one exporter are dropped.

[10]Note that $StayMax = 1 \implies StayVal = 1$, but not vice versa.

2006 data to determine whether or not an importer switched exporting partners.

The results of the Linear Probability Model on switching are in Table 3. From the results using my preferred specification $StayVal$, it is clear that the higher the price a firm paid in 2005, the lower the probability that it would stay with its original (plurality) partner firm. Furthermore, the older and/or larger a Chinese exporting firm was, the lower the probability that a U.S. importer would switch. Finally, larger U.S. firms were most likely to stay with their partner. The majority of the results carry through using the secondary specification $StayMax$, especially the price paid being highly correlated with the decision to switch partners. However, it should not be surprising that the results across specifications are vastly different: the percentage of firms classified as staying differs dramatically across specifications.

In conclusion, price is an important factor in the decision of an importer to switch partners, especially the magnitude of the price paid in the previous year. Exporter and importer characteristics more generally are also important factors in the decision of whether or not to stay with one's partner. I use these results to guide the modeling of the exporter choice problem below.

4 Model

I use a dynamic discrete choice framework to model U.S. importer decisions of exporter choice. Within each industry, exporters set prices and quality based on profit maximization and the elasticity of demand. Importers of products in that industry make a decision each period about which firm to import from, a decision that is based both on their current choice of exporter, the price/quality basket they currently have from their current exporter, and what other price/quality menus are available. Switching exporters involves payment of a set of fixed costs, including both an overall switching cost and an additional cost to be paid if an importer finds a new partner in a previously unused city.

4.1 Exporters

The model is designed to capture trends at the industry level, and I thus describe the product of exporter x_j as a separate *variety* from any other exporter in industry j (i.e. within-industry monopolistic competition). Exporting firms produce intermediate goods that are supplied for use in the production of final goods. Each variety x has a particular price elasticity σ_x, and firms differ in their marginal costs, MC. Variable profits for exporter x are:

$$\pi_x = p_x\left(Q_x\right)Q_x - MC_xQ_x$$

Exporting firms choose quantity Q_x to maximize profits:

$$\frac{dp_x(Q_x)}{dQ_x}Q_x + p_x(Q_x) - MC_x = 0$$
$$\implies p_x\left(\frac{1}{\sigma_x}+1\right) = MC_x$$

And thus the offered price is a markup over marginal cost: $p_x = \frac{\sigma_x}{\sigma_x+1}MC_x$. As in Hallak and Sivadasan (2011), the marginal cost depends on the quality that each exporter chooses, as well as their individual productivity, and takes the form:

$$MC(\lambda, z) = \frac{\kappa}{z}\lambda^{\beta}$$

Trade costs, variable input costs, and location-specifc idiosyncratic shocks specific to exporter x are captured in κ, while z is firm productivity. The quality chosen is λ- higher quality products are reflected in higher marginal costs. Thus the optimum price is a markup over marginal cost, which includes both productivity and quality:

$$p(x) = \frac{\sigma_x}{\sigma_x+1}\frac{\kappa_x}{z_x}\lambda_x^{\beta} \tag{1}$$

4.1.1 Dynamic Evolution of Prices

I assume that prices evolve over time, based on changes in dynamic parameters contained in κ, espcially location-specific shocks to input prices. In particular, Equation (1) holds at each period t. Taking logs of Equation (1) means we can write:

$$p_{xt} = \log\alpha_{xt} - \log z_x + \beta\log\lambda_x \tag{2}$$

I use Equation (2) to estimate λ for each individual exporter, as described below. However, I can write the evolution of prices over time for any single exporter as:

$$p_{x,t+1} = p_{x,t} + \log\alpha_{x,t+1} - \log\alpha_{x,t} \tag{3}$$

Importers know the distribution of shocks that hit any particular exporter as well as the price offered in the previous period. However, they do not know the exact price until the contract is agreed upon, when the shocks embedded in α are fully realized, and importers thus make their choice based on the *expected* price.

This is to avoid a Heckman selection bias, whereby the only prices contained in the data are the prices of successful transactions. This assumption is laid out in greater detail below in the description of importer profits.

4.1.2 Quality Estimation

Given the likelihood of omitted variable bias in industries with a high degree of product differentiation, in this section, I estimate supplier quality given Equation (2) and the data in the LFTTD.

I use the control function methodology of Kim and Petrin (2010) to account for unobserved supplier heterogeneity that is likely to be positively correlated with the price. From the trade data, I cannot observe the productivity of individual Chinese exporters. However, there are a number of variables in the data that I use to proxy for productivity, including total U.S. exports, number of HS products exported, number of years exporting to the U.S., number of import partners, and number of transactions. For each industry, I group these terms into a firm-specific vector of covariates Z_x, and together with time fixed effects contained in α_{xt}, regress the exporter's offered price (firm-level unit value) on these variables. I then take the residual from this regression and include it as a determinant of the importer's choice of exporter. The full choice model, including these estimated residuals, is described in the next section.

4.2 Importers

4.2.1 Profit Maximization

The profits of importing firms are determined according to demand for their final product. Demand for the final product of importer m is according to a constant elasticity of substitution demand curve.

$$Q_m = \frac{X}{P^{1-\varepsilon}} p_m^{-\varepsilon}$$

The final good producer m requires a collection of intermediates $I_j, j = 1, ...J$ in order to produce its final good, and production of final good is Cobb-Douglas in labor and those intermediates:

$$Q_m = L^\alpha \left(\prod_{j=1}^{J} I_j^{\gamma_j} \right)^{1-\alpha}$$

At this point, I build in frictions involved in searching for the correct partner, consistent with the empirical findings of prevalent partner switching found in the trade data. I assume that final good producer m has a choice from which firm $x_j = 1, ...X_j$ to obtain its quantity of input I_j. I include two frictions: a cost from finding a new supplier β_x, and an additional cost if that new supplier is located in another city, β_c. I assume that each importer uses only one supplier each period. The total price of purchasing intermediate j from supplier x at time t, incorporating the frictions involved in searching for a supplier, as:

$$\bar{p}_{j,t}\left(x_{j,t}\right) = p_{j,x,t}e^{\widetilde{\beta_x}\mathbb{1}\{x_{j,t}\neq x_{j,t-1}\}+\widetilde{\beta_c}\mathbb{1}\{c_t\neq c_{t-1}\}}$$

If a firm chooses a new partner in the same city (c_{t-1}) as its old partner, then only $\widetilde{\beta_x}$ is paid, while if an exporter in a separate city is picked, $\widetilde{\beta_x}+\widetilde{\beta_c}$ is paid. This means that the cost of an input bundle differs depending on what supplier is chosen for each input, not just because of a higher or lower offered price, but also because of costs of switching one's current partner. Let $X^J_{m,t}$ denote the vector of supplier choices made by importer m for each input $j = 1, ...J$ at time t. Then the cost of an input bundle for the final good is:

$$c_m\left(X^J_{m,t}\right) = w^{\alpha}\left(\prod_{j=1}^{J}\left[\bar{p}_{j,t}\left(x_{j,t}\right)\right]^{\gamma_j}\right)^{1-\alpha}$$

Producing one unit of the final good for a final good producer with productivity ϕ requires $\frac{1}{\phi}$ input bundles, each with cost depending on the vector of suppliers $X^J_{m,t}$. I assume that the productivity of a final good producer depends on factors unobserved by the econometrician (such as the quality of the supplier's product) that are particular to its individual supplier match. In particular, productivity for producer m is multiplicative in a common element for that producer and a match-specific term.

$$\phi_m\left(X^J_{m,t}\right) = \psi_m\prod_{j=1}^{J}\lambda_{x,j}^{\nu_j}$$

Again, this term depends on the vector of supplier choices made for each input. Putting these together, the marginal cost of an importer m with productivity ϕ_m is:

$$c\left(X^J_{m,t}\right) = \frac{1}{\phi_m\left(X^J_{m,t}\right)}c_m\left(X^J_{m,t}\right) \tag{4}$$

Individual profits for importing firm m have the following setup:

$$\pi^*\left(m\right) = \max_{X^J_{m,t},p_m} p_mQ_m - c\left(X^J_{m,t}\right)Q_m$$

Using the assumption of CES demand, the optimum price of the final good for producer m is a markup over the marginal cost, $p_m = \frac{\varepsilon}{\varepsilon-1} c\left(X^J_{m,t}\right)$, and profits can be rewritten as:

$$\pi^*(m) = \max_{X^J_t} \frac{1}{\varepsilon} \frac{X}{P^{1-\varepsilon}} \left(\frac{\varepsilon}{\varepsilon-1}\right)^{1-\varepsilon} \left[\phi_m \left((X^J_{m,t}\right)\right]^{\varepsilon-1} c_m \left(X^J_{m,t}\right)^{1-\varepsilon}$$

Taking logs, and focusing only on the choice of where to obtain intermediate input j, we can write the supplier choice profit maximization problem as:

$$\ln \pi^*(m) = \max_{x_{j,t}} A + B_{-j} + \nu_j (\varepsilon - 1) \ln \lambda_{x,j,t}$$
$$+ (1-\alpha)(1-\varepsilon)\gamma_j \left[\ln p_{j,x,t} + \widetilde{\beta_x} \mathbb{1}\{x_{j,t} \neq x_{j,t-1}\} + \widetilde{\beta_c} \mathbb{1}\{c_t \neq c_{t-1}\}\right]$$

Here A captures all the terms not associated with the cost of an input bundle for the final good and B_{-j} captures the costs involved in looking for other intermediates other than j.

For elasticities of substitution $\varepsilon > 1$, we see that higher quality inputs leads to higher profits, while higher prices lead to lower profits. Finally, to avoid a Heckman selection problem whereby the only prices actually observed as those of choices that are already made, I assume that final good producers make their decision based on the *expected* price they will receive from exporter x_j. In other words, even though I cannot observe the individual price quotation for a transaction not completed, I estimate the offered price for all suppliers. Lastly, I assume profits from making a particular exporter choice x are subject to a shock ϵ, with known distribution[11]. Putting all the pieces together means that the choice of supplier x at time t (dropping the industry designation j) will be distinguished from any other exporter choice via the *exporter-specific profit* term:

$$\widetilde{\pi}(x_t, x_{t-1}, p_{t-1}) + \epsilon_{m,x,t} = \beta_p \mathbb{E}\left[\ln p_{x,t} | p_{x,t-1}, x_{t-1}, x_t\right] + \beta_x \mathbb{1}\{x_t \neq x_{t-1}\}$$
$$+ \beta_c \mathbb{1}\{c_t \neq c_{t-1}\} + \xi \ln \lambda_{x,t} + \epsilon_{m,x,t} \tag{5}$$

where $\xi = \nu_j$, $\beta_p = -(1-\alpha)\gamma_j$, $\beta_x = -(1-\alpha)\gamma_j\widetilde{\beta_x}$, and $\beta_c = -(1-\alpha)\gamma_j\widetilde{\beta_c}$. To summarize, if importer m chooses a different exporter than they used in the previous period, they must pay a fixed cost β_x, while if they use a different exporter in a different city, they pay the cost $\widetilde{\beta_x}$ and $\widetilde{\beta_c}$. Profits are subject to a shock particular to any importer-exporter combination $\epsilon_{m,x,t}$. The goal of the econometric procedure is to provide estimates for $\boldsymbol{\beta} = \{\beta_p, \beta_x, \beta_c, \xi\}$ for each imported industry j.

The observed exporter choice will be the one such that profits from that exporter are higher than all other potential choices. Thus rather than estimating equation (5) as a regression, I use data on observed

[11] A shock is necesary to allow for the option of an importer using an exporter in another city with similar quality while paying a higher price, an outcome that is possible in the data.

outcomes, prices, and quality data to estimate the parameters via maximum liklihood estimation.

It is possible to estimate the model in (5) without quality considerations. But given the richness of data available, I implement a model that takes more explicity account of "quality" considerations, in particular, those characteristics of an exporting firm that are observed by the potential importer, but unobserved by the econometrician and tend to be correlated with the price. I use the control function approach of Kim and Petrin (2010), namely, regressing the price on a number of observable exporter characteristics, including exporter size, age, number of import partners, number of transactions, and number of HS6 products sold, and using the estimated residuals $\widehat{\lambda}$ as a component of the profit function $\widetilde{\pi}$ described in (5).

4.2.2 Expected Prices

In each of the above specifications of profits, so as to avoid a Heckman-type selelction problem, I assume that firms maximize *expected profits*, as the price a firm will pay is not known exactly until the switch to a new exporter is completed. However, importers know both what prices were paid by other firms in previous periods, and the distribution of shocks to those prices in the next period. I thus am required to specify the transition probability process for import prices. If importer m stays with its current partner x in city c, using (3), we can write the price process as:

$$p_t = p_{t-1} + \eta_{c,t} + u_{m,x,t} \tag{6}$$

Importing firms know there is a city-specific increase in prices, as well as an importer-specific realization of a shock to the exporting firm itself. The city-specific price shocks are correlated for firms in the same city, so there is a city component and an exporter-specific component. Thus this model has the desirable features that a high price increase from one exporter could influence the decision of where, geographically, an importer might go: there is a tradeoff between the probability of a lower average price in a separate city and the probability of a higher price in the current city.

If importer m decides to use a different partner x' in the same city c, then the price process is:

$$p_t = \frac{1}{N_{x'}} \sum_{n=1}^{N_{x'}} p_{n,t-1} + \eta_{c,t} + v_{m,x',t} \tag{7}$$

$N_{x'}$ is the number of firms who imported from firm x' from the previous period, and they are indexed $n = 1, ...N_{x'}$. Each price paid by importer n is $p_{n,t-1}$. As above, there is both a city shock to prices (in this case, the same shock as to firm x, since they are in the same city) and an importer-specific realization of the exporter price shock.

If the importer decides to go to an exporter x'' in another city c', then the price process is:

$$p_t = \frac{1}{N_{x''}} \sum_{n=1}^{N_{x''}} p_{n,t-1} + \eta_{c',t} + w_{m,x'',t} \tag{8}$$

where now we have a separate city-specific price shock $\eta_{c',t}$.

Given the specification of these different prices based on shocks calibrated to data in period $t-1$ and t, I can write down a density function for prices $f(p_t|x_{t-1}, p_{t-1}, x_t)$. I assume the parameters $\{u, v, w\}$ are normally distributed with mean zero and standard deviations $\{\sigma_x^u, \sigma_x^v, \sigma_x^w\}$ (each exporter has a particular distibution of price shocks known to importers, but the specific value of which is observed only after the match occurs). I use the LFTTD data to calibrate the parameters $\{\{\eta_c\}_{c=1}^C, \{\sigma_x^u, \sigma_x^v, \sigma_x^w\}_{x=1}^X\}$ by using observed prices in both pre- and post-periods and estimating equations (6)-(8) for each industry[12].

4.3 Value Function

Individual importers make their choice of exporter based on price concerns, quality concerns and any added costs involved from changing their current exporter. Entering period t, importer m has two state variables: the exporter used last period, x_{t-1} (located in city c_{t-1}) and the price paid to that exporter p_{t-1}. Based on these state variables, knowledge about prices in other locations, and the costs of switching one's current exporter, the importing firm must choose which exporter to use in the current period, x_t. Upon making this choice, the state variables and profit shock ϵ_t evolve according to the density $h(p_t, x_t, \epsilon_t|p_{t-1}, x_{t-1}, x_t, \epsilon_{t-1}) = h(p_t, \epsilon_t|p_{t-1}, x_{t-1}, x_t, \epsilon_{t-1})$.

Infinitely-lived importer m chooses an exporter x in each period in order to maximize the present discounted stream of expected profits, described by the following value function:

$$V(p_{t-1}, x_{t-1}, \epsilon_{t-1}) = \max_{\{x_t, x_{t+1}, \ldots\}} \mathbb{E}\left[\sum_{\tau=t}^{\infty} \delta^{\tau-t} \left(\widetilde{\pi}(p_{\tau-1}, x_{\tau-1}, x_\tau, \beta) + \epsilon(x_\tau)\right)\right] \tag{9}$$

where the expectation operator is taken over the possible evolution of (p_t, ϵ_t), governed by the density $h(p_t, \epsilon_t|p_{t-1}, x_{t-1}, x_t, \epsilon_{t-1})$ at every period t. Recall from Section 4.2.2 that the price from choosing exporter x_t is not known before making the choice, but is predicted based on p_{t-1}, x_{t-1} and x_t, according the density function $f(p_t|p_{t-1}, x_{t-1}, x_t)$. This means the profits in Equation (9) are *expected* profits.

Writing the one-step ahead value of any variable a as a', the value function in (9) can be rewritten as a

[12] If no prior year information is available for a potential supplier- i.e. an importer chooses a supplier that did not exist in the previous year- I allow the expected price to be the average price among all exporters in that city in the previous period. If there is no city information in the previous period, I drop that exporter. If an exporter is only found in the pre-period, then I calibrate $\{\eta_c, u, v, w\}$ using all other firms and use them to form the expected price from using that exporter.

Bellman Equation:

$$V\left(p,x,\epsilon\right)=\max_{x'}\quad \widetilde{\pi}\left(p,x,x',\beta\right)+\epsilon\left(x'\right)+\delta EV\left(p,x,x',\epsilon\right)$$

for

$$EV\left(p,x,x',\epsilon\right)=\int_{p'}\int_{\epsilon'}V\left(p',x',\epsilon'\right)h\left(p',\epsilon'|p,x,x',\epsilon\right)dp'd\epsilon'. \tag{10}$$

At this point, I make a key assumption about the joint density of the state variables and the profit shock: that they evolve separately from each other.

Assumption 1 (Conditional Indepdendence) *The joint transition density of p_t and ϵ_t can be decomposed as:*

$$h\left(p_{t+1},\epsilon_{t+1}|p_t,x_t,x_{t+1},\epsilon_t\right)=g\left(\epsilon_{t+1}\right)f\left(p_{t+1}|p_t,x_t,x_{t+1}\right)$$

I also assume that the profit shock ϵ is distributed according to a multivariate extreme value distribution, with known parameters:

Assumption 2 *The density function of the profit shock is:*

$$g\left(\epsilon\right)=-\exp\{-\epsilon\left(x\right)-\gamma\}\exp\{-\exp\{-\epsilon\left(x\right)-\gamma\}\}$$

while the distribution is

$$G\left(\epsilon\right)=\exp\{-\exp\{-\epsilon\left(x\right)-\gamma\}$$

for $\gamma=0.577...$ (Euler's constant).

These two assumptions permit the computation of choice probabilities for any particular outcome :

Proposition 1 *Let any present time variable a at one period prior be written as a_{-1}, and one period in the future be written as a'. Given Assumptions 1 and 2, and grouping together the state variables as $s=\{p_{-1},x_{-1}\}$, the probability of observing a particular exporter choice x^C conditional on state variables s*

and cost parameters β, $P\left(x^C|s,\beta\right)$, is:

$$P\left(x^C|s,\beta\right)=\frac{\exp\left[\widetilde{\pi}\left(s,x^C,\beta\right)+\delta EV\left(s,x^C\right)\right]}{\sum_{\widehat{x}\in X}\exp\left[\widetilde{\pi}\left(s,\widehat{x},\beta\right)+\delta EV\left(s,\widehat{x}\right)\right]} \tag{11}$$

where the function $EV\left(s,x\right)$ is the solution to the fixed point problem:

$$EV\left(s,x\right)=\int_{s'=0}^{\infty}\log\left\{\sum_{x'\in X}\exp\left[\widetilde{\pi}\left(s',x',\beta\right)+\delta EV\left(s',x'\right)\right]\right\}f\left(s'|s,x\right) \tag{12}$$

Proof *See Appendix B.*

4.4 Maximum Likelihood Estimation

The parameters β can then be solved for via maximum likelihood estimation. Let x_t^m, p_t^m be the actual choices of exporter and price paid at time t for importer m from data. Then the likelihood of observing importer m choosing exporter x_{t+1}^m is:

$$L\left(x_{t+1}^m|p_t^m,x_t^m,\beta\right)=P\left(x_{t+1}^m|x_t^m,p_t^m,\beta\right)\cdot f\left(p_t^m|p_{t-1}^m,x_{t-1}^m,x_t^m\right)$$

And thus the total likelihood function for the set of importer choices at time $t+1$ is:

$$\mathcal{L}\left(\beta\right)=\prod_{m=1}^{M}P\left(x_{t+1}^m|x_t^m,p_t^m,\beta\right)\cdot f\left(p_t^m|p_{t-1}^m,x_{t-1}^m,x_t^m\right)$$

This is solved with the fixed point equation (12) as the vector of constraints. I use the MPEC approach, where the constrained maximization of the augmented log-likelihood function can be written:

$$\max_{\beta}\mathcal{L}\left(\beta\right)=$$

$$\max_{\beta}\sum_{m=1}^{M}\frac{\exp\left[\widetilde{\pi}\left(s,x^m,\beta\right)+\delta EV\left(s,x^m\right)\right]}{\sum_{\widehat{x}\in X}\exp\left[\widetilde{\pi}\left(s,\widehat{x},\beta\right)+\delta EV\left(s,\widehat{x}\right)\right]}+\sum_{m=1}^{M}f\left(p_t^m|p_{t-1}^m,x_{t-1}^m,x_t^m\right) \tag{13}$$

$$s.t$$

$$EV=T\left(EV,\beta\right) \tag{14}$$

where the constraints in (14) are the shorthand notation of fixed point equation (12). Solving this system produces estimates for the vector of parameters β.

5 Estimation

5.1 Implementation

In order to calculate the above model, I need to determine the vector of constraints EV that are used in computing the continuation values. To do this, I discretize the price state space into N intervals, allowing me to rewrite the fixed point equation (12) as:

$$EV\left(\widehat{p}, x, x'\right) = \sum_{\widehat{p}'=1}^{N} \log \left\{ \sum_{x'' \in X} \exp\left[\widetilde{\pi}\left(\widehat{p}', x', x'', \beta\right) + \delta EV\left(\widehat{p}', x', x''\right)\right] \right\} Pr\left(\widehat{p}' | \widehat{p}, x, x'\right) \tag{15}$$

where $\widehat{p}$ is the midpoint of each price interval, chosen such that $\frac{1}{N}$ of all firms are in each interval. My use of MPEC in solving the maximum likelihood model follows the description from Su and Judd (2012) and Dube, Fox, and Su (2012). The MPEC maximization protocol uses values of the vector β that satisfy the fixed point equation (15), given expected prices and price transition probabilities for each potential choice, and selects the vector that delivers the highest likelihood.

Before computing the model on the true U.S. Census trade data, I first set the parameters at fixed values and create 250 Monte Carlo replications of data based on these values. Every importer m is assigned an exporter x_{t-1} and price p_{t-1} from a previous period, and predicts the expected price received from every potential exporter x', i.e. $\mathbb{E}\left[p_t | p_{t-1}, x_{t-1}, x'\right]$. The importer then makes the decision of which exporter to use x_t, given both these expected prices and the pre-set values of the parameters β_p, β_x, and β_c[13]. I then utilize the observed outcomes and prices from each dataset to run the maximum liklihood problem found in (13) and (14), extracting the cost parameters consistent with those choices. I set $\delta = 0.975$ and use $N = 5$ price states.

Since the total number of importers (M), exporters (X), and exporter cities (C) are free to choose, I create three different samples: one small ($M = 6, X = 3, C = 2$), and two samples with larger numbers of observations. For the larger samples, I match the average number of Chinese exporters in an HS6 industry ($X = 33$) and vary the number of cities from $C = 2$ in one set of replications to $C = 9$ (the average number of cities in an HS6 industry) in the other[14]. I then run the estimation routine on each set of data, and report summary statistics for how well the procedure matches the pre-set values. The results of this bootstrapping procedure are presented in Table 4.

[13]For this estimation, I do not include quality estimation terms, given the extra assumptions I would have to make to run the Kim and Petrin (2010) procedure about exporter characteristics. The profit equation is the same as (4), only without the λ term.

[14]The average number of Chinese exporters in an HS6 industry is 33.58[15] This figure is the average number of The median number of exporters is 8. The industry at the 90th percentile of exporters contains 81 exporters. 15.3% of the 3000 or so HS6 codes found in the trade data contain only one exporter. These figures are based on computation of the "main" exporters, i.e. exporters who are found after assigning a "plurality exporter" to each importer. See Section 5.2 for more detail.

It is clear that the estimation routine performs worst on a very small sample. In fact, the procedure sucessfully iterates to a feasible set of parameters in only 45.6% of trials. Furthermore, mean estimates of the exporter switching effect β_x are extremely high. These results occur because with such a small sample space (six importers and three exporters), a number of Monte Carlo runs likely have very few cases of within-city, providing very high estimates for the base exporter switching cost. However, even in this scenario, the median results preserve the ordering of the originally set parameters. In addition, the elasticity of the switching decision with respect to prices, β_p is of reasonable sign and size.

Once the sample size is extended to 30 importers and 33 exporters (the average number of exporters in an HS6 industry), convergence occurs in each Monte Carlo run. For Sample B, which contains fewer cities, we see a vast improvement, both in the measurement of the price coefficient β_p, and the exporter switching cost β_x. With a greater number of exporter possibilities, there are more instances of switching within-city, allowing for better estimation of this parameter. Notably, however, the outside-city switching cost β_c, both in mean and median, is much higher than the pre-set value of the parameter, as the number of cities is small enough to make the estimation procedure assign higher costs of switching cities.

Finally, results for Sample C demonstrate that the procedure improves further when the number of cities is increased to the average number of exporting cities found in the LFTTD, $C = 9$. Not only do estimates of the city switching cost decrease in mean and median to levels much closer to the preassigned values, but the exporter switching cost and price elasticity similarly approach their values. My estimation procedure thus is expected to perform better in industries that have enough observations of within-city, out-of-city, and non-switching observations to estimate the paramters of interest, and in those industries, delivers reasonable results.

5.2 Data Preparation

In order to fit the above model to the trade data described in Section 3, I make a few simplifications. Firstly, with some industry variation, some U.S. importers use multiple exporters each year. Rather than counting every possible permutation of exporters as a discrete choice, I restrict attention to that exporter from which a U.S. importer obtained the plurality (highest percentage) of its imports from each year: an identical definition as the variable $StayVal$ from Section 3.3. Thus the “choice” in the discrete choice model is which exporter the firm imports the most from, rather than which exporter the firm uses.

This simplification introduces the potential for “false switching”, where an importer uses the same exporter in two periods, but changes the source of the plurality of its imports. The possibility is unavoidable, although analysis of the LFTTD indicates that U.S. importers typically import a very large share of their total imports from only one partner. The average share of imports that come from a U.S. importer's main Chinese partner is 83.9%, with a standard deviation of 22%. Furthermore, multiple importers do not dominate in the data. Kamal and Krizan (2012) present some basic statistics on the number of exporting relationships that a U.S. importer may be in: across all U.S. importers, the average number of exporting partners for a U.S. importer is 1.8, and the average number of exporting partners for a "polygamous" U.S. importer is 4. Thus there is a non-negligible amount of importers for which this simplification drops information; however, the high share of imports from a "main exporter" gives some evidence that the simplification is relatively benign.

A second simplification is to use HS6 categories: even though the trade data is measured at the most disaggregated level possible- HS10 - many measures of product differentation that I wish to compare my results with are only at the HS6 level. This also gives more observations and more potential for wider geographic effects. At the same time, any switching behavior that goes on at a more disaggregated level is swamped by this aggegation, and the degree of product heterogeneity across firms is likely much larger than at the more disaggregated level.

Additionally, given the fact that not every exporter is found in both periods, I have to take a stand on the set of potential exporters X. I define the set of possible exporter choices broadly, consisting of a) any exporter used in time t and b) any new exporter in time $t+1$, as long as I know what price they charged in time t. As described above, I am making the exporter choice one of "where do I get my majority of imports from", meaning it is possible that we have some "new" exporters found in time $t+1$ that have price information from time t, even though they did not actually appear as any importer's majority supplier in time t.

Lastly, I clean the LFTTD further by eliminating unreasonable prices. Unit values in the LFTTD are particularly prone to wildly unreasonable outliers, sometimes caused by firms writing down a quantity of 1 instead of the quantity in kilograms, for example. Before averaging prices across transactions, I eliminate any transactions with prices in the 90th percentile for an HS6 industry that are also greater than 10 times the median price in that industry. I then repeat the proces, again eliminating prices that are greater than 10 times the new median price.

I estimate the above model for a large number of industries, using data on U.S.-China trade from 2005-2006. I use TOMLAB / KNITRO to compute the Jacobian and the gradient analytically, and then solve the above MLE problem.

5.3 Quantitative Results

Rather than presenting the full battery of results, in this section I present estimates of the parameters in illustrative industries. In the following sections, I put the results for different industries together to assess model fit and perform counterfactuals.

I begin by presenting results for industries that have noteworthy spatial characteristics related to the location of exporters. The HS6 industries "Fuses, for a Voltage Not Exceeding 1,000v" (HS6 853610) and "Electronic hybrid integrated circuits" (HS 854260) are both characterized by very low degrees of inter-city switching. 46% of all importing firms in HS6 853610 switched partners from 2005 to 2006, but only 12% switched cities. For HS6 854260, the respective figures are 57% and 23%. Thus the estimation routine should reflect the fact that switching cities is more costly through higher city-switching costs relative to partner-switching costs. On the other hand, the HS6 industry "Tapered Roller Bearings, Including Cone and Tapered Roller Assemblies" (HS6 848220) is characterized by a very high level of inter-city switching among switching firms: though only 32% of importers switch partners, 24% find a partner in another city. Thus the size of β_c relative to β_x should be much smaller than in the previous two industries, given that calculations of these parameters take into account how much switching is actually occurring. The first panel of Table 4 demonstrates this to be true: those industries with relative low levels of city switching have higher relative levels of city-switching costs, and the opposite for the industry with greater city switching.

Another illustrative comparison is to examine the "slackness" of the market for imports- how many available exporters there are compared to the number of importers. Though most industries tend to have similar numbers of importers and exporters, the industry "Floor Coverings, Wall or Ceiling Coverings, of Polymers of Vinyl Chloride" (HS6 391810) has many more importers than available exporters: 58 to 42. Thus this is a market where matches are quite important, a trend that should be reflected in high partner-switching costs. The middle panel of Table 4 demonstrates this to be true: the cost of switching exporters is a high proportion of the total exporter costs borne by switching both partner and city.

Next, I present selected results for textile imports from China, for the purpose of illustrating differences in elasticities of substitution. The industries "Boys' Cotton Other T-shirts, Knitted Or Crocheted, Except Underwear" (HS10 6109100014) and "Men's Underpants And Briefs, Knitted Or Crocheted, Of Cotton" (HS10 6107110010) could both be reasonably thought of as industries with very high elasticities of substitution- firms selling these products are likely to have low markups and the products themselves are likely not highly differentiated. These are another type of industry where the costs of an importer staying at a particular supplier are likely to be relatively lower. On the other hand, other textile industries such as "Gloves, Mittens And Mitts, Knitted Or Crocheted, Of Synthetic Fiber: Other Gloves, Specially Designed For Use In

Sports" (HS10 6116930800) and "Women's Or Girls' Not Knit Man-made Fiber Anoraks, Coats, Jackets, Etc, Impregnated Fabric" (HS10 6210505020) are more specialty industries where exporting firms are adding more value and thus might have higher markups. These industries would be expected to have higher costs of switching from an individual exporter for these reasons, relative to city switching costs. The lower panel of Table 4 demonstrates that these conclusions about supplier switching costs and the elasticity of substitution are confirmed: industries with little firm-level value added have lower relative costs of switching.

I further make use of concordances developed by Brandt, Van Biesebroeck, Wang, and Zhang (2012) between HS codes and the China Industry Code (CIC) system to analyze different types of industries based on their domestic characteristics. Using China National Bureau of Statistics firm-level data for 2005, I isolate CIC industries where exporters have particular characteristics relevant to the importer-exporter partnership decision. For example, I compare industries composed of large firms to industries composed of small firms, and industries with highly skilled workers to unskilled workers. I then use the HS6-CIC concordances to estimate the switching behavior parameters among all firms importing in that CIC code. I summarize the estimates according to their underlying traits in Table 5.

The first set of results relates to the labor productivity of workers in different exporting industries. Chinese exporters in the industry "Arms and Ammunition" (CIC 3663) are in the lower tail of value added per worker relative to other industries. On the other hand, exporters in the industries "Rolling and Processing of Rare Earths" and "Tungsten and Molybdenum Smelting" have very high levels of value added per worker. As can be seen from the top panel of Table 5, the industry with lower worker productivity tends to be characterized by lower exporter switching costs relative to city switching costs, meaning relationships are easier to be broken, while those industries with high levels of worker productivity have much higher exporter switching costs. This result is intuitive, as it implies importing firms who are importing products with highly productive workers receive greater relationship-specific benefits breaking up is more costly. On the other hand, firms with unproductive workers have little to distinguish themselves from competing firms, and thus have lower costs of switching from one to another.

I also compare results for firms of diffferent employment sizes. Exporters in the industry "Other Ward Care and Medical Equipment" (CIC 3689) are of very small size, compared to exporters in the industry "Arms and Ammunition" (CIC 3663). The bottom panel shows importers importing a product that is dominated by small firms tend to value the relationship more, while an industry dominated by large firms is characterized by smaller exporter switching costs and more relationship breakups.

In summary, the results are consistent with economic intution, with higher exporter switching costs relative to city switching costs appearing in industries with low levels of inter-city switching, many importers, low elasticies of substition and highly skilled workers, while lower exporter switching costs are found in industries with high levels of inter-city switching, high elasticities of substition, and a high proportion of large firms. The next section uses the whole set of quantitative estimates to perform counterfactual experiments about the size and direction of trade flows.

5.4 Model Fit

Before exploring the implications of changing these parameters on prices and switching behavior, I first check how well the estimated parameters do at matching the underlying data used to generate those parameters. Compared to the size of the discrete choice problem, the simple model I estimate is unlikely to match specific importer-exporter outcomes exactly. Thus I check model fit in three areas: how well prices match, how well the percent of switching importers match, and how well the percent of city-switching importers match. I begin by comparing prices.

The procedure I use is as follows: for each of 50 industries, chosen to represent industries across the spectrum of imported products from China that also have a large enough sample of switching and non-switching importers, I estimate the parameters described above via maximum likelihood[16]. I then generate data according to a new set of parameters for each industry that reflect differences in switching costs. Keeping the state variables the same for each firm (supplier and price in the previous period), I generate outcomes given randomly drawn extreme-value shocks and the estimated parameters. Specifically, for each industry $j \in J$, the industry price index P_j sums together firm-level prices, weighted by the share of one firm's imports in total industry imports:

$$P_j = \sum_{i \in I_j} \omega_i p_i \tag{16}$$

In the above, p_i is a summary measure-the mean or median- of firm i's received price across 1000 replications[17]. I weight each firm i by the value of its imports relative to total imports in that industry, ω_i. Given these industry level price ratios, I aggregate up using the share of industry imports in total trade across the industries in my sample:

$$P = \sum_{j \in J} w_j P_j \tag{17}$$

The result is an aggregate price ratio that accounts for firm size and industry size. I create the same

[16] The list of industries and their trade shares are listed in Table A1.

[17] Above, I used log prices to estimate the model. Since log price is potentially negative in certain industries, I exponentiate the price in each run of the generated data.

index using the trade data (instead of summarizing the result of Monte Carlo replications), and compare the two.

As can be seen in Table 8, the model with the estimated parameters underpredicts the true price index in the data. In most cases, the pattern is repeated at the industry level- in other words, each industry price index predicted by the model tends to be lower than its real-world counterpart. This is occurring for two reasons: first, the discrete choice model places no distinction on different sizes of the importers- as a precondition of solving the model, the fixed point problem (10) is solved assuming that any two importers with the same state will make the same decision. However, empirical results above show a statistically significant difference in the likelihood of switching based on importer firm size. Thus the model may predict a particular large firm to switch to a lower priced exporter, while in the data, this same firm is in fact less likely to do so. Secondly, the decision of which exporter to use is based on *expected prices* that are predicted with some error, rather than the true actual prices, again giving the potential for prices to be misaligned. Thus the true received price is not an object that I am trying to match through estimating parameters, and is rather an outcome based on a probability distribution.

Figures 3A and 3B present a separate summary measure: rather than summarizing 1000 outcomes for each firm, I can alternatively create the price index P across all firms and industries for each Monte Carlo run, and compare them. By either taking the weighted average of the price across firms in an industry (Figure 3A), or the median price across firms in an industry (Figure 3B), I can generate density plots. Again, as the above results also show, the model generally tends to underpredict the price index.

The results for switching and city switching are more straightforward. For each case, I simply calculate the overall number of firms in an industry predicted to switch for each Monte Carlo run, and take either the median or the mean of that industry percentage for each of 1000 runs. I then translate that into how many total firms are predicted to switch in each industry, and sum together across industries to create an overall measure of switching and city swiching behavior. It is clear to see that I match the percentage of firms switching extremely well. I match less well the number of firms switching city, underpredicting the true number by approximately 10%. This is likely because predicting the city puts more pressure on the model of exporter choice to pick the exporter more correctly, while the overall switching percentage does not have to match the chosen exporter in the data as well.

6 Counterfactual Experiments

6.1 Changes in switching costs

The switching costs in this model can be interpreted as information frictions, by which firms would like to import from particular other firms, but for some reason (lack of information, poor logistics, etc) cannot actually import from these partners. The Chinese government is well known for its investment in capital projects, especially infrastructure and its national development strategy focusing on inland provinces. It is plausible that distribution networks to inland cities will improve greatly in the future as China's economy develops, exactly the type of advance that would lower switching frictions. Thus I test how U.S. imports from China would change in response to changes in these lower switching costs such a trend implies. Conversely, I also examine how imports would be affected by increases in switching costs, such that switching occurred far less frequently than is seen in the data. I use the same procedure as above, but constructing the price index in (16) for each different simulation and comparing it to the generated data according to the original parameters (since the generated data underpredicts the true data, where necessary, I also compare the simulations to the data)

I calculate prices for five different scenarios: (I) Generating data according to the originally estimated parameters, in order to check model fit (I call this $M(\boldsymbol{\beta}_1)$); (II) generating data with β_x and β_c at half their original values for each industry ($M(\boldsymbol{\beta}_2)$); (III) generating data with β_x reduced to zero, and β_c at its original value ($M(\boldsymbol{\beta}_3)$); generating data with β_x at its original value, and β_c reduced to zero ($M(\boldsymbol{\beta}_4)$); and generating data with β_x and β_c at three times their original value ($M(\boldsymbol{\beta}_5)$). After estimating the median price for each firm, I construct P using Equation (16), taking both data and the median price for each firm from $M(\boldsymbol{\beta}_1)$ as separate comparison groups in the demoninator of (15).

The results are presented in Table 9. Given the high potential for outliers in prices, my preferred measure of the price a firm pays is the median across 1000 runs. As can be seen in column 1, a decrease in both switching costs by half leads to 12.5% lower prices than in the generated model with original parameters. The two distributions of price indices, where I calculate the price index for each of 1000 Monte Carlo simulations, are shown in Figure 3.

One can see this pattern in individual industries as well. Figure 4 shows the distribution of prices in separate HS codes with higher and lower switching costs. In many cases, the distribution is more skewed to the left, meaning prices are typically lower. However, there are also more cases of higher prices, such as in industry HS 610432, as a reduction in switching costs can also lead to worse matches.

In the model described above, firms do not adjust the quantity imported in response to input price changes. However, for a ballpark estimate of the long-run effect of these changes, we can tie the differences in prices to changes in quantity by means of the industry-specific price elasticity of trade estimated by Broda and Weinstein (2005). Doing this exercise for the first counterfactual implies a 40.05% percent increase in U.S.-China trade.

I repeat the exercise for each of the other three counterfactual scenarios. As can be clearly seen, the price decreases in scenarios (II) and (III), while it increases in response to the increase in switching frictions described in scenario (IV). The results are also intuitive for the increases in the degree of switching and city switching implied by the new parameters.

6.2 Potential for Re-Shoring

Many companies such as Apple have recently announced policies to move production of intermediate inputs back to the U.S. I use my model to estimate how low prices would have to be in order for importers from China to switch to this option. Specifically, I increase the size of the exporter choice set X by one firm, and assign it a different price to create separate scenarios. I also eliminate the geographic switching cost from using this new firm, making it "costless" to switch to this U.S. firm (though not costless to switching from one's previous firm). I also assume this firm has the median "quality" (residual of the regression of price on observable exporter characteristics). I then re-solve the fixed point equation in (16) for each scenario, and see how many importers would choose to switch to this new firm over 1000 simulations. By using each firm's total share of imports in that industry, I can then determine what fraction of trade accrues to this new firm, i.e. how much trade would be "re-shored" to the U.S. given the existence of a firm with those prices and favorable switching costs. The results are found in Table 10.

The results demonstrate the clear inertia involved in rousting importers from their Chinese partners, even with the elimination of geographic switching costs. If the hypothetical U.S. firm in each industry offered a price in the 75th percentile of the price distribution, only about 2% of trade would flow back to the U.S. However, this price is already far lower than the average U.S. exporter price for firms in the same HS6 product. Furthermore, while it is possible to retrieve 3-4% of Chinese imports back to the U.S. by a hypothetical firm offering the mean or median price in each industry, this price is even farther away from the prevailing prices charged by U.S. exporters: a decrease of approximately 57% compared to U.S. exporters producing the same product. Thus efforts to return imports from the U.S. are significantly more difficult than simply offering a competitive price- the considerable benefits involved in maintaining existing relationships means that only a small share of imports would be able to move back to the U.S., even without any costs of a geographic nature.

7 Conclusion

In this paper, I have documented the presence of churning in U.S.-China importer-exporter relationships: 45% of importers change exporters from one year to the next. I also present for the first time facts about the geographic nature of this switching- numerous industries have strong geographic characteristics involved in the stay-or-switch decision. Given reduced form results demonstrating the importance of price in the decision of U.S. importers to find new partners, I estimate a model of dynamic discrete choice of exporter, which produces estimates for overall switching costs and geographic switching costs in the context of U.S. decisions to import from Chinese exporters. The results are intuitive and reflect important properties about the market for Chinese products. Using these structural estimates, I present a number of counterfactuals, including the effects on international trade from improved distribution channels and better information, the effect of rising wages on U.S. importer switching behavior and the movement of suppliers inland, the potential for "re-shoring" industries back to the U.S., exchange rate pass-through, and the effects of this switching on other neighboring countries.

This is the first step in a robust area for growth in the study of international trade transactions. The geographic link between importers and exporters gives us a new way to understand how shocks in a specific area move through international trade, a field of study that has thus far been limited to industry-to-industry linkages. Further research can augment this study that uses U.S.-China data and understand when importers change their country of importing, and where they go when they change. Finally, the increasing availability of firm-level datasets puts the possibility of firm-to-firm linkages through trade transactions between the production data of separate countries closer to being realized, providing the most complete analysis of the micro-underpinnings of international trade.

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Tables and Figures

Table 1: Later Year "Staying" Counts of U.S. Firms Importing from China in 2002

Year	Total Importers	Same Partner	Same City	Same Province	China
2003	99,116	55,272	65,905	69,310	80,963
2004	84,367	35,193	50,478	54,967	67,908
2005	74,506	22,594	40,755	45,865	60,143
2006	64,323	15,683	34,033	39,317	53,514
2007	50,105	9,840	25,697	30,290	42,201

Note: This table tracks U.S. firms that imported from China in 2002. The first column shows how many in the cohort were found importing at all in later years, and later columns show how many "stayed", either with their original partner, in their original city, in their original province, or in China.

Figure 1: Later Year "Staying" Percentages of U.S. Firms Importing from China in 2002

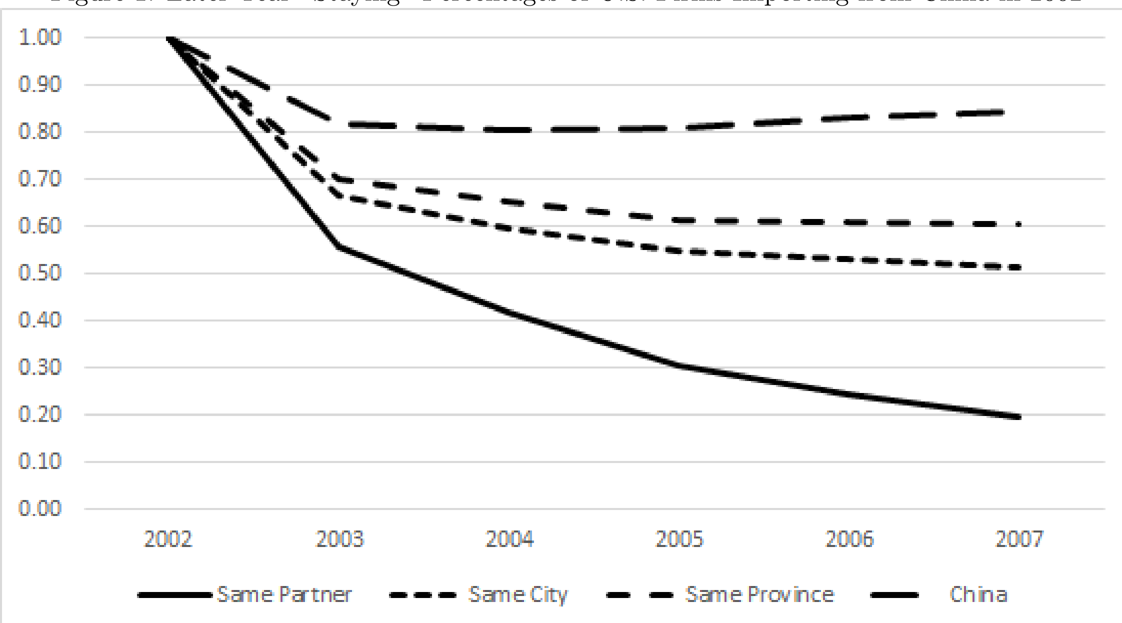


Table 2 Panel A: Importer "Staying" Counts, Exporters Found only in Both Periods

Year	Total Importers	Same Partner	Same City	Same Province	China
2002	141,707	141,707	141,707	141,707	141,707
2003	91,316	55,272	61,552	63,908	76,884
2004	73,865	35,193	42,444	45,297	61,271
2005	61,959	22,594	29,717	32,510	51,515
2006	51,071	15,683	21,768	24,470	43,806
2007	38,109	9,840	14,524	16,676	33,109

Table 2 Panel B: Importer "Staying" Counts, Firm-HS6 as the Unit of Analysis

Year	Total Importers	Same Partner	Same City	Same Province	China
2002	124,702	124,702	124,702	124,702	124,702
2003	83,034	47,639	56,623	59,299	68,704
2004	72,188	31,344	44,588	48,241	59,020
2005	64,933	20,877	36,927	41,235	53,241
2006	57,320	14,754	31,608	36,167	48,347
2007	47,969	9,984	25,592	29,834	40,881

Table 2 Panel C: Importer "Staying" Counts, Manufacturing Firms Only

Year	Total Importers	Same Partner	Same City	Same Province	China
2002	35,453	35,453	35,453	35,453	35,453
2003	24,359	12,931	15,164	15,962	18,742
2004	21,104	8,397	11,737	12,787	15,952
2005	19,009	5,577	9,685	10,914	14,533
2006	17,115	4,046	8,495	9,805	13,443
2007	13,681	2,662	6,545	7,768	10,909

Table 2 Panel D: Importer "Staying" Counts with Firm as the Unit of Analysis

Year	Total Importers	Same Partner	Same City	Same Province	China
2002	27,695	27,695	27,695	27,695	27,695
2003	24,071	16,228	18,183	18,303	20,580
2004	21,934	11,938	15,411	15,987	18,700
2005	20,203	8,997	13,509	14,343	17,261
2006	18,373	6,918	12,048	13,026	16,019
2007	16,804	5,452	10,834	11,812	14,756

Table 2 Panel E: Importer "Staying" Counts, based on Majority of Import Value

Year	Total Importers	Same Partner	Same City	Same Province
2002	159,302	159,302	159,302	159,302
2003	79,958	35,201	48,602	54,303
2004	67,184	19,371	33,542	40,074
2005	59,416	11,157	25,078	31,700
2006	52,895	6,955	19,483	26,156
2007	41,846	4,213	14,091	19,528

Figure 2 Panel A: Later Year “Staying” Percentages, Exporters Found only in Both Periods

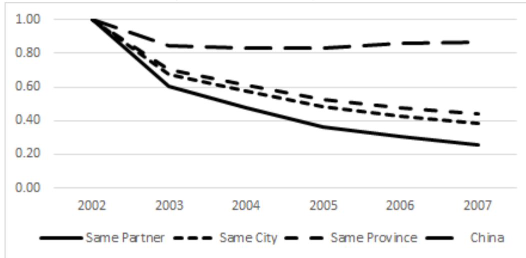


Figure 2 Panel B: Later Year “Staying” Percentages, Firm-HS6 as the Unit of Analysis

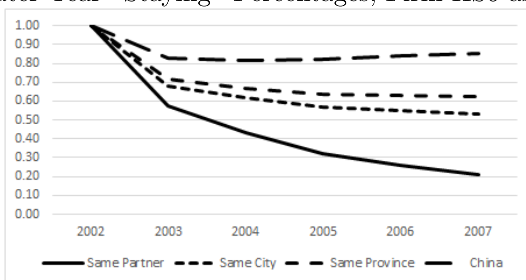


Figure 2 Panel C: Later Year “Staying” Percentages, Manufacturing Firms Only

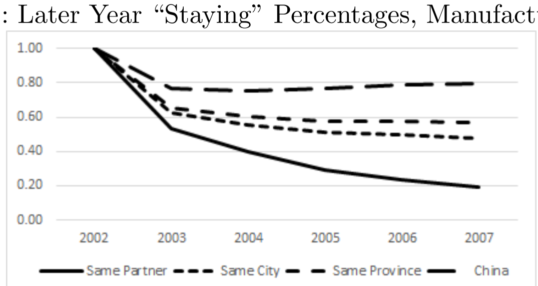


Figure 2 Panel D: Later Year “Staying” Percentages with Firm as the Unit of Analysis

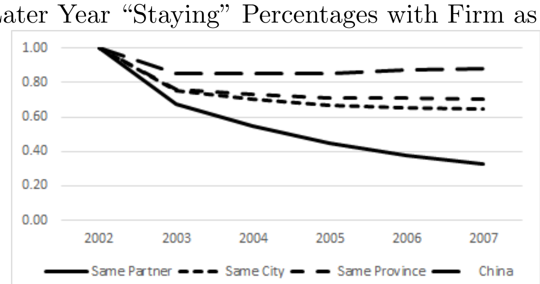


Figure 2 Panel E: Later Year “Staying” Percentages, based on Majority of Import Value

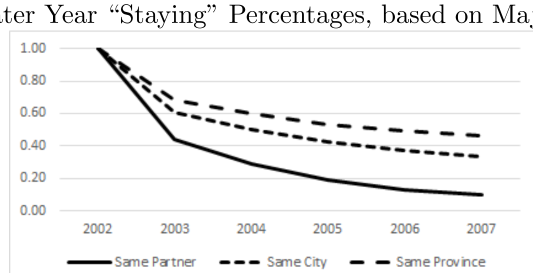


Table 3: Supplier Matching and Importer/Exporter Characteristics

Dependent Variable: "Stayed" with Chinese Supplier, 2005-2006, Based on Value					
	(1)	(2)	(3)	(4)	(5)
Log Price	-0.0220**	-0.0125**	-0.0137**	-0.0031*	-0.0033*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Supplier Size			0.0291**	0.0511**	0.0508**
			(0.001)	(0.002)	(0.002)
Supplier Age			-0.0017**	-0.0026**	-0.0024**
			(0.000)	(0.000)	(0.000)
Total Imports				-0.0222**	-0.0205**
				(0.002)	(0.002)
Total Employment				-0.0224**	-0.0224**
				(0.001)	(0.001)
HS10 Product FE	no	yes	yes	yes	yes
Importer Entry Year FE	no	no	no	no	yes
Observations	95450	95450	95450	95450	95450
R-squared	0.01	0.14	0.15	0.17	0.17

Notes: Standard errors in brackets; *significant at 5% level, ** significant at 1% level. The sample is all U.S. importers (HS10 Product code and firm combination) from China who are found in 2005 and 2006. The dependent variable is equal to 1 if the U.S. importer had the largest (plurality) share of its total import value from the same Chinese supplier in both 2005 and 2006, and is equal to 0 if not. Log price is the log average unit value across transactions with its majority partner in 2005. Supplier size is the total estimated size of the Chinese supplier in 2005, based on cross-section summation of total exports of that supplier to the U.S. Supplier Age is calculated using the first year the Chinese supplier appears in the U.S. customs data, and subtracting it from 2005. Total Imports is the sum of import value for a U.S. importer in 2005, while Total Employment in 2005 is computed from the Longitudinal Business Database and linked to the LFTTD. Importer Entry Year is the first year a U.S. importer is found importing from China. Any importer that has the same share of imports from two separate Chinese suppliers is dropped.

Table 4: Supplier Matching and Importer/Exporter Characteristics

Dependent Variable: "Stayed" with Any Chinese Supplier, 2005-2006					
	(1)	(2)	(3)	(4)	(5)
Log Price	-0.0198**	-0.0112**	-0.0135**	-0.0067**	-0.0163**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
Supplier Size			0.0641**	0.0109**	0.0127**
			(0.001)	(0.001)	(0.001)
Supplier Age			-0.0021**	-0.0003	-0.0009*
			(0.000)	(0.000)	(0.000)
Total Imports				0.0690**	0.0641**
				(0.001)	(0.001)
Total Employment				-0.0247**	-0.0247**
				(0.001)	(0.001)
HS10 Product FE	no	yes	yes	yes	yes
Importer Entry Year FE	no	no	no	no	yes
Observations	95450	99974	99974	99974	99974
R-squared	0.01	0.14	0.19	0.23	0.23

Notes: Standard errors in brackets; *significant at 5% level, ** significant at 1% level. The sample is all U.S. importers (HS10 Product code and firm combination) from China who are found in 2005 and 2006. The dependent variable is equal to 1 if the U.S. importer stayed with at least one of its (potentially many) Chinese suppliers in both 2005 and 2006, and is equal to 0 if not. Log price is the log average unit value across transactions with all suppliers it stayed with in 2005 if the dependent variable is equal to 1 and the same object across all suppliers if the dependent variable is 0. Supplier size is the mean total estimated size of each Chinese supplier in 2005 across all suppliers it stayed with for “stayers”, and the mean total estimated size of each Chinese supplier in 2005 across all suppliers for “non-stayers” , based on cross-section summation of total exports of that supplier to the U.S. Supplier Age is calculated using the first year the Chinese supplier appears in the U.S. customs data, and subtracting it from 2005, where the mean across suppliers stayed with is used for “stayers”, and the mean across all suppliers is used for “non-stayers” . Total Imports is the sum of import value for a U.S. importer in 2005, while Total Employment in 2005 is computed from the Longitudinal Business Database and linked to the LFTTD. Importer Entry Year is the first year a U.S. importer is found importing from China.

Table 5: Monte Carlo Replication Results, based on 250 Replications

	β_p	β_x	β_c	Conv. Rate
Pre-Set Values	-0.5	-1	-3	
Sample A: $M = 6, X = 3, C = 2$				.456
Mean	-0.378	-35.45	-3.633	
Median	-0.341	-2.293	-3.429	
Sample B: $M = 30, X = 33, C = 3$				1
Mean	-0.543	-0.843	-8.209	
Median	-0.540	-0.837	-5.017	
Sample C: $M = 30, X = 33, C = 9$				1
Mean	-0.538	-0.985	-3.427	
Median	-0.512	-1.055	-3.081	

Table 6: Selected Quantitative Estimates, HS Industrial Classification

HS6 Industry	β_p	β_x	β_c	β_c/β_x
Geographic Characteristics				
Low City Switching				
Fuses for a Voltage Not Exceeding 1000V	-0.0189	-2.5703	-2.3085	0.90
Electronic Hybrid Integrated Circuits	-0.0366	-1.7401	-1.6848	0.97
High City Switching				
Tapered Roller Bearings, Including Cone and Tapered Roller Assemblies	-0.0051	-3.1145	-0.7326	0.23
Market Size Characteristics				
Many more Importers than Exporters				
Floor Coverings, Wall or Ceiling Coverings, of Polymers of Vinyl Chloride	0.0784	-3.6941	-1.3791	0.37
Substitutability of Product				
High Elasticity of Substitution				
MEN'S UNDERPANTS AND BRIEFS OF MANMADE FIBERS,KNIT	-0.0562	-3.5588	-0.9726	0.27
SKI/SNOWMOBILE GL1OVES OF SYNTHETIC FIBERS, KNIT	-0.0457	-2.8158	-0.6882	0.24
Low Elasticity of Substitution				
GLVS IMPREG PLAS N 4CHTT $<$ 50% COT MMF VEG FIB, KT	0.5109	-1.4464	-1.6351	1.13
FTWR SOL R/P/L/C-L UPPER LEATHER OTH PROT TOE-CAP	0.2494	-2.7635	-1.7530	0.63

Table 7: Selected Quantitative Estimates, China Industry Code (CIC) Industrial Classification

CIC Industry	β_p	β_x	β_c	β_c/β_x
Worker Characteristics				
Low Skilled Workers				
Arms and Ammunition	$-.0349$	-1.6725	-2.6552	1.58
High Skilled Workers				
Rolling and Processing of Rare Earths	-0.0068	-2.632	-1.8585	0.70
Tungsten and Molybdenum Smelting	0.0388	-2.6382	-1.7336	0.71
Firm Size Characteristics				
Large Firms				
Arms and Ammunition	$-.0349$	-1.6725	-2.6552	1.58
Small Firms				
Other Medical and Ward Care Equipment	-0.0008	-2.9754	-1.3049	0.44

Table 8: Model Fit

	Data	Median over 1000 runs	%
Price Index			
Weighted Average	84.6239	76.4979	90.4
Median	66.1725	61.7019	93.2

	Data	Industry Median	%	Industry Mean	%
Total Switching Partner	714	711	99.6	708.85	99.3
Total Switching City	416	469	112.7	469.76	112.9

Notes: Objects computed by the model simulated with the estimated parameters are compared to the same objects in the data. To compute the Price Index, I first take the median received price across 1000 simulations for each importer. I then either weight each importer by its industry share, and sum up ("Weighted Average") or I simply compute the median across importers in an industry. I then apply industry weights based on total trade among along simulated industries to make an aggregate price index. The switching and city switching figures are the number of importers switching partner or city in the data compared to either the mean number of firm switching/city switching for each industry, or the median number of firms switching/city switching for each industry.

Figure 3A: Price (Weighted Average) Kernel Density Plot

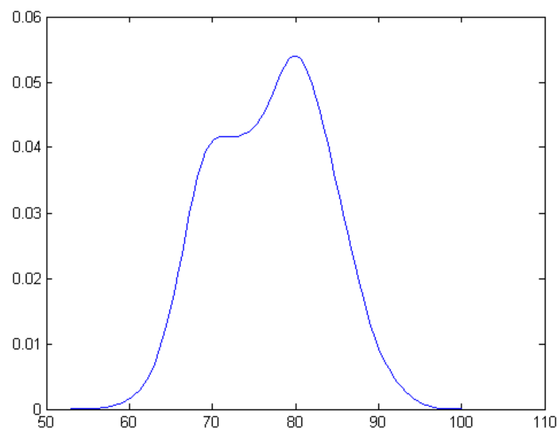


Figure 3B: Price (Median) Kernel Density Plot

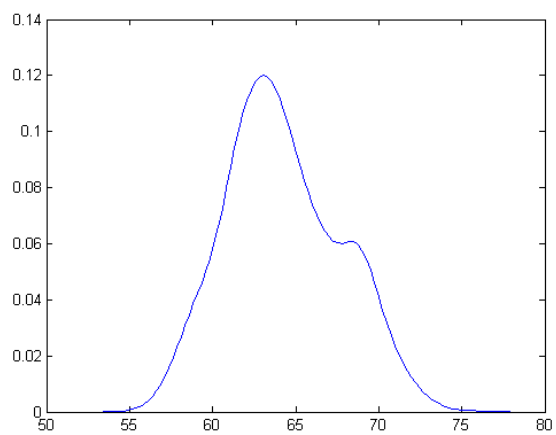


Table 9: Counterfactual Results (I)

	$M(\boldsymbol{\beta}_2)$ v. $M(\boldsymbol{\beta}_1)$	$M(\boldsymbol{\beta}_3)$ v. $M(\boldsymbol{\beta}_1)$	$M(\boldsymbol{\beta}_4)$ v. $M(\boldsymbol{\beta}_1)$	$M(\boldsymbol{\beta}_5)$ v. $M(\boldsymbol{\beta}_1)$
Price Index	-12.50%	-15.20%	-7.37%	+7.62%
Trade Flows (Spec.)	+40.05%	+37.92%	+38.92%	-19.60%
Trade Flows (Gen.)	+62.50%	+76.00%	+36.85%	-38.10%
Switching	+92.55%	+115.19%	+60.62%	-76.93%
City Switching	+128.36%	+112.79%	+117.59%	-71.86%

Notes: Objects computed by the model simulated with the originally estimated parameters ($M(\beta_1)$) are compared to the same objects in each of four counterfactual experiments: partner cost and city cost each reduced by half ($M(\beta_2)$); partner cost reduced to zero, city cost unchanged ($M(\beta_3)$); partner cost unchanged, city cost reduced to zero ($M(\beta_4)$); and partner cost and city cost increased by three times ($M(\beta_5)$). To compute the Price Index, I take the median received price across 1000 simulations for each importer, then weight each importer by its size within the industry. I then apply industry weights based on total trade among along simulated industries. It is possible to predict the change in trade flows based on these changes in the price index, either by applying the HS6 price elasticity estimated from the work Broda and Weinstein (2005) individually to each industry to compute the overall effect on trade volumes ("Trade Flows (Spec.)"), or simply by applying the estimate of the general price elasticity $-(\varepsilon-1)$ used in di Giovanni and Levchenko (2012) ("Trade Flows (Gen.)"). The switching and city switching percentages are the changes in the number of firms switching partner or city under the new parameter estimates.

Figure 3: Kernel Density Plots, M(β_1) v. M(β_2)

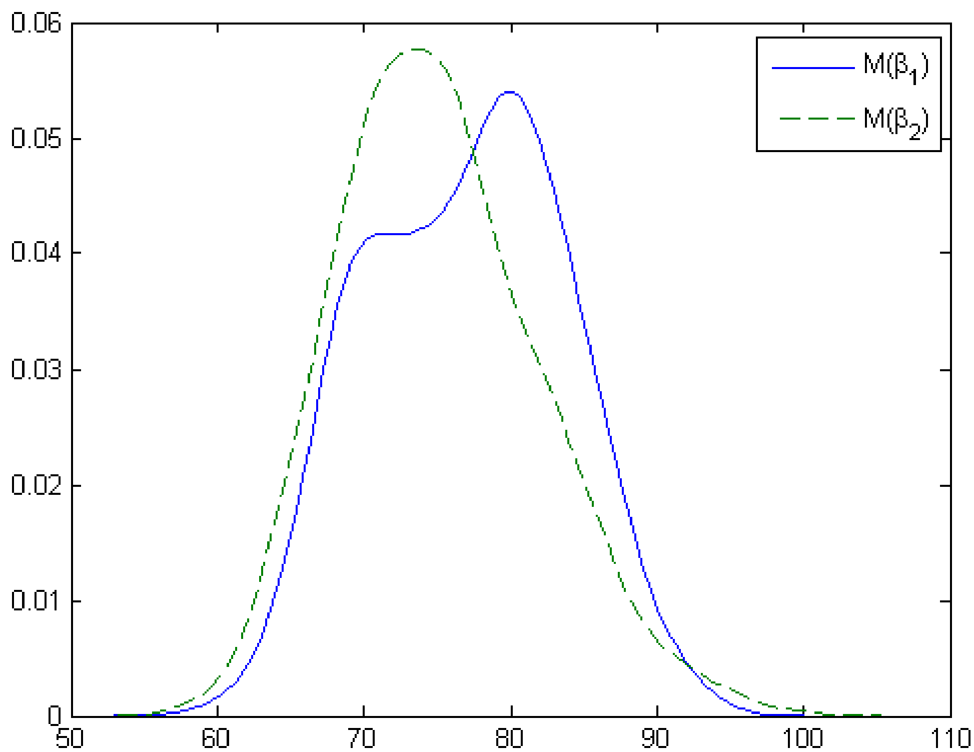


Figure 4: Kernel Density Plots, M(β_1) v. M(β_2), Selected Industries

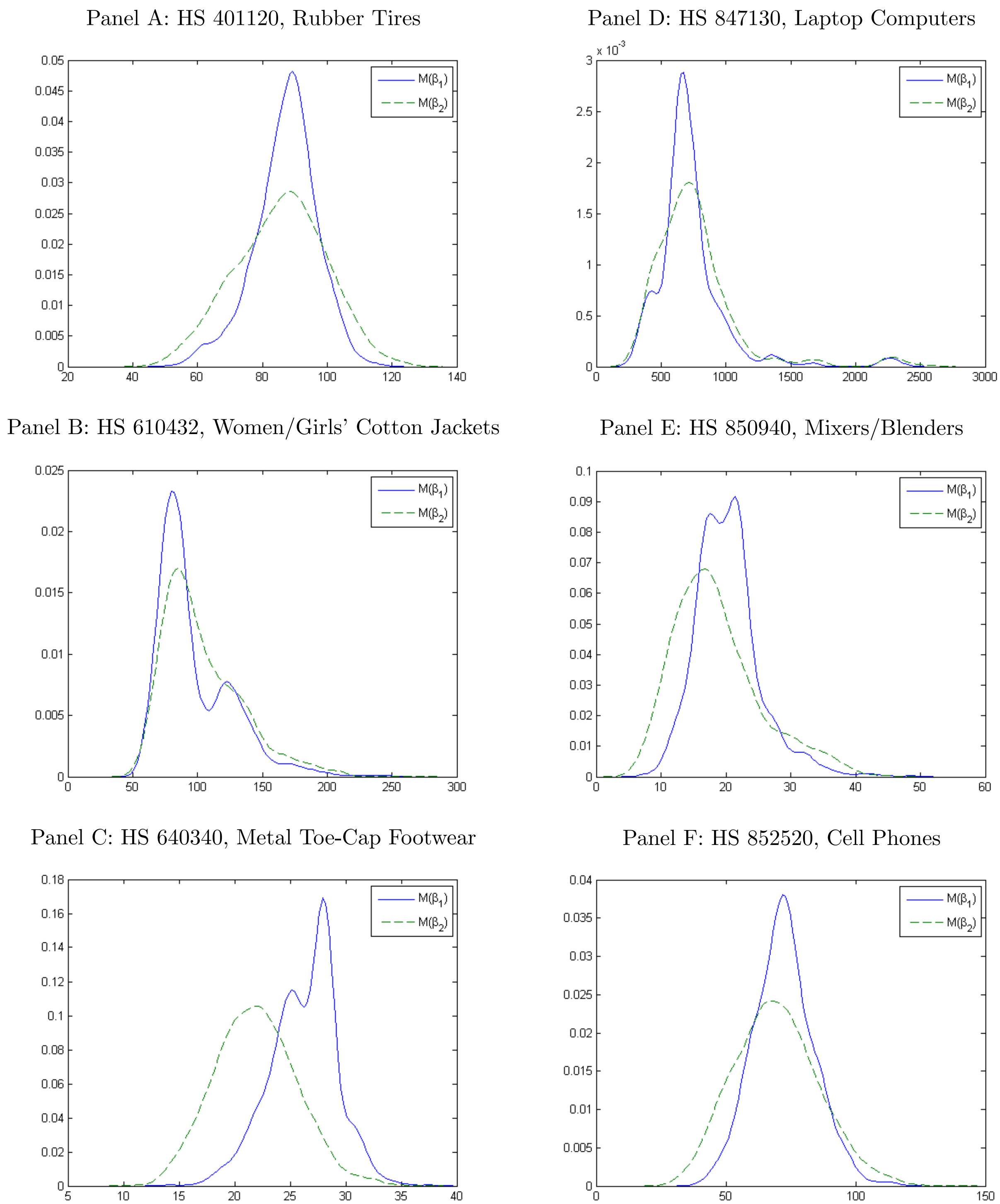
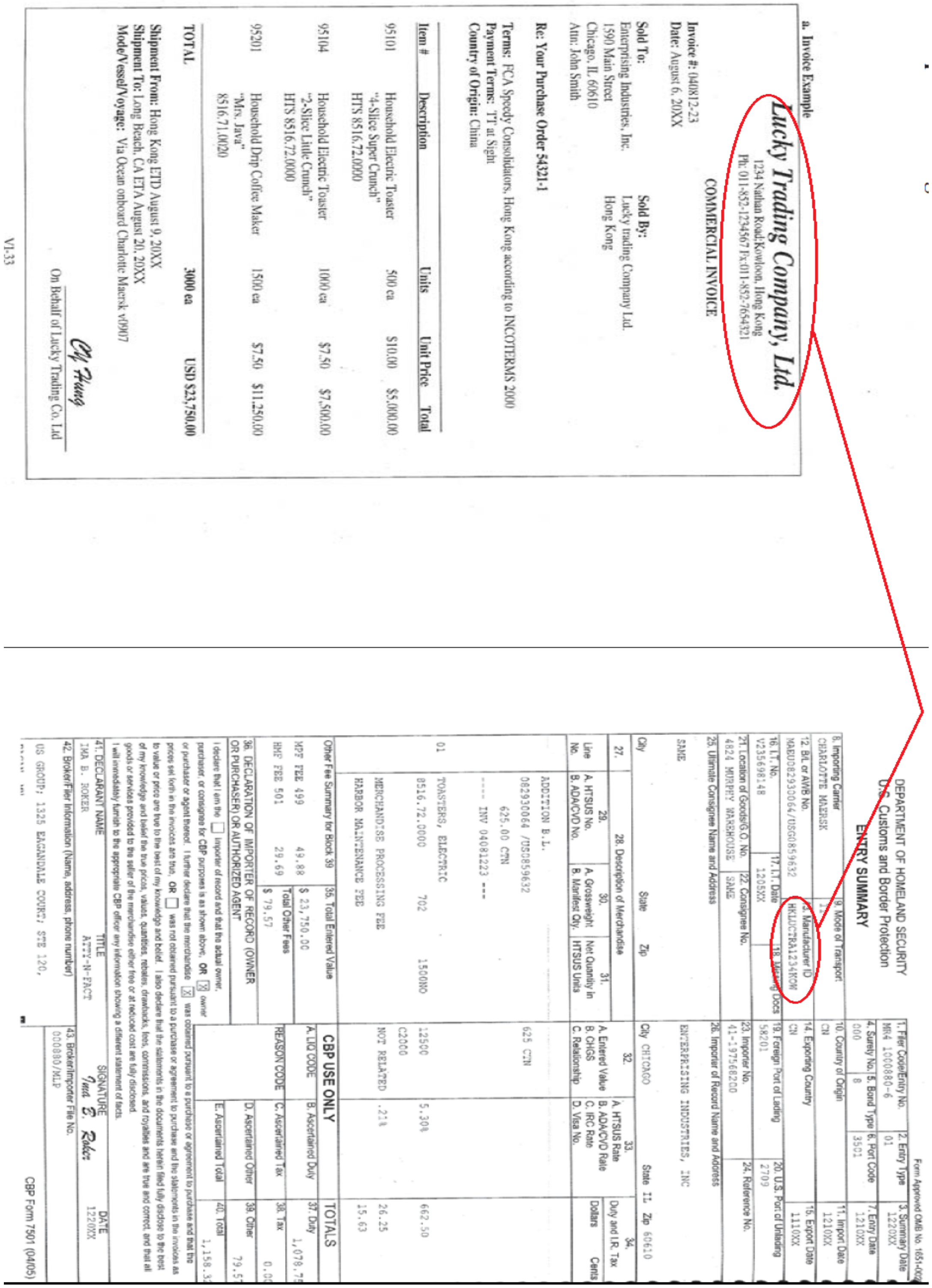


Table 10: Counterfactual Results (II)

Price	Mean Sim. Trade Share	Median Sim. Trade Share	Reduction from average U.S. Exporter Price
Median	3.86%	1.75%	56.27%
Mean	3.76%	1.53%	47.47%
75th Pct.	3.18%	0.77%	34.04%

Figure A1: Sample Invoice



a. Invoice Example

Lucky Trading Company, Ltd.
1234 Nathan Road,Kowloon, Hong Kong
Ph: 011-852-1234567 Fx:011-852-7654321

COMMERCIAL INVOICE

Invoice #: 040812-23
Date: August 6, 20XX

Sold To:
Enterprising Industries, Inc
1590 Main Street
Chicago, IL 60610
Attn: John Smith

Sold By:
Lucky trading Company Ltd.
Hong Kong

Re: Your Purchase Order 54321-1

Terms: FCA Speedy Consolidators, Hong Kong according to INCOTERMS 2000
Payment Terms: TT at Sight
Country of Origin: China

Item #	Description	Units	Unit Price	Total
95101	Household Electric Toaster "4-Slice Super Crunch" HTS 8516.72.0000	500 ea	$10.00	$5,000.00
95104	Household Electric Toaster "2-Slice Little Crunch" HTS 8516.72.0000	1000 ea	$7.50	$7,500.00
95201	Household Drip Coffee Maker "Mrs. Java" 8516.71.0020	1500 ea	$7.50	$11,250.00
TOTAL		3000 ea		USD $23,750.00

Shipment From: Hong Kong LTD August 9, 20XX
Shipment To: Long Beach, CA ETA August 20, 20XX
Mode/Vessel/Voyage: Via Ocean onboard Charlotte Maersk v0907

On Behalf of Lucky Trading Co. Ltd

VI-33

DEPARTMENT OF HOMELAND SECURITY
U.S. Customs and Border Protection
ENTRY SUMMARY

CBP Form 7501 (04/05)

Note: Exporter specific information and location information from the invoicing party is extracted from trade data.

Table A1: Analysis of MIDs as Constructed from China Industrial Production Data, Selected Industries

Panel A: Uniqueness of the "MID", 2005

Industry (CIC)	# of Exporters	# of "MID"s	%
CIC 3663	39	38	97.4
CIC 3689	27	26	97.3
CIC 3353	37	37	100
CIC 3331	35	35	100
CIC 4154	74	73	98.6

This panel uses name, address, and city information from China NBS firm data to construct a "MID" for each firm, according to the rules laid out in U.S. CBP Form 7501. In constructing the name of the firm in English, I use the Hanyu Pinyin romanization of Chinese characters, with two to three characters per word of the English name. The second column states the number of firms with positive export values in the given industry in 2005. The third column states the number of unique constructed "MID"s.

Panel B: Uniqueness of the City Code

Industry (CIC)	# of Cities	# of City Codes,2005	%
CIC 3663	22	21	95.5
CIC 3689	15	14	93.3
CIC 3353	28	24	85.7
CIC 3331	15	13	86.7
CIC 4154	19	18	94.7

Panel B uses city information from China NBS firm data to construct city information as found in the MID, where only the first three letters of city are given. The second column states the true number of cities with at least one exporting firm in the data from 2005, while the third column states the number of unique city codes.

Panel C: Changes in the "MID" over Time, 2005-2006

Industry (CIC)	# of Exporters	# of with Identical "MID"	%
CIC 3663	33	33	100
CIC 3689	26	26	100
CIC 3353	31	28	90.3
CIC 3331	20	17	85.0
CIC 4154	63	62	98.4

Panel C uses name, address, and city information from China NBS firm data to track whether constructed "MID"s change over time for the same firm, identified here using the *"faren daima"* firm identifier from the NBS data. The second column states the number of exporting firms found in both 2005 and 2006, while the third column states the number of firms that have identical "MID"s in both 2005 and 2006.

Source: China National Bureau of Statistics.

Table A2: List of Industries Used

HS6 Code	Description	Trade Share
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01
290561	Something	0.01

Appendix A Robustness and External Validity of the MID

At this point, I describe the foreign exporter identifier in more detail. As shown in Figure A1, two characters on the country of the manufacturer, six characters related to the name of the manufacturer, four characters (in certain circumstances) related to the address of the manufacturer, and three characters related to the city of the manufacturer make up the exporter identification variable. The MID is assembled by the U.S. importing firm (or more likely, by a specialty customs broker utilized by the importing firm) according to an exhaustive list of regulations found in the instructions to the baseline U.S. Customs Document CBP Form 7501, along with the other particulars of the import transaction[18]. I use this identifier to study the behavior of U.S. importers over time, namely what exporter they choose, where the exporting firm is located, and what guides the decision for what partner U.S. importers will choose in the future.

Clearly, the reliability of this variable is important for the stylized facts laid out above. I therefore first present some background on how the U.S. government encourages honest construction of this variable. According to the U.S. Customs and Border Protection, over 99% of entry summary transactions are filed electronically, reducing the risk of misread or misspelled codes. As mentioned above, these forms are also overwhelmingly filed by professional customs brokers well aware of the rules for constructing these codes. Another concern is that the code does not capture the actual producer of a good, but rather some "middleman", the use of which are very common among firms importing from China (Tang and Zhang 2012). Importantly, even if a U.S. importer makes use of an intermediary to help them find an exporting firm, information about the actual source of the product is carried through on the final invoice through the entire process[19]. It should also be noted that importers are explicitly warned by the U.S. CBP to make sure that the MID they assemble is reflective of the true producer of the good, not any type of intermediary or processing firm:

"Trading companies, sellers other than manufacturers, etc. cannot be used to create MIDs. Entries and entry summaries in which the first two characters of the MID do not meet the country of origin ISO code, or are created from a company that is known to be a trading house or agent and not a manufacturer, will be rejected for failure to properly construct a MID...Repetitive errors in the construction of MIDs for entries of textile or apparel products will result in the assessment of broker and importer penalties for failure to exercise reasonable care." — U.S. Customs and Border Protection

I augment these facts with a number of checks on this variable by utilizing a rich panel dataset on Chinese firms. This comprehensive dataset from China's National Bureau of Statistics covers all state-owned enterprises (SOEs) and non-SOEs whose annual sales are more than five million *renminbi*, and includes more than 100 financial variables listed in the main accounting sheets of firms.[20]. Industries are classified according to the China Industry Code (CIC). Sadly, due to confidentiality and security concerns, the datasets cannot be merged at the firm-to-firm level at this time, despite the availability of plausibly consistent identifiers in both datasets related to name and address. However, this dataset has many other uses in the context of studying importer-exporter behavior.

One application where the NBS industrial database is useful is I can follow the rules laid out for how to construct Manufacturer IDs and assess how commonly multiple firms in an industry possess the same MID- a type of outside check on the uniqueness of the foreign exporter identifier. I do this for five industries in 2005, with uniqueness statistics illustrated in Table A1 Panel A. Although this analysis is subject to some qualification- namely, the NBS data is not the entire universe of Chinese firms, nor is there any gurantee that the name of the firm in Chinese characters (as in the NBS data) is the same as the romanized version of the name of the firm- it appears that the MID does a good job of uniquely identifying foreign firms at the industry level.

An additional complication for studying geographic switching behavior is that only three letters of the city are given in the MID. For example, a city code of "SHE" would be assigned to both Shenyang and Shenzhen, both major cities of more than 8 million people. Again, I use the China Industrial Database in 2005 to check how widespread the problem would be in particular industries. Table A1 Panel B shows

[18]See CBP Form 7501 Instructions, p. 30-32 for the exact details.

[19]Krizan (2012), p.10-11, makes clear that this information is available at all stages of the trade transaction.

[20]For more information on this database, see Feenstra, Li, and Yu (2011).

that such cases do indeed occur, but not with fatal frequency. It should be noted too that the figures on city-switching from Table 1 will only be misspecified if a U.S. importer switches from a city to another city that happens to start with the same first three letters.

A final concern raised by the construction of the MID is that an importing firm may in fact choose to stay with a supplier, but if the supplier changes its name or address, a new MID means that I will classify that importer as a switching firm. The China Industrial Database tracks firms over time with a unique firm identifier, so I can collapse the data into a panel and see how many firms would fall into this hypothetical scenario by having a change in name or address from 2005 to 2006 that changes their MID. The results of this test are in Table A1 Panel C. Again, though such situations do happen, the vast majority of Chinese exporting firms in the NBS data do not have undergo such a change.

Appendix B Proof of Proposition 1

Assumption 1 (Conditional Indepdendence) *The joint transition density of p_t and ϵ_t can be decomposed as:*

$$h\left(p_{t+1}, \epsilon_{t+1} | p_t, x_t, x_{t+1}, \epsilon_t\right) = g\left(\epsilon_{t+1}\right) f\left(p_{t+1} | p_t, x_t, x_{t+1}\right)$$

I also assume that the profit shock ϵ is distributed according to a multivariate extreme value distribution, with known parameters:

Assumption 2 *The density function of the profit shock is:*

$$g\left(\epsilon\right) = -\exp\{-\epsilon\left(x\right) - \gamma\}\exp\{-\exp\{-\epsilon\left(x\right) - \gamma\}\}$$

while the distribution is

$$G\left(\epsilon\right) = \exp\{-\exp\{-\epsilon\left(x\right) - \gamma\}$$

for $\gamma = 0.577...$ (Euler's constant).

These two assumptions permit the computation of choice probabilities for any particular outcome :

Proposition 1 *Let any present time variable a at one period prior be written as a_{-1}, and one period in the future be written as a'. Given Assumptions 1 and 2, and grouping together the state variables as $s = \{p_{-1}, x_{-1}\}$, the probability of observing a particular exporter choice x^C conditional on state variables s and cost parameters β, $P\left(x^C | s, \beta\right)$, is:*

$$P\left(x^C | s, \beta\right) = \frac{\exp\left[\widetilde{\pi}\left(s, x^C, \beta\right) + \delta EV\left(s, x^C\right)\right]}{\sum_{\widehat{x}\in X}\exp\left[\widetilde{\pi}\left(s, \widehat{x}, \beta\right) + \delta EV\left(s, \widehat{x}\right)\right]} \tag{18}$$

where the function $EV\left(s, x\right)$ is the solution to the fixed point problem:

$$EV\left(s, x\right) = \int_{s'=0}^{\infty} \log\left\{\sum_{x'\in X}\exp\left[\widetilde{\pi}\left(s', x', \beta\right) + \delta EV\left(s', x'\right)\right]\right\} f\left(s' | s, x\right) \tag{19}$$

Proof: Let any present time variable a at one period in the past be represented as a_{-1}, and one period in the future be written as a'. Group the state variables together as $s = \{p_{-1}, x_{-1}\}$.

Theorem 1 in Rust (1987) states that, using Assumption 1, for the social surplus function defined as

$$\begin{aligned} &S\left(\left[\widetilde{\pi}\left(s, \beta\right) + \delta EV\left(s\right)\right]\right) \\ \equiv &\int_{\epsilon}\max_{x}\left[\widetilde{\pi}\left(s, x, \beta\right) + \delta EV\left(s, x\right)\right] g\left(\epsilon\right) \end{aligned} \tag{20}$$

the choice probability of any particular exporter choice x occurring can be written

$$P\left(x | s, \beta\right) = S_x\left(\left[\widetilde{\pi}\left(s, \beta\right) + \delta EV\left(s\right)\right]\right)$$

where G_x is the derivative of S with respect to $\widetilde{\pi}\left(s, x, \beta\right)$. Furthermore, the function $EV\left(s, x\right)$ can be written as the contraction mapping:

$$EV\left(s, x\right) = \int_{s'} S\left(\left[\widetilde{\pi}\left(s', \beta\right) + \delta EV\left(s'\right)\right]\right) f\left(s' | s, x\right)$$

Therefore, we need to compute the social surplus function S given the specific functional form of the density of ϵ.

The location parameter μ for a random variable ϵ with multivariate extreme value distibution is defined such that μ satisfies:

$$Pr\left(\epsilon < y\right) = \exp\{-\exp\{-\left(y-\mu\right)\}\}$$

Additionally, the expectation of ϵ is $\mu+\gamma$, where γ is Euler's Constant. Following a procedure similar to the one in McFadden (1981), Assumption 2 means that the location parameter for the multivariate extreme value distibution of the profit shock ϵ is equal to $-\gamma$. This means that the expectation of ϵ is equal to 0, and we can rewrite the integral in (20) as:

$$\int_{\epsilon}\max_{x}\left[\widetilde{\pi}\left(s,x,\beta\right)+\delta EV\left(s,x\right)+\epsilon\left(x\right)\right]g\left(\epsilon\right) = \mathbb{E}_{\epsilon}\left\{\max_{x}\mu_{x}+\epsilon\left(x\right)\right\} \tag{21}$$

So the social surplus function will be the expectation of the expression inside the brackets.

For any n indepdent random variables, $\{\epsilon_1,...\epsilon_n\}$:

$$\begin{aligned} Pr\left(\max\left\{\epsilon_1,...,\epsilon_n\right\}<y\right) &= Pr\left(\epsilon_1<y,\ldots,\epsilon_n<y\right) \\ &= Pr\left(\epsilon_1<y\right)\cdots Pr\left(\epsilon_n<y\right). \end{aligned}$$

Thus for any n independent random variables distributed according to the multivariate extreme value distubtion with location parameters $\mu_1,\ldots,\mu_n$, with cumulative distribution function in Assumption 2:

$$\begin{aligned} Pr\left(\max\left\{\epsilon_1,...,\epsilon_n\right\}<y\right) &= Pr\left(\epsilon_1<y\right)\cdots Pr\left(\epsilon_n<y\right)=\prod_{i=1}^{n}\exp\left\{-\exp\left\{-\left(y-\mu_i\right)\right\}\right\} \\ &= \exp\left\{-\sum_{i=1}^{n}\exp\left\{-y\right\}\exp\left\{\mu_i\right\}\right\} \\ &= \exp\left\{-\left(\exp\left\{-y\right\}\exp\left[\log\sum_{i=1}^{n}\exp\left\{\mu_i\right\}\right]\right)\right\} \\ &= \exp\left\{-\exp\left\{-\left(y-\log\sum_{i=1}^{n}\exp\left\{\mu_i\right\}\right)\right)\right\} \end{aligned}$$

Thus the maximum of n random variables $\{\epsilon_i\}_{i=1}^{n}$ distibuted mulitvariate extreme value with location parameters $\{\mu_i\}_{i=1}^{n}$ is distributed multivariate extreme value with location parameter $\log\sum_{i=1}^{n}\exp\{\mu_i\}$. The expression inside the brackets in equation (21) is therefore distibuted multivariate extreme value with location parameter $-\gamma+\log\sum_{x\in X}\exp\left(\mu_x\right)$. Since the expectation of any random variable distibuted multivariate extreme value with location parameter μ is $\mu+\gamma$, the social surplus function from (21) can be written as:

$$\mathbb{E}\left\{\max_{x}\mu_x+\epsilon\left(x\right)\right\}=\log\sum_{x\in X}\exp\left(\mu_x\right)=\log\sum_{x\in X}\exp\left[\widetilde{\pi}\left(s,x,\beta\right)+\delta EV\left(s,x\right)\right]$$

Following Theorem 1 in Rust (1987), the derivative of the social surplus function is the choice probability:

$$\begin{aligned} P\left(x^{C}|s,\beta\right) &= S_{x^{C}}\left(\left[\widetilde{\pi}\left(s,\beta\right)+\delta EV\left(s\right)\right]\right) \\ &= \frac{1}{\sum_{x\in X}\exp\left[\widetilde{\pi}\left(s,x,\beta\right)+\delta EV\left(s,x\right)\right]}\cdot\exp\left[\widetilde{\pi}\left(s,x^{C},\beta\right)+\delta EV\left(s,x^{C}\right)\right] \end{aligned}$$

, and the function EV satisfies the fixed point equation:

$$\begin{aligned} EV(s,x) &= \int_{s'} S\left(\left[\widetilde{\pi}(s',\beta) + \delta EV(s')\right]\right) f(s'|s,x) \\ &= \int_{s'=0}^{\infty} \log\left\{\sum_{x'\in X} \exp\left[\widetilde{\pi}(s',x',\beta) + \delta EV(s',x')\right]\right\} f(s'|s,x) \end{aligned}$$

as desired. ■