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"It's Not You, It's Me": Prices, Quality and Switching in U.S.-China Trade Relationships*

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Abstract

Costs from switching suppliers can affect prices by discouraging buyer movements from high- to low-cost sellers. This paper uses confidential data on U.S. importers and their Chinese exporters to investigate these costs. I find barriers to supplier adjustments: nearly half of importers keep their partner over time. Importers switch less if their supplier has higher quality or provides lower prices. I propose and structurally estimate a dynamic discrete choice model to compute switching costs. Cost estimates are large, heterogeneous across products, and matter for trade prices: halving switching costs reduces the U.S.-China Import Price Index by 7.6%.

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

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1 Introduction

Choosing the right supplier is one of the most difficult decisions a firm can make. There are many relevant considerations, including the supplier's price, location, and quality. History also matters, as previous successful transactions with a supplier are likely to predispose a firm towards continuing to buy from that supplier instead of searching for a new supplier. The relationship inertia implied by such a practice can lead to higher prices: if a firm is unaware of acceptable, lower-priced alternatives to its current supplier, or it is unwilling to bear the costs and uncertainty involved in such a change, then that firm would be effectively paying a higher price than if switching were easy. In this paper, using data on U.S.-China sourcing patterns, I demonstrate that buyer-supplier relationships are persistent, and I study the aggregate implications of this persistence using a model where switching suppliers is costly.[1]

Little is known empirically about how importers source from their foreign suppliers– thus, the first part of the paper uses novel U.S. Customs data to establish some baseline facts about international sourcing patterns. First, U.S. buyers source most of their Chinese imports from one, main supplier.[2] Second, over time, buyers are quite likely to remain with the same seller from year to year: although the average product has more than 40 Chinese suppliers, 45% of importers kept the exact same supplier from one year to the next. Third, even if buyers change suppliers, they often still buy from the same geographic location: one-third of importers that switched their primary supplier remained in the same city as that supplier, which is substantially higher than random selection would imply. Fourth, sectors that are more contract intensive, more skill intensive and less capital intensive tend to have more relationships that stay together. Finally, the buyer's sourcing decision is correlated with price and quality: importers that transact with a supplier that charges a high price or has low quality are less likely to stay with that supplier. Putting these facts together indicates that additional supplier switching could lead to lower prices.

To explore this possibility, I develop a dynamic discrete choice model centered on an importer's

[1] I use the term "importer" to refer to a *firm-HS10 product pair*. HS10 is a 10-digit *harmonized system* product code, the most disaggregated product code used by U.S. firms in international trade.

[2] As in Muûls (2015), I find it is rare for importers to import a product from more than one country.

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choice of supplier. The model positions a discrete choice framework within a firm-based model of international trade. The importing firm decides which supplier to use by comparing partner-specific profits across all possible choices, including its current match. The choice of supplier depends not only on the price and quality of each supplier, but also on the cost of switching, at both the partner and city levels. The key tradeoff for the importer is that switching to either a cheaper or a higher–quality partner raises profits, but changing one's partner or location is costly. The model produces closed-form expressions of choice probabilities for each potential outcome, allowing computation of the switching cost parameters via maximum likelihood. I use the Mathematical Programming with Equilibrium Constraints (MPEC) techniques developed by Dubé et al. (2012) and Su and Judd (2012) to estimate the model. I compute the parameters of the model product-by-product for 50 of the largest HS10 categories by value that the United States imports from China.

Model estimates of switching costs are large and heterogeneous across products. How big are switching costs? Just to be indifferent between its current partner and an otherwise identical partner, an importer would require a boost to profits that is two standard deviations higher than average that is specific to that new partner. Calculating marginal effects for the structural parameters– how the probability of staying changes when a supplier adjusts its price or quality– confirms that, as in the reduced-form results, price and quality affect the decision of whether to stay with a supplier. Including price and quality as explanatory variables also improves the fit of the model. The magnitude of the switching costs is robust to a number of different specifications, including accounting for serially correlated unobservables affecting the supplier choice decision.

One key difference in this paper compared to other works in the structural estimation of switching costs is that I use the estimated parameters to derive implications for aggregate import prices. In a counterfactual, I lower switching costs and allow importers to re-optimize their supplier choice, which demonstrates that switching frictions have a sizable effect on importer prices: the U.S.-China Import Price Index that arises from cutting frictions in half is 7.6% lower, a decline achieved by shrinking the percent of staying importers from 50% to 13%.

What drives these large effects of switching costs on exporter choice and import prices? The

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costs in the model can be thought of as anything preventing matching between buyers and suppliers that may have lower prices and higher quality. Therefore, a reduction in those costs could be interpreted as anything that would reduce those frictions: technological advancements making the search for potential suppliers easier, an improvement in contracting institutions, greater use of intermediaries, an easing of supplier capacity constraints, better metrics for measuring supplier quality, or greater bargaining power for importing firms. In sum, there are many valid ways to think about why switching suppliers is hard, few of which involve paying a monetary cost directly. Although the data are not able to separate out these interpretations, the paper shows policies that reduce matching frictions can lead to a significant reduction in import prices.

Similar to this paper, a number of studies have provided empirical insight into relationships between importing and exporting firms. Kamal and Sundaram (2016) use the same U.S. Customs data to determine the likelihood that textile producers in Bangladeshi cities will follow other exporters in their same city and export to a particular partner, while Heise (2016) also uses this data to study exchange rate pass-through in the life cycle of importer-exporter relationships. Bernard et al. (2018) develop a model of relationship-specific fixed costs to exporting using Norwegian buyer-supplier trade data, while Blum et al. (2010) use exporter-importer pair data on Chile to study the effects of intermediaries. This paper shows that relationships between U.S. buyers and Chinese suppliers tend to be persistent, and it explores implications of that persistence on prices.

There is a growing literature on understanding firm-level sourcing decisions. Antras et al. (2017) show that the importing decisions of U.S. firms are very linked across source countries and use this finding to quantify how importers react to trade shocks. Blaum et al. (2018) demonstrate that considering the effects of differential domestic input shares enables an intuitive quantification of the gains from trade and consider a firm's sourcing strategy across different imported products. The type of interdependency by which firms create an overall sourcing strategy that is studied in those papers is one I abstract away from in this work, as I consider only within-product supplier decisions. Muûls (2015) shows in a study of credit constraints and importing behavior that firms only very rarely import the same product from multiple countries. Blaum et al. (2019) show that

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within-firm sourcing patterns across different exporting countries are very different and are systematically related to the size of the importing firm. Monarch and Schmidt-Eisenlohr (2017) show importer-exporter relationships that survive have greater trade, and they estimate a dynamic model to understand how this pattern shapes trade flows. This work fits in with this literature by using buyer-supplier level data to understand the structure of U.S. importer sourcing strategies over time.

In order to model the frictions in buyer-supplier relationships, I estimate a structural demand model that incorporates the factors underpinning importer-exporter switching behavior, including price, quality, and geographic components. For this measurement, I use a model of dynamic discrete choice as in Rust (1987). I implement the problem in a similar way, using the MPEC methodology for solving the discrete choice problems found in Su and Judd (2012) and Dubé et al. (2012). As in those studies, my model includes costs entering into a firm's profit/utility function– namely, supplier switching costs at both the partner and city levels. Estimates are retrieved through maximizing a likelihood function based on observed outcomes for importer-exporter switching. Similar to the use of wages as a driving force behind employee switching behavior in Fox (2010), 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. Using this type of demand model on the buyer-supplier data permits the estimation of structural parameters that measure relationship frictions as well as counterfactual experiments that underscore the importance of such frictions on import prices.

The rest of the paper is organized as follows. Section 2 describes the data sources used in this paper and presents the empirical results. Section 3 presents the dynamic discrete choice model with supplier adjustment costs. Section 4 describes the implementation of the model. Section 5 describes the results, including a discussion of the parameter estimates and the counterfactual experiment used to quantify the importance of the supplier switching channel. Section 6 concludes.

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2 Data and Stylized Facts

2.1 Importer-Exporter Data

I work with trade relationship data from 2002 through 2008 from the Longitudinal Foreign Trade Transaction Database (LFTTD), which contains confidential information on all international trade transactions by firms in the United States and is maintained jointly by the U.S. Census Bureau and U.S. Customs.[3]. Every transaction of a company located in the United States importing or exporting a product requires filing a form with U.S. Customs and Border Protection, and the LFTTD contains the universe of these transactions.[4] In particular, the import data consist of all the information included in customs documents provided by U.S. firms purchasing goods from abroad, including the quantity and value exchanged for each transaction, HS 10 product classification, date of import and export, port information, country of origin, and a code identifying the foreign supplier firm. Known as the *manufacturer ID*, or *MID*, the foreign partner identifier contains limited information on the name, address, and city of the foreign supplier. Kamal and Monarch (2018) find substantial support for the validity of the MID and its applicability toward studying buyer-seller relationships, and Redding and Weinstein (2017) show that many of the salient features associated with exporting activity (such as the prevalence of multi-product firms and high rates of product and firm turnover) are replicated for MID-identified exporters.[5]

My unit of observation throughout will be a U.S.-China arm's-length trade relationship, comprising a U.S. *importer* (a combination of an importing firm located in the United States and an HS10 product) and a Chinese supplier. The sample is limited to arm's-length relationships for simplicity, as the factors determining why a within-firm related-party relationship survives are likely

[3]The dataset referred to as the LFTTD is transaction-level trade data merged with the Longitudinal Business Database, and was first created by Bernard et al. (2009). I clean the LFTTD using methods outlined in their study, and, as they did, I drop all transactions with imputed quantities or values (which are typically very low-value transactions) or converted quantities or values.

[4]Import transactions under $2,000 and export transactions under $2,500 are excluded.

[5]Kamal and Monarch (2018) describe the institutional background for the creation of the variable, propose various cleaning methods, and compare the number and composition of exporters from U.S. data with international data. I include a brief summary of the variable, including its construction and the relevant laws surrounding information provided in trade transactions, in Appendix A.

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to be very different. I predominantly use the buyer-seller-product unit for observation so that price variation can be used as an explanatory variable for relationship formation and dissolution, though I do also present results eliminating the product dimension.[6]

I focus on U.S.-China trade relationships for three reasons. First, individual suppliers within HS10 codes are more likely to be comparable within a country. That is, different Chinese suppliers are arguably producing more similar products to each other than to a typical Canadian supplier. This also means that quality differences within a product made by Chinese exporters are likely much smaller than overall quality differences for that product. Second, China became the largest exporter to the United States in the timeframe I use (2002 through 2008), presenting a sizable sample for analyzing arm's-length supplier relationships in trade.[7] Third, Kamal and Monarch (2018) show– by translating firm names and addresses from Chinese production data and generating MIDs– that for Chinese firms, the MID is likely to uniquely identify individual foreign suppliers.[8]

2.2 The Structure of U.S.-China Relationships

I start by presenting summary statistics for U.S.-China trade relationships. Table 1 Panel A illustrates the structure of relationships with different breakdowns for non-wholesale/retail U.S. importers, including the number of buyers per supplier, suppliers per buyer, products per relationship, and supplier per product.[9] The table shows what relationships between U.S. firms and Chinese suppliers look like: for example, the average HS10 product had 48 suppliers and 28 buyers. The median buyer imported two HS10 products, while the median supplier exported one product. The median relationship had one product, the median U.S. buyer had one supplier per product, and the

[6]The baseline definition means that a single U.S. firm could be counted as many importers.

[7]Only 16% of importers whose main supplier is Chinese will change to a main supplier from another country (including Hong Kong) in the following year.

[8]One drawback of focusing only on U.S. imports from China is that there is selection bias relative to the universe of U.S. importers. Firms that import from China are more likely to be purchasing more labor-intensive product categories that match up with China's comparative advantage, which conditions on the type of U.S. firm included in the analysis.

[9]A non-wholesale non-retail importer is any importer whose primary sector from the Longitudinal Business Database is not classified as wholesale or retail, where primary sector is defined as the NAICS code with the highest employment across establishments within a firm.

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median Chinese supplier had one buyer per product.[10]

Trade is not spread evenly across suppliers: the first row of Table 1 Panel B shows that most buyers heavily cluster their imports from one supplier.[11] This is not a result of the widespread prevalence of single-supplier importers: rows 2 and 3 show that even when restricting to importers with multiple suppliers, the median importer buys 61% of its imports from its primary supplier. The distribution of trade from the secondary supplier makes it clear that importers tend to buy more than twice as much from their primary supplier compared to their secondary supplier.

Given that some suppliers have more than one importer, the U.S. import data on relationships can also be used to tease out how the same supplier interacts with different importers. Indeed, within multi-importer suppliers, prices (constructed as buyer-supplier-product level unit values) often are fairly different across importers: HS10 prices charged are within one standard deviation of the mean for only about 55% of relationships. Although nearly 90% of suppliers only have a single buyer, differential pricing across buyers is present in the data.

One common research question that often arises in the literature on trading relationships is the extent to which changes in the extensive margin– especially the entry of new buyers or new suppliers– explain movements in total trade flows.[12] This can be done with the sample of U.S. import data I use by decomposing total U.S. imports in every HS10 category from China into the product of the number of Chinese suppliers, the number of U.S. buyers, the average value per buyer-supplier-product triad, and a "density" term representing the share of possible buyer-supplier-product combinations with positive trade.[13] Regressing the logarithm of each component individually on the logarithm of total U.S. imports from China shows the relative importance of each margin- supplier, buyer, and intensive (trade per relationship). Table 2 indicates that although exit and entry of buyers and suppliers into international trade matter, the amount of trade between individual importers and their suppliers is the most important factor explaining variation in import

[10] These findings are mirrored by results for Norway in Bernard et al. (2018). Table A1 replicates this table using all U.S. importers, including wholesalers and retailers.

[11] This fact resembles the finding from Blaum et al. (2019) that French importers tend to concentrate their imports from one source country.

[12] See especially Bernard et al. (2018) and Carballo et al. (2018).

[13] The density is a rump term that ensures the product of all the terms is total imports in an HS10 category.

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growth across products.[14] The last column of Table 2 shows that the result is magnified even further when shutting down the supplier's extensive margin– the amount each buyer from China purchased mattered significantly for overall U.S. imports from China during this time period.

2.3 Switching Behavior in U.S.-China Trade Relationships

I next leverage one of the key advantages of the U.S. import data– the fact that both buyers and suppliers are identified consistently over time– to examine the main question of interest: how often do buyers and suppliers stay together, and what are the key variables correlated with that decision?

My baseline definition of staying is a simple one: a dummy variable $Stay_{mxht}$ that captures whether an importer m importing an HS10 product h in year t from a supplier x purchased that product from that supplier in the following year.[15] However, there are some important nuances that this definition misses, due to the fact that, as previously shown, some buyers have more than one supplier in a product category. For example, if a buyer purchases 90% of its imports from one supplier and the remaining 10% from a set of two other suppliers, the most important relationship to understand from the perspective of overall trade flows is the first one. The variable $Stay_{mxht}$, however, makes no distinction between the different suppliers of this buyer and treats them as three equally relevant observations. For this reason, guided by the result in Section 2.2 that trade flows are fairly concentrated in an importer's main supplier, I also create a dummy variable $StayVal_{mht}$ that captures whether buyer m stayed with its primary supplier of product h from t to $t+1$.[16] Generating $StayVal_{mht}$ has an additional benefit: as described in Section 2.1, the MID variable also contains information on the geographic location of the supplier. With $StayVal_{mht}$, I can also examine the geographic component of switching behavior: how often does a buyer switch from one primary

[14]The importance of the intensive margin is also consistent with the large number of Chinese suppliers per product shown in Table 1.

[15]Importers that do not import the same product category in the following year are dropped. Also, any relationships that switched from arm's length to "related" will also be dropped. Although this may lead to false identification of staying, Kamal and Monarch (2018) show that related party relationships are only 7% of the total, meaning those relationships that become related are a further subset (and likely a very small one).

[16]Appendix A.3 demonstrates that observed relationship switching according to the $StayVal_{mht}$ measure is rarely the result of small changes in import shares in a buyer's supplier network.

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supplier to another in the same city? The answer offers insight into the attractiveness of suppliers to U.S. buyers located in the same area. I generate these two variables for the universe of U.S. non-wholesale non-retail importers from China from 2002 through 2008.

A sizable share of U.S. importers maintain the same supplier over time. The share of importer-exporter-product interactions that are repeated ($Stay_{mxht}$) is 43%, while the share of importers using the same primary product supplier ($StayVal_{mht}$) is 45%.[17] Random supplier selection is a useful benchmark: the average HS10 product has 48 Chinese exporters to the United States, meaning that if each supplier was equally likely to be chosen, the probability of staying would be 1/48, or 2%. Thus, path dependence is higher than if buyers chose suppliers randomly.

Significant heterogeneity exists across industries in staying shares. Summing $Stay_{mxht}$ across products in an HS2, the share of importers staying with their supplier for a product ranges from 20% to 90%.[18] These shares are correlated with industry characteristics: Figure 1 shows HS2 industries with higher trade-weighted stay shares are more contract intensive (measured as in Nunn (2007)), more skill intensive, and less capital intensive.[19]

There is also a strong geographic element to the stay-or-switch decision: among those that switch their primary supplier ($StayVal_{mht} = 0$), 30% pick a primary supplier in the same city as their original supplier. Using a similar benchmark as earlier, random exporter selection would imply a 12% to 13% chance of staying in the same city.[20] Thus, there are frictions keeping importers buying from the same city, even if they choose not to use the same supplier.

[17] The share of trade accounted for by these relationships from 2002 through 2008 is about 43%.

[18] The full set of HS2 staying shares, both unweighted and weighted by importer size, is in Appendix Table A2, along with their description.

[19] The strength of each of these correlations is maintained when using stay shares and intensity measures defined at the HS6 level. There is no meaningful correlation between the share of relationships that stay together and the product-level elasticity of substitution from Broda and Weinstein (2006) Skill intensity refers to the share of non-production workers to total employment, while capital intensity is the ratio of capital expenditures to total employment. The details of how each of the measures are constructed are in Appendix A.2.

[20] Each HS10 product has an average of nine cities, but the number of exporters are not distributed equally across cities. I first calculate the probability an importer originally in city c picks a random supplier also in c as $\frac{X_{ic}}{\sum_c X_{ic}}$, where X_{ic} is the number of exporters of product i in city c. Therefore, the probability *any* importer picks a random supplier also in its original city is the weighted average of these probabilities, where the weights are the number of importers M_{ic} buying from each city. Calculating this object using 2006 data gives a 12% probability of staying in the same city under random supplier choice. Replacing X_{ic} with the value of trade in a city (meaning the probability of staying depends on the distribution of exports, not exporters) gives a 13% probability of staying.

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The core fact that, relative to what random supplier choice would imply, a significant share of U.S.-China trade relationships persist over time is robust to alternative specifications. One potential concern is that switching is driven by exit on the exporter side: given the massive changes in the Chinese economy over this period, exporter churning was very prevalent. Recreating the staying variables previously described using only on those matches where the MIDs that are switched away from are still found in the data delivers a similar result: 55% of importers stay with their primary supplier. Redefining the staying decision to a buyer staying with at least one of its suppliers within a product also gives a staying share of 56%. These facts are also robust to a number of other specifications, including using all U.S. importers including wholesalers and retailers, or changing the definition of a relationship to a buyer-supplier HS6 product or a buyer-supplier match.

2.4 Prices, Quality, and Switching Behavior

There are many potential explanations for the persistence of U.S.-China trade relationships that the LFTTD can shed light on. The individual transaction between the buyer and supplier contains information that can be used to construct a price (unit value), while other explanatory variables (such as buyer or supplier size, or the number of products in a relationship) can be constructed by aggregating individual transactions.

Another measure that could be correlated with whether a buyer stays with its supplier is the underlying quality of that supplier. Khandelwal (2010) provides an estimator of quality at the country-product-time level, based on the idea that if two varieties charge the same price but have different market shares, the one with the higher market share has a higher quality. All of the ingredients needed to use this estimator are also available in the more disaggregated relationship data. I therefore follow Khandelwal (2010) to generate quality at the supplier-product-time level by using the estimating equation:

$$\ln(s_{xht}) - \ln(s_{0t}) = \lambda_{1,xh} + \lambda_{2,t} + \alpha p_{xht} + \sigma \ln(ns_{xht}) + \lambda_{3,xht} \tag{1}$$

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where s_{xht} is the market share of supplier x's exports of product h in its HS4 sector, s_{0t} is the "outside option" represented by 1 minus the import share for product h's HS4 category, p_{xht} is the unit value of supplier x for its exporters of product h, ns_{xht} is the market share of x within product h, and $\lambda_{1,xh}$ and $\lambda_{2,t}$ are fixed effects. This equation captures the demand curve for a variety under a nested logit framework. As in Khandelwal (2010), I instrument for price with transaction-level per-unit transportation costs and instrument for the within-product market share ns_{xht} with the number of suppliers of that product and the average number of products per exporter.[21] I run Equation (1) for each HS4 category. Quality for a supplier-product λ_{xht} is the sum of the λ components.

The results of the quality estimation procedure are summarized in Table 3. The bottom panel shows that about 41% of HS4 sectors imported from China feature a coefficient on price that is statistically significant, representing about 85% of all Chinese suppliers exporting to the United States. Rows 1 and 2 illustrate the importance of instrumenting for price– under a standard OLS procedure, price and market share are positively correlated. The IV coefficient is negative as expected, and it is consistent with an average own-price elasticity of about negative 0.44.[22] Row 4 indicates that the average and median HS4 regressions pass the over-identifying restriction test, while Rows 5 and 6 indicate they have fairly low first-stage F-statistic p-values, indicating the instruments perform well. Although the mean p-value for the first stage is slightly outside a 95% confidence interval, the percentile columns indicate that the majority are significant at the 1% level. After instrumenting for the within-product market share, the mean coefficient is slightly negative but has a large variance. Altogether, λ_{xht} has a mean near 0, with a standard deviation of about 2.

I use the following linear probability model to examine the determinants of longevity in U.S.-

[21] Although transportation costs may be correlated with quality, Khandelwal (2010) notes that the exclusion restriction for the instrumental variables procedure remains valid as long as transportation costs do not affect deviations from average quality $\lambda_{3,xht}$. I do not use tariffs as an instrument, because there is no variation within HS10 imports from China.

[22] This elasticity is calculated as $\widehat{\alpha}^{IV} \cdot p_{mxht} \cdot (1 - s_{xht})$ as in Nevo (2000), and it is only calculated for those sectors with negative IV price coefficients. As the elasticity exists for each variety but the summary table is across HS4 categories, the table uses the within-HS4 median elasticity for each sector.

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China trade relationships from 2002 through 2008:

$$Stay_{mxht} = \alpha_0 + \alpha_p p_{mxht} + \alpha_\lambda \lambda_{xht} + f_h + f_t + v_{mxht} \quad (2)$$

where $Stay_{mxht}$ is defined as above, p_{mxht} is the log price (unit value) for the relationship at time t, λ_{xht} is exporter quality, and f_h and f_t are HS10 and year fixed effects, respectively. Some specifications below also include the logged total value of HS10-level exports for a Chinese exporter to the United States, $Size_{xt}$, and the logged total value of HS10-level imports from China for a U.S. importer, $Size_{mt}$. Bootstrapped standard errors (clustered at the HS10 level) are used as exporter quality is itself a regressor generated from a regression.[23] Clearly, this simple framework only suggests correlation between the variables and the probability of staying, not causation.

The main finding is apparent from the coefficient estimates in Column (1) of Table 6 Panel A: lower prices and higher quality are strongly correlated with a higher probability of a U.S. buyer maintaining its supplier over time. Including size terms in Column (2) indicates that smaller importers and larger suppliers are more likely to remain in relationships together, while the importance of price and quality is maintained.[24] Unsurprisingly, the relationship between quality and $Stay_{mxht}$ is dampened, as the quality estimator in Equation (1) is based in part on a supplier's market share. Adding the number of products per relationship as an additional regressor in Columns (3) and (4) solidifies the original result while also showing that a relationship trading two additional products tends to have a 1 percentage point higher probability of staying together. Columns (5) to (8) show the results from using the primary-supplier measure *StayVal* instead of *Stay*– the key results on price and quality strongly survive. Table 6 Panel B shows that even when using all U.S. importers, rather than non-wholesale, non-retail firms, higher prices and lower quality lead to less staying, measured either by *Stay* (Columns (1) and (2)) or *StayVal* (Columns (3) and (4)).

Next, I show that the results survive many alternative specifications. First, even when drop-

[23] I thank an anonymous referee for this suggestion.

[24] The assumption that supplier quality does not vary across individual buyers within a product h likely contributes to the small estimated standard errors for λ_{xht}. That said, Table 1 shows that the median number of buyers per supplier within an HS10 is 1, and the mean is 1.2, so this is not likely driving the overall significance of the result.

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ping the product dimension from relationships, price and quality remain strongly correlated with the probability an importer stays with a supplier. In particular, by generating a weighted average of product-level staying decisions, it is possible to consider overall importer-exporter relationships free of the product dimension. Columns (1) and (2) of Table 6 Panel A show that (weighted) price and quality matter at the firm level– higher prices or lower quality accompany a lower weighted-average staying share. Columns (3) through (6) show the same conclusion arises when using *StayAny* (that is, did an importer and supplier stay together in any of their HS10 products) as a dependent variable or *StayAll* (that is, did an importer and supplier stay together in all products) as a dependent variable.[25] Second, considering those buyers that only have one supplier in their HS10 product, Columns (1) and (2) of Table 6 Panel B shows that price is negatively correlated with staying while quality is positively correlated. As for those buyers with a single supplier overall (but potentially multiple products), Column (3) again uses the weighted average of product-level staying decisions as the dependent variable on the weighted average of product-level prices and quality, with the same results. Column (4) finds the same result for *StayAny*, while Column (5) shows the same for *StayAll*[26] Third, I consider whether the results are driven mainly by newly formed relationships. Columns (1) and (2) of Table 6 Panel C exclude first-year relationships from the regression specification above. Although the price and quality coefficients are reduced, they remain important correlates with the probability of U.S. importers remaining with their supplier. It is also possible to leverage the multi-year data to consider why relationships stay together for longer. Columns (3) and (4) report the results of the specification in Equation (2) when considering whether a relationship has lasted two years (*Stay*2), while Columns (5) and (6) show the results for whether a relationship has lasted five years (*Stay*5). Price, quality, and size all have the same sign as the single-year case, although the coefficients are reduced due to the lower probability of a relationship surviving multiple years.[27]

[25] The coefficient on supplier size flips to negative for some of the specifications in Table 6 Panel A. One possible explanation for this that is not explored could be that large suppliers can both provide competitive pricing for individual buyers and search for new buyers more easily, a tension that materializes when considering *StayAny* versus *StayAll*.

[26] Appendix A.4 considers how the high prevalence of processing trade in Chinese exports might affect the results.

[27] The results for the *StayVal* variable defined over different time horizons are omitted but are quantitatively and qualitatively in line with these estimates.

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To summarize the regression results, lower prices and higher supplier quality are strongly correlated with a higher probability of a buyer staying with its supplier. I use these results to guide the modeling of the supplier choice problem below.

3 Model

This section lays out a dynamic discrete choice framework used to model U.S. importer decisions of supplier choice. Different suppliers set different prices for the same product j and have heterogeneous quality. Importers of products in that industry make a decision each period about which firm to import from, based on both their current supplier and information about other available price and quality menus. Switching suppliers involves payment of a set of per-unit costs, including both an overall switching cost and an additional cost to be paid if an importer finds a new partner in a new city. Each individual supplier of product j at time t is denoted as $x_{j,t}$, and suppliers are distinguished both by the price they charge to importer m, $p^m_{x,j,t}$ and by the quality of their individual variety $\lambda_{x,j,t}$. If importer m chooses the supplier indexed $x_{j,t}$, I denote this match as $x^m_{j,t}$.

3.1 Importers

Importers are final good producers, and demand for their variety m has a constant elasticity of substitution demand curve $Q_m = Bp_m^{-\sigma}$, where B is a demand shifter, p_m is the final good price for variety m, and σ is the elasticity of substitution.

Final good producer m requires J inputs, indexed $j = 1, ...J$, in order to produce its final good, and production of the final good is Cobb-Douglas in labor and quantity $\{I_j\}_{j=1}^{J}$ of those intermediates:

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

Although the production function and final demand for its variety are fixed, importer m can

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choose its supplier for each input. By considering all possible suppliers in the market, importers are able to make a profit-maximizing decision between suppliers. All contracts are signed for a single period. A number of components affect the decision of which supplier to use.

First, importers make a decision based in part on the expected price they will pay from any supplier, $\mathbb{E}\left[p^m_{x,j,t}\right]$. In particular, importers form expectations about the price from their original partner, and from every other supplier. As the expectation differs depending on which partner was used, this expectation is both *importer-specific* (m) and *supplier-specific* (x), which allows the same supplier to charge different prices to different importers, a key feature of the data. Indeed, it is not possible to observe prices between potential importer-supplier pairs that do not result in a transaction, necessitating the use of a price expectation.[28]

Second, there are frictions involved in finding a different supplier in the following period, modeled as a multiplicative component of the per-unit price paid. The cost of switching suppliers is denoted as $\zeta_{X,j}$. Reflecting the geographic nature of switching previously discussed, I also include an additional geographic cost $\zeta_{C,j}$ which is paid if an importer uses a partner in a separate city.

I define importer m's expected per-unit cost of purchasing intermediate j from supplier $x_{j,t}$ at time t, incorporating the frictions involved in searching for a supplier, in the following manner:

$$\bar{p}^m_{x,j,t} = \mathbb{E}\left[p^m_{x,j,t}\right] \exp\left\{\zeta_{X,j}\ \mathbb{1}\{x^m_{j,t} \neq x^m_{j,t-1}\} + \zeta_{C,j}\ \mathbb{1}\{c^m_{j,t} \neq c^m_{j,t-1}\}\right\} \tag{3}$$

where $\bar{p}^m_{x,j,t}$ is the expected cost of purchasing one unit of the intermediate from seller $x_{j,t}$, and the indicator functions are equal to one if an importer picks a different partner $x_{j,t}$ from its current match $x_{j,t-1}$, or a different city $c_{j,t}$ from its current city $c_{j,t-1}$. If final good producer m chooses a new partner in the same city (c_{t-1}) as its old partner, then only $\zeta_{X,j}$ is paid, while if a supplier in a separate city is chosen, $\zeta_{X,j} + \zeta_{C,j}$ is paid. This implies that the cost of an input bundle differs depending on what supplier is chosen, not just because of different prices, but also because of costs of switching one's current partner. It also means that switching costs are per-unit costs, rather than

[28] The role of possible price-quality menus of other suppliers affecting the decision of which supplier to use is absent from the empirical exercise.

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fixed costs. Although the cost of switching suppliers is likely to have both fixed and marginal components, this assumption makes the model more tractable, as it ensures that sourcing decisions are independent across inputs. Setups where individual product sourcing decisions are part of an overall sourcing strategy as in Blaum et al. (2018) would break this property.

Let $X_t^m = \left\{x_{j,t}^m\right\}_{j=1}^J$ be the vector of supplier choices made by importer m across inputs at time t. Then, with wage w, the expected cost of an input bundle for the final good is

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

Producing one unit of the final good for a final good producer with productivity ϕ requires $\frac{1}{\phi}$ input bundles, each with a cost depending on the vector of suppliers X_t^m. I assume that the productivity of a final good producer depends on factors unobserved by the econometrician that are particular both to itself and to its individual supplier match. In particular, productivity for producer m is multiplicative in a common element for that producer ψ_m and the "quality" of the variety from supplier x, $\lambda_{x,j,t}$: $\phi_m\left(X_t^m\right) = \psi_m \prod_{j=1}^{J} \lambda_{x,j,t}^{\nu}$.

The marginal cost of an importer m with productivity ϕ_m is

$$MC\left(X_t^m\right) = \frac{1}{\phi_m\left(X_t^m\right)} c_m\left(X_t^m\right) \tag{4}$$

Maximizing expected profits at time t means that importer m must set the price of its final good optimally and choose the optimal vector of supplier choices X_t^m:

$$\pi_t^m = \max_{p_m, X_t^m} p_m Q_m - MC\left(X_t^m\right) Q_m$$

Using the assumption of CES demand, the optimum price of the final good for producer m is a markup over the marginal cost, $p_m = \frac{\sigma}{\sigma-1} MC\left(X_t^m\right)$. Plugging this and the expression for marginal

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costs (4) into the above profits equation gives the following equation:

$$\pi_t^m = \max_{X_t^m} \frac{1}{\sigma} B \left(\frac{\sigma}{\sigma - 1} \right)^{1-\sigma} \left[\phi_m \left(X_t^m \right) \right]^{\sigma-1} c_m \left(X_t^m \right)^{1-\sigma} \tag{5}$$

The multiplicative nature of Equation (5) and its subcomponents means that supplier choices are independent across inputs. To show this, taking logs of (5), plugging in, and defining log expected profits attributable to input j as $\ln \pi_{j,t}^m$, we have

$$\ln \pi_t^m = A^m + \ln \pi_{j,t}^m + \sum_{k \neq j} \ln \pi_{k,t}^m$$

where

$$\ln \pi_{j,t}^m = \max_{x_{j,t}^m} \nu \left(\sigma - 1 \right) \ln \lambda_{x,j,t} + \omega_j \Big(\mathbb{E} \left[\ln p_{x,j,t}^m \right] + \zeta_{X,j} \mathbb{1} \{ x_{j,t}^m \neq x_{j,t-1}^m \} + \zeta_{C,j} \mathbb{1} \{ c_{j,t}^m \neq c_{j,t-1}^m \} \Big), \tag{6}$$

$\omega_j = (1-\alpha)(1-\sigma)\gamma_j$, and $A^m = \ln \left\{ \frac{1}{\sigma} B \left(\frac{\sigma}{\sigma-1} \right)^{1-\sigma} w^{\alpha(1-\sigma)} \psi_m^{\sigma-1} \right\}$ captures all the terms not associated with the cost of an input bundle for the final good from a particular supplier.[29] As the decision of input j is wholly separate from the decision of other inputs, I now focus attention only on the market for one input and drop the j subscript.

How does an importer decide which supplier maximizes profits? It is a maximization problem of discrete choice, so expected profits are calculated for each choice, and the partner with the highest expected profits will be chosen. I define the *supplier-specific* expected log profit term for any choice x_t^m as $\overline{\pi}_t^m \left(x_t^m, \beta \right)$:

$$\overline{\pi}_t^m \left(x_t^m, \beta \right) = \xi \ln \lambda_{x,t} + \beta_P \mathbb{E} \left[\ln p_{x,t}^m \right] - \beta_X \mathbb{1} \{ x_t^m \neq x_{t-1}^m \} - \beta_C \mathbb{1} \{ c_t^m \neq c_{t-1}^m \} \tag{7}$$

where $\xi = \nu(\sigma - 1)$, $\beta_P = -(1-\alpha)(\sigma-1)\gamma$, $\beta_X = (1-\alpha)(\sigma-1)\gamma\zeta_X$, and

[29] In Equation (6), I use Jensen's Inequality and the fact that the expected price is almost-surely constant to assert that the log of the expected price is equal to the expected log price.

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$\beta_C = (1-\alpha)(\sigma-1)\gamma\zeta_C$. I summarize the vector of unknown parameters as $\boldsymbol{\beta} = \{\beta_P, \beta_X, \beta_C, \xi\}$.

The final element of the importer's decision is a stochastic profit shock. For the dynamic profit problem, as in Rust (1987), I allow for a shock from choosing x_t that is observable to the importer, $\varepsilon^m_{x,t}$. This profit shock stands in for all of the other unobservable traits not included in Equation (7) that may result in a match. Although I will assume that these error terms are independent and identically distributed, it is possible that these error terms could be serially correlated over time, meaning that something beyond price, quality, or switching costs could be driving an importer to choose a particular supplier in successive years. I discuss this concern in Section 5 and perform an adjustment for the main results with serially correlated errors.

Equation (7) is the cornerstone of my estimation strategy. Starting from a general model of trade, I have derived a choice-specific profit equation that can be estimated using MPEC. To summarize this equation in words, if importer m chooses a different supplier than it used in the previous period, then this firm must pay a per-unit cost β_X, whereas if it uses a different supplier in a different city, it pays $\beta_X + \beta_C$. The parameter β_p is a measure of how sensitive switching is to changes in price, while ξ is a of measure of how sensitive switching is to quality. Estimating $\{\beta_P, \beta_X, \beta_C, \xi\}$ product-by-product will provide a measure of the frictions firms face in switching partners and locations, and it will enable the posing of a counterfactual to consider the price effects from lowering such frictions.[30] Importers pick the supplier that delivers the highest $\overline{\pi}^m_t$. Thus, the model solution is the set of parameter values by which observed supplier choices in the data deliver the highest expected profits for all importers compared to other potential choices.

[30]It is important to stress that even though, according to the model of importer behavior, the elements of $\boldsymbol{\beta}$ share common components such as the demand elasticity (σ) and the production function parameters (γ_j,ν, and α), these commonalities are not actually imposed in the estimation routine. An alternative route for estimating the model would be to calibrate these parameters, and recover $\lambda_{x,t}$ and the ζ parameters directly, similar to the method used in Khandelwal et al. (2013). One complication in this context is that supplier–specific profits are unobservable, making the interpretation of λ more difficult.

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3.2 Suppliers

Within any product category j there are numerous suppliers (indexed by x) producing individual varieties. They set price at time t based upon their firm-specific marginal cost, which in turn depends on their quality choice $\lambda_{x,t}$. I follow the same functional form for supplier quality as in Hallak and Sivadasan (2013), and continue to drop the j subscript. The optimal price is

$$p_{x,t} = \mu_x MC_{x,t} = \mu_x \frac{w_{x,t}}{z_x} (\lambda_x) \tag{8}$$

where z is the idiosyncratic productivity of supplier x, w is the wage, and, as before, λ is quality. I assume that suppliers simply set a constant markup μ_x over time. As shown in Appendix A.5, this functional form allows an importer to form price expectations for every supplier according a density $f(p_{x,t}|\mathbf{p_{t-1}}, x_{t-1})$, where $\mathbf{p_{t-1}}$ is the set of all supplier prices charged in the previous period.

This setup imposes two key assumptions on supplier quality, λ_x. First, quality does not vary over time. In the data, this assumption is borne out– the average change in the estimated $\lambda_{x,t}$ over time is only an increase of 0.1, for a variable centered at zero, with a standard deviation close to 2. That said, this does imply that quality evolution is not a determinant of which supplier an importer chooses. Second, estimating quality according to Equation (1) as in the empirical section forces me to ignore the potential for a supplier to offer different qualities of its variety to different importers.

3.3 Value Function

Entering period t, importer m has a collection of state variables that affect its optimal choice x_t^m, following the supplier-specific profit term given by $\overline{\pi}_t^m(x_t^m, \boldsymbol{\beta})$ in Equation (7). Those state variables are the identity of the supplier used the previous period, x_{t-1}^m with location c_{t-1}^m, and (in order to form price expectations) the set of prices charged by all suppliers the previous period $\mathbf{p}_{t-1}$. Based on these state variables, the profit shock $\varepsilon_{x,t}^m$, the costs of switching one's supplier, and the other components of $\boldsymbol{\beta}$, the importing firm will choose which supplier to use in the current period, x_t^m. After all choices are made, the true vector of prices $\mathbf{p_t}$ is realized, as is the matrix of next period's

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profit shocks ϵ_{t+1}. These states evolve according to the joint density $h(\mathbf{p_t}, \epsilon_{t+1})$.

Infinitely lived importer m chooses an supplier x in each period in order to maximize the present discounted stream of expected profits. With single-period expected profits described by Equation (7), the infinite-time problem for any importer (dropping the m superscript) is summarized by the following value function:

$$V(x_{t-1}, \mathbf{p_{t-1}}, \epsilon_t) = \max_{\{x_t, x_{t+1}, \dots\}} \mathbb{E}\left[\sum_{\tau=t}^{\infty} \delta^{\tau-t} \left(\overline{\pi}_\tau (x_\tau, \mathbf{p}_{\boldsymbol{\tau}-\mathbf{1}}, x_{\tau-1}, \boldsymbol{\beta}) + \varepsilon_{x,\tau}\right)\right] \tag{9}$$

where the expectation is taken over the importer's knowledge about the possible evolution of $(p_{x,t}, \varepsilon_{x,t+1})$, governed by the density $h(p_{x,t}, \varepsilon_{x,t+1})$ at every period t. The price from choosing supplier x_t is not known before making the choice, but it is predicted based on $\mathbf{p_{t-1}}, x_{t-1}$ and x_t, according to the density function $f(p_{x,t} | \mathbf{p_{t-1}}, x_{t-1})$.

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

$$V\left(x, \mathbf{p}, \boldsymbol{\epsilon}'\right) = \max_{x'} \ \overline{\pi}\left(x', \mathbf{p}, x, \boldsymbol{\beta}\right) + \varepsilon'\left(x'\right) + \delta EV\left(x', \mathbf{p}, x, \boldsymbol{\epsilon}'\right) \tag{10}$$

for

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

4 Implementation

This section describes how I take the model to the data. I begin by discussing the standard assumptions on the error terms $\varepsilon_{x,t}^m$ that generate the probability of observing any particular match.

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4.1 Conditional Choice Probability

First, as is common in the discrete choice literature, I make a key assumption about the joint density of the state variables and the profit shock: they evolve separately from each other.

Assumption 1 (Conditional Independence) *The joint transition density of $p_{x,t}$ and $\varepsilon_{x,t+1}$ can be decomposed as $h(p_{x,t}, \varepsilon_{x,t+1}) = g(\varepsilon_{x,t+1}) f(p_{x,t}|\mathbf{p_{t-1}}, \mathbf{x_{t-1}})$.*

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

Assumption 2 *The profit shock is distributed Type I Extreme Value (Gumbel). The cumulative distribution function G is $Pr(\varepsilon_t < y) = G(y) = \exp\{-\exp\{-y-\gamma\}\}$, for $\gamma = 0.577...$ (Euler's constant).*

These assumptions allow computation of conditional choice probabilities for any outcome.[31]

Proposition 1 *Let the value of a present time variable a one period ago 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 $s = \{\mathbf{p_{-1}}, x_{-1}\}$, the probability of observing a particular supplier choice x^C conditional on state s and parameters β, $P\left(x^C|s,\beta\right)$, is*

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

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

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

Proof *See Appendix B.*

[31] Artuç and McLaren (2015) derive a very similar conditional choice probability function for their model of mobility costs for workers affected by offshoring.

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4.2 Maximum Likelihood Estimation

The parameters β can be computed via maximum likelihood estimation. Let x_t^m be the observed choice of supplier at time t for importer m. Then the likelihood of observing m choosing x_t^m is

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

Thus, the total likelihood function for the set of importer choices ($m = 1,...M$) at time t is:

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

The constraints for the maximization problem are the system of fixed point equations defined by Equation (12). To solve this problem, I follow the MPEC approach as described in Su and Judd (2012) and Dubé et al. (2012), namely an inner loop for solving the fixed point problem in Equation (12) for the constraint vector **EV** and β, and testing each candidate β within the (log) likelihood function to see where the function is maximized. Thus the problem to solve is

$$\max_{\beta} \log \mathscr{L}(\beta) =$$

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

$$s.t.$$

$$EV\left(x_t,s_t\right) = \int_{s_{t+1}} \log\left\{\sum_{x_{t+1}\in X}\exp\left[\overline{\pi}_{t+1}\left(x_{t+1},s_{t+1},\beta\right)+\delta EV\left(x_{t+1},s_{t+1}\right)\right]\right\} f\left(s_{t+1}|s_t\right) \tag{14}$$

Solving this problem produces maximum likelihood estimates for β for each product.

In order to estimate the above model, I need to solve the system of equations defined by Equation (14) for the unknown elements EV and β. To do this, I discretize the price state space into N

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intervals, allowing me to rewrite Equation (14) as:

$$EV(x_t, \widehat{s}_t) = \sum_{\widehat{s}_{t+1}=1}^{N} \log \left\{ \sum_{x_{t+1} \in X} \exp\left[\overline{\pi}_{t+1}(x_{t+1}, \widehat{s}_{t+1}, \boldsymbol{\beta}) + \delta EV(x_{t+1}, \widehat{s}_{t+1})\right] \right\} Pr(\widehat{s}_{t+1} | \widehat{s}_t, x_t) \quad (15)$$

where $\widehat{s}_t = \{\widehat{p}_{t-1}, x_{t-1}\}$, and $\widehat{p}$ is the midpoint of each price interval, chosen such that $\frac{1}{N}$ of all firms are in each interval. The MPEC maximization protocol uses values of the vector $\boldsymbol{\beta}$ 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. As an example to fix ideas, suppose there are 30 exporters in an industry and N discrete price states. Then there are $30N$ possible state values and 30 possible choices, meaning that the vector **EV** contains $900N$ elements, one for each value of $EV(x_t, \widehat{s}_t)$. Thus, the constraint set in Equation (15) is a fixed point problem of $900N$ equations and $900N + 4$ unknowns, where the additional four unknowns are $\boldsymbol{\beta} = \{\beta_P, \beta_X, \beta_C, \xi\}$. Each of the possible values of $\boldsymbol{\beta}$ and **EV** that satisfy these constraints are tested in the objective function Equation (13) to see which gives the closest match between the estimated probabilities of a set of choices and the true choices. Asymptotic normal standard errors are calculated following Rust (1994). I set the number of discrete price states at $N = 5$.

Taking a step back, it is worth noting the important assumptions that the estimation procedure relies on for identification of the structural parameters. In particular, the model is designed so that there is no cross-product coordination between buyers and suppliers (a scenario considered in Blaum et al. (2018)), no size or market power effect on the decision of which supplier to buy from or what price would be charged, and no capacity constraint for suppliers. An additional assumption that underlies the model is that any supplier with the lowest price, accounting for quality, would be desired by all buyers if switching costs were minimal. Finally, the model assumes that switching costs are paid as per-unit costs, rather than as fixed costs. Each of these properties is likely violated to some degree in the buyer-supplier matches observed in the data, so the actual estimates of switching costs should be considered together with those caveats.

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4.3 Data Preparation

Next, I describe how to run the MLE problem of Equation (13) with the constraints in Equation (15) using LFTTD data. I must calculate the one-period log expected profits from an importer choosing each potential exporter x_t as given in Equation (7). There are four data elements to this profit equation: (1) whether x_t is different from an importer's previous partner, (2) whether x_t is located in a different city from an importer's previous partner, (3) the expected price of x_t, and (4) the quality of x_t. The first two are easily identified using the MID variable discussed in Section 2. The expected price is determined by the formulation in Section 3.2.[32] The process through which I estimate the quality of an exporter, λ, is identical to its construction in Section 2.4.

As emphasized in Section 2, 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 each year– the *StayVal* measure. Thus, the "choice" in the discrete choice model is the primary supplier for an importer. Recall from Section 2 that the key results about price and quality were consistent between $Stay$ and $StayVal$. I also only use those importers that are found in both years– any importer that dropped out in the second year is not included in the estimation.[33] I also exclude wholesalers and retailers from the analysis, as in the bulk of the empirical section.

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 at $t+1$ broadly, consisting of (a) any exporter found in time t and (b) any new exporter in time $t+1$, as long as I know what price it charged in time t. Because the choice is restricted to the primary exporter, it is possible to find some "new" exporters in time $t+1$ that have price information from time t, even though they did not actually appear as any importer's main supplier in time t.

The last step is to clean the LFTTD by eliminating unreasonable prices. Before averaging prices across transactions, I eliminate any transactions with prices both (a) outside the 95th percentile

[32] More detail on this is in Appendix A.5.

[33] The empirical results demonstrate that the selection bias from winnowing the sample in this way is likely small.

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range and (b) 10 times the median price for each product.[34] I follow the above procedure to estimate the model for 50 of the largest imported HS10 products by value, using data on U.S.-China trade from 2005 and 2006, and the software TOMLAB / KNITRO to implement MPEC.[35]

5 Results

5.1 Parameter Estimates and Magnitudes

A key result consistent with the empirical finding of significant persistence in relationships is the large size of switching costs. Table 6 Panel A summarizes the results: the mean values of the switching costs across the sample of products are $\beta_X = 2.84$ and $\beta_C = 1.38$, while the value-weighted averages are $\beta_X = 2.97$ and $\beta_C = 1.22$. The numeric results are interpreted in units of the Type I Extreme Value shock, which has mean 0 and standard deviation $\sqrt{\frac{\pi^2}{6}} \approx 1.29$, giving the following implication: for an importer to be indifferent between its current primary supplier and some other potential primary supplier in the same city charging the same price and having the same quality, the new partner must provide a shock to profits that is approximately $2.84/1.29 = 2.2$ standard deviations above the mean. If that partner is located in a separate city, then the shock to profits must be $(2.84 + 1.38)/1.29 = 3.3$ standard deviations from the mean.[36] The average quality shifter ξ is positive, meaning that higher quality boosts the profits from remaining with a supplier, while the price shifter β_P is negative. Asymptotic standard errors computed as in Rust (1994) indicate that essentially all of the switching cost parameters are statistically significant from zero at a 95% confidence level, along with 68% of the quality shifters and 40% of the price shifters.[37]

Another empirical finding that is consistent with the structural estimates is the importance of

[34]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 standard quantity that should be used for a product, for example. This procedure allows me to reduce egregious outliers while still maintaining prices that are not too far away from the median values.

[35]These products, taken together, account for 22.4% of U.S. imports from China in 2006. Appendix A.6 describes how products are selected. The products, their descriptions, and their trade shares are listed in Appendix Table A3.

[36]Because there are very different prices for the products I use, the measure of deviations from the mean shock is appealing in that differences in costs across products can be analyzed meaningfully.

[37]The full set of estimates is found in Appendix Table A4.

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price and quality for the switching decision. This can be seen by calculating marginal effects–how the probability of staying changes when one's primary supplier unilaterally adjusts its price or quality. This means that, for a small change in price or quality Δ, I calculate

$$ME = \frac{1}{M}\sum_{m=1}^{M}\left[\frac{\partial\left(P\left(x_t^m|x_{t-1}^m,\mathbf{p_{t-1}},\boldsymbol{\beta}\right)\right)}{\partial\Delta}\right] \tag{16}$$

where, as above, $P\left(x_t^m|x_{t-1}^m,\mathbf{p_{t-1}},\boldsymbol{\beta}\right)$ is the probability of staying with one's partner x_t^m and M is the total number of importers.[38] For each of the variables being adjusted to calculate marginal effects (price or quality), I solve the dynamic program for each importer twice, once for $\Delta = 0$ and once for a small Δ, taken as a one standard deviation increase in price or quality. The difference in $P\left(x_t^m|x_{t-1}^m,\mathbf{p_{t-1}},\boldsymbol{\beta}\right)$ is the change in the probability of staying attributable to a one-standard deviation increase in price or quality and thus mirrors the setup of the Linear Probability Model for staying in Section 2.4. Standard errors of this change in probability are calculated using the Delta method, which involves calculating how the expression in Equation (16) changes when changing a component of $\boldsymbol{\beta}$, either β_P or ξ.[39]

Table 6 Panel B summarizes the average marginal effects across HS10 products in the estimation. The results indicate that a one standard deviation increase in price decreases the probability of staying by about 0.3 to 0.5 percentage points, while a one standard deviation increase in quality with increase the probability of staying by about 2 percentage points. Table 6 Panel B also shows that the vast majority of HS10 products have statistically significant effects on the probability of staying. These results are thus in line with the findings in the empirical section showing the importance of price and quality for the probability of staying with a supplier.[40]

The switching cost estimates should be correlated with the rate of switching in a product. Figure 2 plots the share of staying importers for a product against the estimated switching costs. As

[38]This calculation is similar one in Fox (2010).

[39]I use the estimated standard errors to calculate this change using the Delta Method. That is, I increase either β_P or ξ by one asymptotic standard error to see how $\frac{\partial P(\cdot)}{\partial\Delta}$ changes. I do not compute the cross-partial derivatives, that is, the derivative of the price-change-by-Δ expression with respect to quality.

[40]The full set of marginal effects are included in Appendix Table A5.

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expected, there is a strong positive relationship– the larger the fraction of importers staying (either with their primary supplier or in the same city), the larger the switching cost. Figure 2 also shows that one of the HS10 products used in the estimation–HS 7202700000 "Ferromolybdenum"– actually has a negative switching cost, alongside an extremely low staying rate. This product also has by far the largest (in absolute value) price sensitivity parameter, negative 1.167, as well as a quality parameter that is not significantly different from 0. The results make sense because, as a metal alloy, it is likely characterized by homogeneous suppliers in terms of price and quality.

Table 6 Panel C shows the relationship between the structural estimates for my sample of 50 product codes and other product-level characteristics. The first column shows that higher switching costs are correlated with higher contract intensity in that category. Products with more elastic demand tend to have lower switching costs, as do more capital–intensive products. Skill–intensive products have higher switching costs. Outside of the demand elasticity correlation based on Broda and Weinstein (2006) estimates, for which no correlation at the aggregated HS2 level was found, all of these findings are consistent with Figure 1.

Although the switching cost estimates do not translate easily into money-metric terms, it is possible to get some sense of the dollar value. There are two complicating factors- First, although switching costs can be converted into dollars in certain discrete choice models such as Dubé et al. (2009) , because I drop non-continuing importers, the model I estimate lacks an outside option for importing firms. Thus the costs cannot simply be rescaled by the price parameter to generate dollar values (prices also enter the profit equation only in terms of the expected log price). Second, the price coefficient β_P is estimated based on discretized prices (with the number of price state values $N = 5$), hampering the ability to translate the results into dollar terms. However, one simple way to think about the value of the switching costs is in terms of Equation (3). Recall from that equation that $\exp\{\zeta_{X,j}\mathbb{1}\{x^m_{j,t} \neq x^m_{j,t-1}\}\}$ is a multiplicative term to the expected price for an importer's expected per-unit cost from purchasing intermediate j, and that $\beta_X = (1-\alpha)(\sigma-1)\gamma\zeta_X$. For HS category 8525209070, taking $\alpha = 0.5$, $\gamma = 1$, the switching cost of 2.61, and a Broda-Weinstein

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elasticity of $\sigma = 10.6$, this would translate into $\zeta_X = 0.59$.[41] Thus the multiplicative factor on the expected price would be exp$\{0.54\}$=1.7, meaning that paying the cost to switch to a supplier (with the same price and quality as the previous supplier) would lead to per-unit costs increasing by a factor of 1.7. Because the mean unit value in this product category is $71, this back-of-the-envelope calculation would put switching costs at about $49 per unit for this product.[42] Although these estimates of switching costs are large, they should be thought of as more than only a narrowly defined monetary payment, justifying the surprisingly high level of supplier inertia often observed in the data.

5.2 Goodness of Fit and Robustness

Next, I check the performance of the model against one that does not include prices or quality. In particular, I assess goodness of fit by computing the likelihood function using both the full model and a simple benchmark model with no prices or quality. Comparing these via a likelihood ratio test can illustrate whether including price and quality in the dynamic program offers additional explanatory power at matching the data.[43] The average likelihood ratio test statistic across products from this exercise is 3.26, which indicates that including price and quality improves the fit.[44]

The magnitude of the structural estimates for switching costs and the other shifters are consistent across various estimation and sample adjustments. First, there is reasonable concern that the MID supplier identifier in the U.S. import data may be failing to identify foreign exporters to the United States uniquely, one of the reasons why Kamal and Monarch (2018) present a list of sectors where

[41] These parameter values are not imposed in the structural estimation, nor is the constraint that β_P and β_X share the common parameter combination $(1-\alpha)(\sigma-1)\gamma$.

[42] Even though I showed in the empirical analysis that the number of relationships with multiple products is fairly small, switching costs are likely biased upwards somewhat due the possibility of multi-product relationships, as well as the assumption that switching costs do not have a fixed component. Using an average elasticity of substitution of $\sigma = 5$ with the average estimated cost of 2.84 would produce a cost multiplier of around 4.

[43] The Likelihood Ratio Test statistic is $-2\ln\left(\frac{\mathscr{L}(\beta_X,\beta_C)}{\mathscr{L}(\beta_P,\beta_X,\beta_C,\xi)}\right)$, where $\mathscr{L}$ is maximized according to Equations (13) and (14) for each parameter set.

[44] Though the statistic is large for some products, the χ^2 test with 2 degrees of freedom implies that I can only reject the null hypothesis– i.e., the simple model is sufficient to explain the data for the average product– at the 80% level. Even so, including prices and quality in the model is still sensible as they inform the decision about which supplier is chosen when a buyer switches (which is not a part of the switching cost estimate). It also permits the computation of a counterfactual where the reaction to prices and quality can affect the aggregate import price index.

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MIDs are most likely to be constructed correctly. In particular, comparing the number of foreign suppliers exporting to the United States implied by U.S. import data to the same statistics in the World Bank's Exporter Dynamics Database generates a coarse measure of reliability for each sector. The left side of Table 7 Panel A presents the estimates from only those 43 product categories where the number of foreign suppliers in the sector does not exceed the number in the Exporter Dynamics Database by more than 25%. The cost estimates are of very similar magnitude.[45] Second, the empirical section showed that importer size matters for the staying decision. To account for the role of size, I re-estimate the parameters using only the 50 largest importers in each product category, reducing the sample in some categories by more than 50%. The right side of Table 7 Panel A shows the estimates are smaller– larger importers tend to switch more often, especially across cities– but close to the baseline.

5.3 Accounting for Serial Correlation

As mentioned in Section 3.1, another barrier to identification with the estimation procedure is the possibility of serial correlation in the error terms. The ML estimation protocol relies on the error terms being identically and independently distributed Type I Extreme Value, but there may be non-price, non-quality reasons to stay with a supplier. Any unobservable factor for why relationships would stay together would bias the switching cost estimates upwards. Although there are strategies to build in serial correlation directly, because this involves calculating a very complex integral (the likelihood function) over unobserved, serially correlated state variables, I do not estimate such a model.[46] Indeed, in this setting, both the state space and the number of unobservables (one for each possible buyer-supplier pair) are large and vary across products, which makes designing the algorithm challenging and the computational burden high. However, to address this concern, I

[45] If the same supplier has two different MIDs over time, this mis-identification of the MID would likely imply "too much" switching and thus bias the switching costs downward.

[46] Methods for doing so include approximating the likelihood via Monte Carlo methods at a few places and then interpolating the remaining values with a regression (such as in Keane and Wolpin (1994)) or using Bayesian techniques to solve for the EV terms via a Markov chain Monte Carlo process (such as in Norets (2009)). Like this paper, studies such as Miller et al. (2019) also feature a control for a previous purchase without accounting for serial correlation.

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generate relationship data based on serially correlated errors and run the structural model on that data to get a sense of the bias serial correlation could cause.

Specifically, I create 50 importers and 50 exporters within one product category from the estimation sample, HS 8525209070, and draw supplier quality (50, one for each supplier) and buyer-supplier prices (2500, one for each buyer-supplier) from the distribution of those variables in that product category.[47] I then draw 2500 Type I Extreme Value buyer-supplier error terms for each year of the data, but load in a sizable amount of serial correlation– the ε^{m}_{xt} term that enters the importer's decision problem in the choice year is equal to 30% of the previous year's random value plus 70% of the decision year's random value. Buyer-supplier matches are then calculated in each year based on the sum of the components for each potential match, which I then take as data for re-estimating the structural model.[48] I repeat this Monte Carlo procedure 50 times.

Table 7 Panel B shows the results of this exercise. As expected, the resulting estimates of the switching costs using the model known to be misspecified are higher, with the mean estimate of the switching cost parameter over 50 Monte Carlo about 1.6 times higher than the true inputted parameter value. The mean estimate of the city switching cost is about 1.5 times higher. Thus, serial correlation upwardly biases the structural estimates. At the same time, these results do not shake the conclusion of the structural estimation routine– even accounting for bias in this way, the switching cost estimates are still fairly large relative to the Gumbel error term, which has a standard deviation of 1.26 (applying the correction would imply a mean β_X of 1.78 and a mean β_C of 0.95). In particular, the deterministic portion of the supplier-specific profit equation, given by Equation (6), remains important to the decision of whether to remain with one's supplier, relative to the stochastic error component, even when the data are (by construction) strongly serially correlated outside of observable price and quality data. Even if the modeling assumption of purely independent error

[47] I impose the normality assumption for prices and quality, where any draw of the variables is distribution normal with mean and standard deviation from the data. I also draw 2500 prices for the choice year.

[48] To be specific, there are actually three stages: in the first stage, buyers are randomly assigned a supplier; in the second stage, they choose a supplier (which will be the "initial match") based on the observables, the structural parameters and a Type I Extreme Value error term; and in the third stage, they choose based on prices, quality, and an error term consistent with serial correlation. The second stage ensures that initial matches (the state variable) are created using an error term that affects the decision in the same way as the new matches (the choice variable).

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terms is unrealistic, this exercise confers additional validity on the baseline estimates from the import data even in the presence of serial correlation.[49]

5.4 Counterfactual Experiment

Switching costs in this model can be interpreted as import market frictions, meaning firms would like to import from other suppliers but do not. The structural model allows me to assess how U.S. import prices from China would change in response to reduced frictions.

I follow the procedure outlined by the BLS Handbook of Methods to calculate the Import Price Index for my sample.[50] Using the same sample of products as earlier, I then generate data reflecting different switching cost parameters for each product, keeping the state variables the same for each firm (supplier and price in the previous period). I use actual prices charged by suppliers, rather than the discretized price used to estimate the model.[51]

The thought experiment is to reduce both β_X (the partner-switching cost) and β_C (the city-switching cost) by half for all products and track what happens when more importers can separate and potentially find better matches. As the switching cost is measured in units of the Type I Extreme Value ε shock, and results from Section 5.1 implied that a two standard deviation shock would be necessary to countenance switching to an identical partner, this exercise can be thought of as a reduction by one standard deviation in the necessary size of the shock. Running this counterfactual experiment implies that the U.S.-China Import Price Index would decrease by 7.6% in response to such a change.[52] Interestingly, although the overall import price index declines when switching

[49]Table A6 performs the same exercise with non-serially correlated i.i.d. error terms distributed Type I Extreme Value. The procedure returns numbers very close to the inputted parameters, indicating that the maximum likelihood routine delivers unbiased estimates under zero serial correlation.

[50]More detail is provided in Appendix A.7. I make one deviation from the BLS methodology, as I compute the index for the counterfactual and then compare, while the BLS measure compares individual prices first before aggregating to a comparative index. This is because I am comparing model simulations to other simulations. Results are qualitatively similar, but more subject to outliers, if I compare each price first and make one index, rather than making two indices and then comparing.

[51]This exercise relies on the assumption of CES demand with constant markups. If greater market power allowed suppliers with more customers to charge higher prices, the price effects would be smaller.

[52]There is no fixed cost of being in a relationship in the model, since I do not model entry and only consider those importers that exist in both years. If a reduction in switching costs leads to a reduction in prices for incumbents as predicted by the counterfactual, this could induce more entry and more competition, as well as push prices back up.

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increases, average quality also increases slightly under the counterfactual. Another way to think about the counterfactual is that at the original parameter values (and in the data), approximately 50% of firms stayed with their partner, and once the counterfactual is run, that share falls by almost three-fourths, to 13%. Reductions in the supplier cost have a greater effect on exporter switching than reductions in the city cost on switching, as the share of firms staying in the same city drops only by half, from 67% to 31%.[53]

How important would such a reduction in prices be for U.S. buyers? According to official Census data (which is based on the microdata used in this project), China supplied 15.5% of total U.S. imports in 2006, about US$300 billion. This means that if the U.S.-China import price index would decline by 7.6% upon reducing the estimated switching cost by half, then the overall import price index would fall by about 1.2% if switching costs were reduced for China only. Furthermore, according to the World Input-Output Database for 2006, total intermediate usage in U.S. manufacturing was about $3.2 trillion in 2006, about $31 billion (or 1%) of which was imported from China. Therefore, reducing U.S.-China import prices by 7.6% would lower U.S. input costs by about 0.1%. This means that the effects of reducing switching costs even in one country would be fairly small for the overall U.S. economy. On the other hand, if switching costs were reduced for all importing countries, then the effects would be correspondingly larger.[54]

The implications of the counterfactual on prices are robust to other specifications. First, the results are not driven by size differences across firms– when again restricting the sample to only the 50 biggest buyers in each product category, import prices decline by about 7.7%, slightly more than the baseline. Second, I consider the serial correlation correction previously estimated. Recall that when estimating the model on serially correlated data, the estimated switching costs were upwardly biased by about 1.6 times for β_X and 1.5 times for β_C. Applying these shares to switching cost estimates for each product and performing the counterfactual reduces import prices by 4.5%.

How should such a decrease in switching costs be interpreted? The costs in the model can be thought of as anything – positive or negative – preventing the matching of buyers to lower-priced,

[53]The counterfactual results are shown in Table A7.

[54]The share of imported intermediates from all sources in 2006 was about 17% for U.S. manufacturing.

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higher-quality suppliers. Thus, the cost reductions could entail better infrastructure lowering the cost of adjusting import supply chains, better information acquisition about potential suppliers, better contracting institutions, productivity-enhancing measures that could increase overall production capacity, or increases in the bargaining power of U.S. importing firms. Although these are possible interpretations, the current setup cannot distinguish which channel is most prevalent in the data.

The results of these counterfactual experiments point more broadly to the role of importer-exporter dynamics in considering the gains from trade. If, as is typically assumed in trade models, importers equally pay the lowest price available in a market, then this is actually best possible scenario for welfare. Any buyer's divergence from the lowest price will necessarily lower estimates of the gains from trade. At the same time, a robust prediction of the counterfactual is that a reduction in relationship frictions can contribute to lower prices, which can thus be welfare enhancing.

6 Conclusion

In this paper, I have documented, empirically and analytically, that frictions to switching suppliers are large and have important effects on import prices. U.S.-China importer-supplier relationships are characterized by much less turnover than would be expected if supplier choice was random: nearly half of importers remain with their supplier from one year to the next, and one-third of importers switching their primary supplier stay within the same city. I estimate a model of dynamic discrete choice, which uses partner switching costs and geographic switching costs in the context of U.S. decisions to import from Chinese exporters. Switching costs are sizable, while price and quality matter for the supplier decision. I perform a counterfactual experiment to understand the effects on import prices from improved distribution channels and better information. Reducing switching costs such that U.S. importers form alternative matches leads to 7.6% lower prices as well as a higher average quality of supplier.

This project is one step in a robust area for growth in the study of international trade transactions and sourcing patterns. Further research can help us understand when importers change their

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country of importing and, when they do go, where they go. In addition, the literature on information frictions provides a number of clues that might clarify the extent to which persistent firm-to-firm relationships are due to information asymmetries. For example, comparing switching cost estimates for the same product across different countries could help separate out the importance of information frictions. Tracking switching costs as export promotion increases or internet platforms ease matching could be additional tests for the role of informational barriers.

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Table 1: Summary Statistics for U.S.-China Trade Relationships

Panel A: Structure of U.S.-China Relationships

Measure	Median	Mean
Products per Relationship	1	2.1
Products per Supplier	1	3.0
Products per Buyer	2	6.0
Buyers per Supplier (Within HS)	1	1.2
Buyers per Supplier (Total)	1	1.8
Suppliers per Buyer (Within HS)	1	2.3
Suppliers per Buyer (Total)	2	6.8
Suppliers per Product	5	48.3
Buyers per Product	4	28.2

Notes: A buyer is a U.S. importing firm identified in the LFTTD, a supplier is a Chinese supplier, and a relationship is a combination of a buyer and supplier. A product is an HS10 product code. Data includes only non-wholesale, non-retail U.S. importers over the years 2002 through 2008. Wholesalers and retailers are identified by the NAICS code of their primary sector in the Longitudinal Business Database (wholesalers have a NAICS code beginning with 42, while retailers have a NAICS code of 44 or 45.).

Panel B: Distribution of Imports by Partner

Percentile	10	25	Median	75	90	N
Share of Imports at First Partner (All)	0.50	0.72	1	1	1	63000
Share of Imports at First Partner ($>$ 1 Partner)	0.35	0.49	0.61	0.78	0.90	23000
Share of Imports at Second Partner ($>$ 1 Partner)	0.08	0.15	0.24	0.33	0.42	23000
Share of Imports at Second Partner ($>$ 2 Partners)	0.10	0.16	0.23	0.29	0.36	13000

Notes: This table is generated using the sample of non-wholesale non-retail importers from 2002 through 2008. Total imports from each importer's Chinese supplier are calculated in each year. Observation counts are rounded for disclosure purposes.

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Table 2: Margins of Trade

	Suppliers	Buyers	Density	Intensive	Intensive (Buyers Only)
Trade (log)	0.126***	0.069***	0.021***	0.785***	0.932***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
N	20,000	20,000	20,000	20,000	20,000
R^2	0.724	0.541	0.063	0.989	0.995

Notes: For each HS10 product, each of the margins (supplier extensive margin, buyer extensive margin, and the buyer-supplier intensive margin) is regressed on the log value of trade in each product category. Together with the density term- the number of nonzero matches over the total number of possible combinations- the coefficients sum to one. The last column shows the role of the intensive margin when shutting down supplier information. Observation counts are rounded for disclosure purposes.

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Table 3: Summary Statistics for Quality Estimation

	Mean	Median	25th %ile	75th %ile
OLS Price Coefficient	0.005	-0.000	-0.004	0.001
IV Price Coefficient	-0.071	-0.003	-0.047	0.000
Own-price elasticity	-0.439	-0.117	-0.444	-0.019
Over-Identifying Restriction Test, P-Value	0.25	0.10	0.00	0.43
1st Stage F-Statistic P-Value, Price	0.06	0.00	0.00	0.00
1st Stage F-Statistic P-Value, Nest Share	0.07	0.00	0.00	0.01
Conditional Market Share Coefficient	-0.02	-0.11	-0.32	0.14
R^2	0.33	0.28	0.19	0.41
Observations per estimation	3,900	600	200	2,600

Estimations with Statistically Significant Price Coefficient	339
Observations with Statistically Significant Price Coefficient	2,761,000
Total Estimations	823
Total Observations	3,238,000

Notes: The top panel of the table presents summary statistics from the quality estimation procedure described in Section 2.4 across all imported HS6 sectors from China. The bottom panel describes the overall statistics for the estimation procedure. The price coefficients from each sector-level regression generate an own-price elasticity for each variety, so the summary statistics above are the within-sector median. These own-price elasticities are only computed for sectors with negative price coefficients. “Statistically Significant” in the bottom panel is at the 95% level.

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Table 4: Determinants of the Stay-Switch Decision

Panel A: Non-Wholesale/Retail U.S. Firms

Dependent Variable: Stayed with Chinese Supplier Year-to-Year, 2002 through 2008

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
p_{mxht}	-0.026***	-0.016***	-0.026***	-0.022***	-0.022***	-0.018***	-0.022***	-0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
λ_{xht}	0.052***	0.012***	0.050***	0.012***	0.023***	0.004***	0.023***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0004)	(0.001)	(0.001)	(0.001)
$Size_{xt}$		0.057***		0.058***		0.049***		0.052***
		(0.002)		(0.001)		(0.002)		(0.002)
$Size_{mt}$		-0.018***		-0.017***		-0.027***		-0.030***
		(0.001)		(0.001)		(0.001)		(0.001)
$Prod_{mxt}$			0.007***	0.007***			0.003***	0.003***
			(0.0002)	(0.0002)			(0.0001)	(0.0001)
Sample	*Stay*	*Stay*	*Stay*	*Stay*	*StayVal*	*StayVal*	*StayVal*	*StayVal*
N	1,088,000	1,088,000	1,088,000	1,088,000	324,000	324,000	324,000	324,000
R^2	0.12	0.13	0.14	0.14	0.11	0.12	0.12	0.12

Notes: Regression results are based on estimating Equation (2) on U.S. import data from China from 2002 to 2008 for non-wholesale non-retail U.S. firms. The dependent variable for Columns (1) through (4) is whether an importer stayed with a particular supplier year-to-year, while the dependent variable for Columns (5) through (8) is whether an importer stayed with its primary supplier. Year and HS10 fixed effects are included. Bootstrapped standard errors clustered by HS10 product are shown in parentheses. *** denotes significance at the 99% level, ** at the 95% level, and * at the 90% level. Observation counts are rounded for disclosure purposes.

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Panel B: All U.S. Firms

Dependent Variable: Stayed with Chinese Supplier Year-to-Year, 2002 through 2008

	(1)	(2)	(3)	(4)
p_{mxht}	-0.029***	-0.018***	-0.021***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.001)
λ_{xht}	0.050***	0.013***	0.022***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
$Size_{xt}$		0.061***		0.048***
		(0.001)		(0.002)
$Size_{mt}$		-0.026***		-0.028***
		(0.001)		(0.001)
Sample	*Stay*	*Stay*	*StayVal*	*StayVal*
N	2,024,000	2,024,000	714,000	714,000
R^2	0.11	0.12	0.08	0.09

Notes: Regression results are based on estimating Equation (2) on U.S. import data from China from 2002 to 2008 for all U.S. firms. The dependent variable for the Columns (1) and (2) is whether an importer stayed with a particular supplier year-to-year, while the dependent variable for Columns (3) and (4) is whether an importer stayed with its primary supplier. See Section 2 for more detail on how the quality measure λ is constructed. Year and HS10 fixed effects are included. Bootstrapped standard errors clustered by HS10 product are shown in parentheses. *** denotes significance at the 99% level, ** at the 95% level, and * at the 90% level. Observation counts are rounded for disclosure purposes.

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Table 5: Determinants of Staying, Alternative Measures

Panel A: Importer-Exporter Level

	$\widetilde{Stay}_{mxt}$	$\widetilde{Stay}_{mxt}$	$StayAny_{mxt}$	$StayAny_{mxt}$	$StayAll_{mxt}$	$StayAll_{mxt}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\widetilde{p}_{mxt}$	-0.014***	-0.015***	-0.015***	-0.016***	-0.012***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\widetilde{\lambda}_{xt}$	0.027***	0.029***	0.031***	0.033***	0.018***	0.007***
	(0.0003)	(0.0004)	(0.0004)	(0.001)	(0.0004)	(0.0003)
$Size_{xt}$		-0.012***		0.002		0.041***
		(0.001)		(0.001)		(0.001)
$Size_{mt}$		0.012***		-0.019***		-0.022***
		(0.0004)		(0.001)		(0.001)
N	748,000	748,000	545,000	545,000	545,000	545,000

Notes: Regression results from estimating Equation (2) on U.S. import data from 2002 to 2008 for non-wholesale non-retail U.S. firms. The dependent variable for Columns (1) and (2) is the weighted average of staying decisions across products, the dependent variable for Columns (3) and (4) is whether an importer stayed with its supplier for any product, and the dependent variable for Columns (5) and (6) is whether an importer stayed with its supplier for all products. Year and primary HS10 fixed effects are included. Bootstrapped standard errors clustered by HS10 product are shown in parentheses. *** denotes significance at the 99% level, ** at the 95% level, and * at the 90% level. Observation counts rounded for disclosure purposes.

Panel B: Single-Supplier Importers

	$Stay_{mxht}$	$Stay_{mxht}$	$\widetilde{Stay}_{mxt}$	$StayAny_{mxt}$	$StayAll_{mxt}$
	(1)	(2)	(3)	(4)	(5)
p_{mxht}	-0.027***	-0.019***			

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	(0.001)	(0.001)			
λ_{xht}	0.039***	0.007***			
	(0.001)	(0.002)			
$Size_{xt}$		0.010***			
		(0.003)			
$Size_{mt}$		0.049***			
		(0.002)			
$\widetilde{p}_{mxt}$			-0.015***	-0.009***	-0.007***
			(0.001)	(0.002)	(0.003)
$\widetilde{\lambda}_{xt}$			0.022***	0.016***	0.015***
			(0.001)	(0.001)	(0.001)
N	148,000	148,000	51,000	17,000	17,000

Notes: Regression results from estimating Equation (2) on U.S. import data from China from 2002 to 2008 for non-wholesale non-retail U.S. firms with one supplier, either within an HS (Columns (1) and (2)) or overall (Columns (3) through (5)). The dependent variable for Column (3) is the weighted average of staying decisions across products, and the dependent variable for Columns (4) and (5) is whether an importer stayed with its supplier for any or all products. Price and quality regressors are weighted across products. Year and HS10 fixed effects are included. Bootstrapped standard errors clustered by HS10 product shown in parentheses. *** denotes significance at the 99% level, ** at the 95% level, and * at the 90% level. Observation counts rounded for disclosure purposes.

Panel C: Multi-year Relationships

	$Stay_{mxht}$	$Stay_{mxht}$	$Stay2_{mxht}$	$Stay2_{mxht}$	$Stay5_{mxht}$	$Stay5_{mxht}$
	(1)	(2)	(3)	(4)	(5)	(6)
p_{mxht}	-0.020***	-0.010***	-0.013***	-0.007***	-0.003***	-0.002***
	(0.002)	(0.002)	(0.0003)	(0.0004)	(0.0004)	(0.0004)

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λ_{xht}	0.058***	0.012***	0.031***	0.008***	0.008***	0.003***
	(0.001)	(0.002)	(0.0002)	(0.0004)	(0.0002)	(0.0005)
$Size_{xt}$		0.069***		0.025***		0.005***
		(0.003)		(0.0006)		(0.0006)
$Size_{mt}$		-0.023***		0.011***		0.003***
		(0.001)		(0.0002)		(0.0002)
N	269,000	269,000	764,000	764,000	136,000	136,000

Notes: Regression results from estimating Equation (2) on U.S. import data from China from 2002 to 2008 for non-wholesale non-retail firms. Columns (1) and (2) eliminate 1-year relationships, the dependent variable for Columns (3) and (4) is if an importer stayed with a partner after 2 years, and the dependent variable for Columns (5) and (6) stayed with a partner after 5 years. Year and HS10 fixed effects included. Bootstrapped standard errors clustered by HS10 product in parentheses. *** denotes significance at the 99% level, ** at the 95% level, and * at the 90% level. Observation counts rounded for disclosure purposes.

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Table 6: Summary of Estimation Results

Panel A: Parameter Estimates

		Mean	Weighted Average	Mean S.E.	Statistically Significant %
β_X	Partner Cost	2.84	2.97	0.11	100
β_C	City Cost	1.38	1.22	0.12	98
ξ	Quality Shifter	0.04	0.03	0.02	68
β_P	Price Shifter	-0.07	-0.06	0.10	40

Notes: These estimates are the mean and weighted average (by total import value of the product) across the 50 HS10 products used in the analysis. The switching cost estimates are different from zero at the 1% level when calculating asymptotic standard errors as in Rust (1994). The results are in units of the Type I Extreme Value Distribution. Statistical significance is calculated using asymptotic standard errors at the 95% level.

Panel B: Average Marginal Effects

	Mean	Weighted Average	Mean S.E.	Statistically Significant %
Price	-0.35	-0.54	0.09	98
Quality	2.51	2.16	0.04	92

Notes: This table summarizes the average marginal effects, calculated by determining the increase in the probability of staying with a supplier given a one standard-error increase in that supplier's price or quality. Statistical significance is determined at the 95% level using standard errors calculated using the Delta Method.

Panel C: Parameter Correlations

	Contract Intensity	Elasticity of Substitution	Capital Intensity	Skill Intensity
β_X	0.22	-0.18	-0.15	0.18
β_C	0.00	-0.06	-0.15	-0.21
$\beta_X + \beta_C$	0.21	-0.21	-0.27	0.02
β_P	0.32	-0.27	-0.26	0.11
ξ	-0.09	0.01	0.08	-0.10

Notes: These are the correlations of model parameters with other product-specific and industry-specific variables, including the contract intensity measure z_1 defined in Nunn (2007), the elasticity of substitution parameter σ estimated in Broda and Weinstein (2006), and capital and skill intensities calculated from the 2007 U.S. Census of Manufactures.

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Table 7: Model Estimates: Robustness

Panel A: Alternative Sample Estimations

Good MID Measurement				Biggest Buyers Only			
		Mean	Weighted Average			Mean	Weighted Average
β_X	Partner Cost	2.88	2.97	β_X	Partner Cost	2.77	2.92
β_C	City Cost	1.40	1.23	β_C	City Cost	1.40	1.23
ξ	Quality Shifter	0.04	0.04	ξ	Quality Shifter	0.04	0.03
β_P	Price Shifter	-0.06	-0.07	β_P	Price Shifter	-0.04	-0.05

Notes: The first table presents a summary of the model estimates using only those 23 sector categories in which the MID is found to measure suppliers better, as based on the comparison with the Exporter Dynamics Database found in Kamal and Monarch (2018) Table 9. The second table limits the estimation to only the top 50 importers by size in each product category.

Panel B: Monte Carlo Replication: Model Estimates with Serially Correlated Errors

	Parameter	Mean	Median	Standard Deviation
β_X	2.61	4.23	4.18	0.70
β_C	1.33	1.93	1.87	0.99

Notes: This table presents the results of 50 Monte Carlo runs of the model, in which the underlying unobservables exhibit serial correlation. The true input parameters, corresponding to model estimates for HS 8525209070, are given in the first column.

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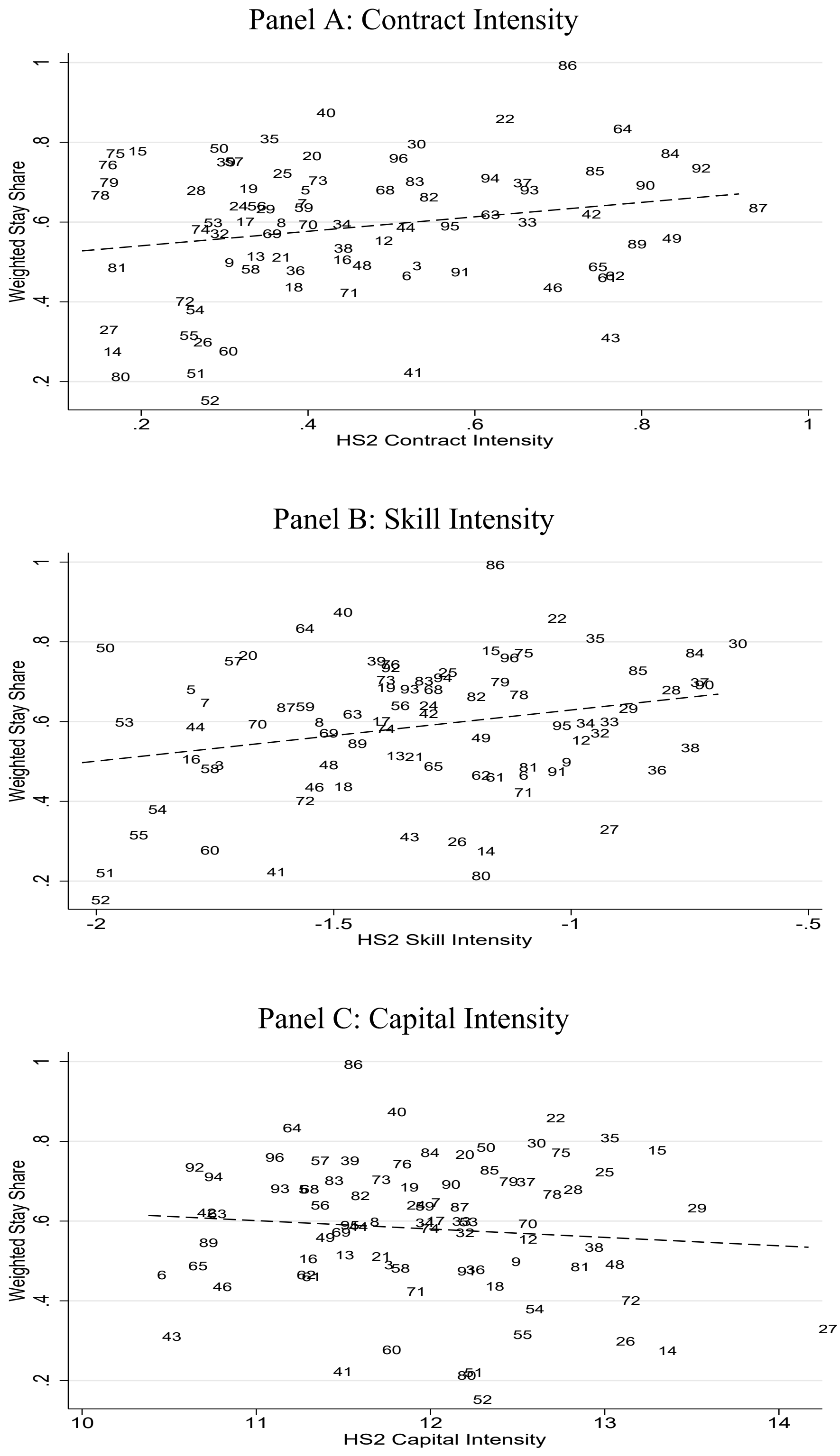
Figure 1: "Staying" Share vs. HS2 Industry Characteristics



Notes: These figures plot weighted HS2 staying shares against industry characteristics. Appendix A.2 details how these measures are constructed.

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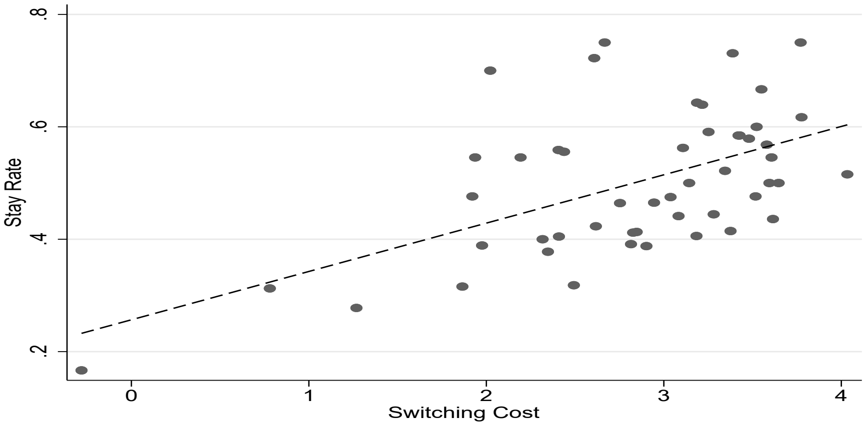
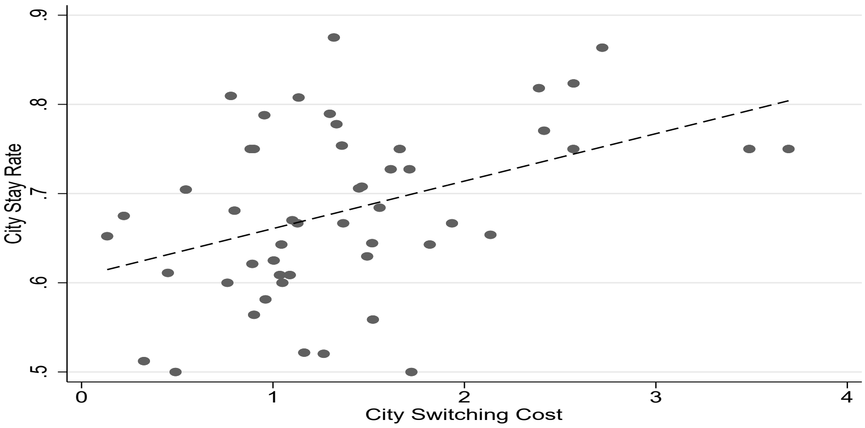
Figure 2: Switching Cost Estimates and Staying Rates

Panel A: β_X vs. Staying Rate



Panel B: β_C vs. City Staying Rate



Notes: These figures plot the estimated switching costs β_X and β_C against the respective staying rates for each product in the estimation routine.