

Firm-to-Firm Relationships and Price Rigidity

Theory and Evidence^{*}

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Abstract

Economists have long suspected that firm-to-firm relationships might increase price rigidity due to the use of explicit or implicit fixed-price contracts. Using transaction-level import data from the U.S. Census, I study the responsiveness of prices to exchange rate changes and show that prices are in fact substantially *more* responsive to these cost shocks in older versus newly formed relationships. Based on additional stylized facts about price setting and trading volumes throughout a relationship's life cycle, I develop a model of relationship dynamics in which a buyer and a seller interact repeatedly under limited commitment and accumulate relationship capital in proportion to sales to lower production costs. In a new relationship, capital is low, and the seller responds little to shocks and sets low mark-ups to incentivize the buyer to maintain the association and to build up relationship capital. These motives are weaker in old relationships, which on average have more capital, increasing the price response to shocks and raising mark-ups. Once structurally estimated, the model generates countercyclical mark-ups and countercyclical pass-through of shocks through variation in the economy's average relationship length, which rises in recessions.

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1 Introduction

This paper examines how relationships between firms affect price flexibility, where I define a relationship as a buyer-seller pair that has been engaged in trade for a certain period of time. Economists have long suspected that relationships might be important for monetary policy, increasing price rigidity due to the use of fixed-price contracts (e.g., [Barro \(1977\)](#), [Carlton \(1986, 1989\)](#)). Such contracts might for example explain why pass-through of exchange rate shocks into prices is low, an important puzzle in international trade.¹ In fact, using U.S. import data I show that long-term relationships – presumably more likely to use either implicit or explicit contracts – display a *higher* responsiveness of prices to cost shocks than new relationships. My finding implies that an economy’s aggregate responsiveness of prices to shocks may vary with the average length of its underlying relationships.

A well-documented fact in the management literature is that long-term relationships account for a large and growing fraction of buyer-seller pairs in the U.S. economy.^{2,3} However, little work has been done to investigate relationships’ aggregate effects, since large-scale datasets mapping the linkages between domestic buyers and sellers are generally unavailable.⁴ To make progress on this issue, I study relationships using trade data from the Longitudinal Firm Trade Transactions Database (LFTTD) of the U.S. Census. These data identify both the U.S. importer and the foreign exporter for each of 130 million arms’ length import transactions conducted by U.S. firms during the past two decades. As in the domestic economy, long-term relationships are common in U.S. imports – in an average quarter, about 53% of U.S. arms’ length imports are sourced within importer-exporter pairs that have been transacting with each other for at least 12 months.

The trade data reveal that prices become more responsive to cost shocks the longer a relationship has lasted. Specifically, within an importer-exporter relationship, the pass-through of exchange rate shocks into import prices is 50% higher when the relationship is four years older. In a new relationship, price movements on average reflect 15% of the exchange rate change since the last transaction,

¹See e.g., [Krugman, Baldwin, Bosworth, and Hooper \(1987\)](#), [Goldberg and Knetter \(1997\)](#), [Gopinath and Rigobon \(2008\)](#), [Gopinath, Itskhoki, and Rigobon \(2010\)](#), [Burstein and Gopinath \(2014\)](#).

²For example, [Cannon and Perreault Jr. \(1999\)](#) survey a sample of more than 400 buyer-supplier pairs from a cross-section of sectors and find that the pairs sampled have on average been transacting with each other for 11 years - even though the buyer has multiple suppliers for the product in 76% of the cases. [Kotabe, Martin, and Domoto \(2003\)](#) find that suppliers in the U.S. automotive industry have on average been transacting with major buyers for 26 years.

³Surveys suggest that long-term relationships have become more common over the last three decades. See e.g. [Lyons, Krachenberg, and Henke Jr. \(1990\)](#), [Han, Wilson, and Dant \(1993\)](#), [Helper and Sako \(1995\)](#), [Gadde and Snehota \(2000\)](#), [Liker and Choi \(2004\)](#).

⁴There exists a large management literature on firm-to-firm relationships. This literature is almost exclusively based on qualitative surveys. See e.g. [Noordewier, John, and Nevin \(1990\)](#), [Parkhe \(1993\)](#), [Cannon and Homburg \(2001\)](#), [Palmatier, Dant, and Grewal \(2007\)](#). In economics, [Drozd and Nosal \(2012\)](#) and [Gourio and Rudanko \(2014\)](#) study customers as capital. However, they do not examine how customer relationships evolve over time and how relationship length affects aggregate outcomes.

compared to 23% in a four-year relationship. The result is robust to a wide range of specifications, and holds for positive and negative exchange rate shocks.

I document several additional characteristics of relationships, which will form the basis of a model. I analyze the dynamics of value traded, price setting, and the break-up probability of buyer-seller pairs, and show that relationships follow a life cycle. New relationships trade small values and have a high likelihood of separation. As the relationship ages and survives, the value traded rises while the transaction price relative to the market and the separation probability fall. Trade declines again near the relationship's end. This life cycle is quantitatively important: a six-year relationship trades at its peak in year three 21% more than in year one, and exhibits price reductions of about 2% on each transaction relative to the market price. I relate my findings to the survey-based management literature on the relationship life cycle (e.g., [Dwyer, Schurr, and Oh \(1987\)](#), [Ring and van de Ven \(1994\)](#)) and show that my results are consistent with that work. My findings are also consistent with qualitative evidence from 16 interviews I conducted with purchasing managers of mostly large, international firms.

To rationalize the empirical findings, I develop a model of relationship dynamics under two-sided limited commitment. A buyer and a seller firm interact repeatedly, and have the outside option to leave the relationship to search for an alternate partner. The seller's production costs are subject to aggregate shocks, which I will interpret as arising from exchange rate movements. In addition to that, marginal production costs are affected by the pair's level of *relationship capital*, which represents the extent to which the partners have built up customized assets or learnt about each other, as suggested in the management literature.⁵ Relationship capital accumulates in proportion to the quantity traded, for example because a larger volume makes investment into specialized machines more worthwhile. Relationship capital is also subject to idiosyncratic shocks, reflecting for example staff turnover. This setup generates an incentive for the seller to charge a lower price than under static profit optimization to sell more and to build up capital more quickly, similar to models with *customer capital* in which a seller lowers price to build up a stock of customers ([Gourio and Rudanko \(2014\)](#), [Paciello, Pozzi, and Trachter \(2016\)](#)). Since relationship capital is subject to diminishing returns, this motive is strongest for low capital levels. A new feature of my model is that price setting is also affected by both firms' outside options. When the buyer's outside option binds, the seller has to lower the price to provide more surplus to and maintain the relationship with the buyer. When the seller's outside option binds, the relationship separates endogenously because the seller's maximized relationship value is lower than the value of searching for an alternate customer.

The model generates the relationship life cycle and higher average pass-through in older relation-

⁵[Parkhe \(1993\)](#), [Dyer \(1996\)](#), [Doney and Cannon \(1997\)](#), [Artz \(1999\)](#), [Palmatier, Dant, and Grewal \(2007\)](#), among others, find that customized assets are a key source of the value of long-term relationships.

ships. A new relationship on average starts with a low level of relationship capital. Production costs are high and prices are therefore elevated, implying low purchases by the buyer and a high likelihood of separation. Since an extra unit of relationship capital is very valuable, the seller sets a low mark-up to build up relationship capital quickly. Furthermore, cost shocks that cause the buyer's outside option to bind lead the seller to reduce her mark-up to maintain the relationship, implying on average lower pass-through of shocks. Relationships that experience good idiosyncratic shocks to relationship capital manage to reduce their production costs, leading to lower prices, more trade, and a smaller likelihood of separation. Since additional relationship capital becomes less valuable, the seller increases her mark-up. Prices also become more responsive to shocks since the buyer's outside option less frequently binds. On the other hand, relationships that experience idiosyncratic shocks that are sufficiently bad to overcome the endogenous accumulation force lose relationship capital and therefore trade less, and are terminated once capital becomes sufficiently low. Each individual relationship therefore follows a life cycle. However, older relationships on average have more relationship capital through selection. They therefore on average have lower prices and display a higher responsiveness of prices to shocks, as in the data. My model generates a novel source of pass-through and mark-up dynamics that arises endogenously from relationship capital accumulation under limited commitment.

I examine two alternative models. First, I show that a model with variable mark-ups in the spirit of [Atkeson and Burstein \(2008\)](#), in which older relationships are associated with higher market shares, counterfactually generates declining pass-through with relationship age, since higher market shares lead firms to price more to market. [Berman, Martin, and Mayer \(2012\)](#) corroborate this intuition and show that higher market shares lead to lower pass-through into prices measured in importer currency. Second, I show that a model in which prices are set by Nash bargaining generates flat pass-through since in that case the price splits the joint surplus, which includes the value of the outside options.

Several other implications of the baseline model are supported in the data. First, I examine the effect of the buyer's outside option on the responsiveness of prices to shocks. If firm size is correlated with outside option values, the buyer's outside option should be more binding in young relationships when the buyer is large or when the seller is comparatively small. Consistent with this view, pass-through rises strongly with relationship age in both these cases, while pass-through is relatively flat for large sellers since the buyer's outside option might not be relevant in that case. While previous work has documented that small exporters have higher pass-through into import prices ([Berman, Martin, and Mayer \(2012\)](#), [Chatterjee, Dix-Carneiro, and Vichyanond \(2013\)](#)), my work is the first to document that firms' outside options are important for pass-through. Three additional implications of the relationship life cycle also find empirical support. First, pass-through increases with the value and the number of products a relationship trades relative to the first year, in line with pass-through increas-

ing with relationship quality. Second, pass-through is diminished in the year before the relationship is terminated, when relationship capital is likely to be low. Third, relationships that have high pass-through in the first year last longer, consistent with such relationships having had a high initial draw of relationship capital.

I structurally estimate the model with a continuum of buyer-seller relationships using simulated method of moments. Each buyer-seller pair sells a differentiated variety to a representative household. I show that, when calibrated to the life cycle, the model quantitatively matches the untargeted empirical correlation between pass-through and relationship age.⁶ I then examine how cyclical variation in relationship length affects pass-through and mark-ups. The average length of relationships rises in recessions: for example, the number of relationships of age less than one year fell by one fifth in 2008-09, compared to a significantly smaller drop for longer relationships. My calibrated model suggests that an increase in average relationship length in the economy by one month can generate an increase in the responsiveness of prices to shocks by about one third and in consumer mark-ups by about 16%. Variation in the average relationship length in the economy thus provides a novel explanation for why prices become more responsive to shocks in recessions ([Berger and Vavra \(2018\)](#)) and for countercyclical mark-ups (e.g., [Rotemberg and Woodford \(1999\)](#)), and is therefore of importance for monetary policy.

Related literature. My paper contributes to two broad strands of literature. First, it is related to the growing body of work that uses two-sided international trade data to study the properties of relationships. For example, [Eaton, Eslava, Jinkins, Krizan, and Tybout \(2015\)](#) study associations between U.S. importers and Colombian suppliers, and calibrate a search and matching model of exporter learning. [Monarch \(2015\)](#) examines break-ups and switching in relationships with Chinese firms, while [Monarch and Schmidt-Eisenlohr \(2016\)](#) present evidence on the value of long-term relationships. They develop a model in which importers learn about the quality of their supplier, and show that the value of relationships differs across countries. [Macchiavello and Morjaria \(2015\)](#) test a model of relational contracting in the Kenyan flower industry, and show that longer relationships can relax limited commitment constraints. While these papers have focused on the micro-level properties of customer-supplier matches, my work presents novel evidence on how relationship price setting and the evolution of relationships over the business cycle can affect aggregate outcomes.

Second, my work contributes to a large literature on exchange rate pass-through and the responsiveness of prices to shocks (e.g., [Goldberg and Knetter \(1997\)](#), [Gopinath and Rigobon \(2008\)](#)). This literature argues that pass-through is heterogeneous across firms. For example, [Atkeson and Burstein](#)

⁶Since the model generates complete pass-through when neither agent is constrained, while in the data pass-through is generally incomplete, I assume that imported inputs insulate part of the seller's costs from exchange rates, as documented by [Goldberg and Verboven \(2001\)](#).

(2008) embed a model of imperfect competition into a quantitative international trade model, and show that firms with a larger market share price more to market and therefore have lower pass-through into import prices. [Berman, Martin, and Mayer \(2012\)](#) document that pass-through into import prices is lower for high performance firms. [Neiman \(2010\)](#) shows that the responsiveness of prices to exchange rate shocks is higher in intrafirm relationships than in arms’ length associations. [Berger and Vavra \(2018\)](#) find that pass-through rises in recessions, and suggest that this finding could be driven by time variation in the super elasticity of demand. My paper shows that pass-through also depends of the average age of relationships. I develop a novel mechanism that generates countercyclical pass-through and mark-ups through variation in the economy’s average relationship length.

This paper proceeds as follows. In Section 2, I present the empirical analysis. I first introduce the data, define a relationship, and provide some summary statistics. I then present reduced-form evidence on pass-through and relationship length. Finally, I document additional stylized facts on the evolution of relationships. These facts form the basis of a model, which I introduce in Section 3. I characterize the model equilibrium, discuss alternative setups, and test model implications in the data. In Section 4, I estimate the model and examine its aggregate implications. Section 5 concludes.

2 Firm-to-Firm Relationships: Stylized Facts

2.1 Data

Due to the lack of data mapping customer-supplier linkages in the U.S. domestic economy, I study relationships between U.S. firms and their overseas suppliers using international trade data from the *Longitudinal Firm Trade Transactions Database (LFTTD)* of the U.S. Census Bureau.⁷ This dataset is based on customs declarations forms collected by U.S. Customs and Border Protection (CBP), and comprises the entire universe of import transactions in goods⁸ made by U.S. firms during the period 1992-2011. These data record for each import transaction an identifier of the U.S. importer (called “alpha”) as well as a foreign exporter ID (the “manufacturer ID”). This information on both transaction partners makes the study of relationships possible. Recent work by [Monarch \(2015\)](#) and [Kamal, Krizan, and Monarch \(2015\)](#) suggests that the foreign firm identifiers are reliable over time and in the cross-section. I will draw on survey evidence throughout the paper to link my findings to results for domestic relationships.

In addition to the firm identifiers, the LFTTD dataset also comprises the 10-digit Harmonized Sys-

⁷Recent work in international trade using this dataset includes [Bernard, Jensen, and Schott \(2009\)](#), [Eaton, Eslava, Jinkins, Krizan, and Tybout \(2015\)](#), [Monarch \(2015\)](#), and [Monarch and Schmidt-Eisenlohr \(2016\)](#).

⁸Trade in goods accounted for 83% of all U.S. imports in 2013.

tem (HS10) code of the product traded⁹, the country of the foreign exporter, the value and the quantity shipped (in U.S. dollars), the date of the shipment, and an identifier whether the two transaction parties are related firms.¹⁰ The U.S. firm identifier can be linked to other Census products such as the *Longitudinal Business Database (LBD)*, which provides annual information at the establishment-level about payroll, number of employees, and NAICS code of the establishment. I aggregate information in the LBD across all of a firm’s establishments in each year, and assign each firm to the industry that is associated with most of its employees.

I focus on arms’ length relationships only and exclude related party transactions, which include for example intra-firm trade, by dropping all transactions in years for which a relationship records at least one related party trade. Associations between related parties are likely to be much deeper than relationships between unrelated firms, due to the substantial equity investments made. I compute (log) prices as unit values by dividing the shipment value by the quantity shipped, as in [Monarch \(2015\)](#) and [Monarch and Schmidt-Eisenlohr \(2016\)](#). This is only an imperfect measure of the true price, since it assumes that products are homogeneous within an HS10. In reality, there is likely to be some heterogeneity even within HS10 codes, for example due to quality differences. In my analyses, I treat the same HS10 shipped from different countries as different products, and run regressions using country fixed effects or focus on price changes within the same relationship to alleviate this problem. For all analyses involving prices, I trim the dataset in each quarter by removing transactions whose prices lie below the 1st or above the 99th percentile of the price distribution for the associated product-country pair, and drop price changes larger than four log points within the same relationship. Appendix [A](#) discusses the variables and data cleaning operations in more detail.

2.2 Relationships in the Data

I define a relationship as an importer-exporter pair trading at least one, but possibly many, products, and compute relationship length as follows. First, I assign a relationship length of one month at the first time an importer-exporter pair appears in the data. Since many relationships in 1992-1994 are likely to have started before the beginning of the dataset, the data in these years will only be used to initiate relationships, and will be dropped from all analyses. Next, whenever another transaction of the importer-exporter pair occurs in any good, the relationship length is increased by the number of

⁹Examples of HS10 products are “Coconuts, in the inner shell” or “Woven fabrics of cotton, containing 85 percent or more by weight of cotton, weighing no more than 100g/m2, unbleached, of number 43 to 68, printcloth”.

¹⁰Based on Section 402(e) of the Tariff Act of 1930, related party trade includes import transactions between parties with various types of relationships including “any person directly or indirectly, owning, controlling, or holding power to vote, 6 percent of the outstanding voting stock or shares of any organization”.

months passed.¹¹ To determine the termination date of a relationship, I first take all importer-exporter-product (HS10 code) observations in the data and record the time passed until the next observation of the same triplet. This provides an idea about how much time typically elapses, for each product, between a relationship's subsequent transactions of that good. I take the distribution of these gap times for each HS10 product across the entire dataset and determine the 95th percentile of this distribution. I refer to this product-level statistic as the product's *maximum gap time*. A relationship is assumed to have ended if for a given importer-exporter pair, first, none of the products previously traded is traded within its maximum gap time, and, second, no new products are traded within that time interval. Based on this definition, a relationship is terminated if no transactions for any product are observed for a significantly longer time period than would be normal. If an importer-exporter pair appears again in the data after the end of a relationship, I treat this as a new relationship.¹² This definition allows me to handle the fact that the data are right-censored in 2011, and to determine more clearly whether relationships that stop trading in, e.g., 2010 are terminated. Second, a number of importer-exporter pairs trade very rarely, which generates zero trade in most years of the association. My definition focuses on relationships that trade regularly.

Table 1 provides some summary statistics for both the entire dataset (Column 1) and for transactions in relationships that last for more than 12 months in total (Column 2). I find that 38% of trade in an average quarter takes place in relationships that are arms' length in the year of the transaction (Row 1). Relationships that are unrelated at any point of their existence account for 27% of trade (Row 2).

The remaining rows present additional statistics for arms' length relationships. Rows 3-5 show that each importer has on average more than two arms' length suppliers per HS10 product, while each exporter tends to have about one U.S. customer. From other datasets, it is well-known that there is significant heterogeneity across importers, with a few large firms having an extremely large number of counterparties.¹³ The average time gap between transactions of the same importer-exporter-product triplet is less than one month across all products, and the average maximum gap time is about 10 months. The last four rows document average relationship lengths for the entire dataset and by industry of the importer, based on the firm's NAICS code. Figure I.12 in Appendix I.1 shows the distribution of trade by industry of the importer in the average quarter. In terms of relationship lengths, I do not find significant differences for these industries.

Figure 1 provides a more detailed distribution of value traded by relationship length.¹⁴ The blue

¹¹As an alternative to the number of months, I could also define age based on the number of transactions. The results are generally similar.

¹²I keep track of the fact that this is a continued relationship using a dummy variable, which I use in some of the regressions below.

¹³See e.g. [Blaum, Lelarge, and Peters \(2013\)](#), for France; [Gopinath and Neiman \(2014\)](#), for Argentina

¹⁴I compute the trade value by relationship length in each quarter, and average across quarters. To account for relation-

Table 1: Summary statistics of the dataset

		Length of Included Relationships	
		(1) All	(2) >12 months ¹
(1)	Arms' length trade	38%	32%
(2)	Arms' length trade (always unrelated)	27%	21%
Arms' length trade			
(3)	Exporters per importer-HS10, p.a.	2.7	2.2
(4)	Importers per exporter-HS10, p.a.	1.2	1.2
(5)	HS per importer-exporter, p.a.	1.9	3.0
(6)	Average gap time between transactions (months)	0.6	0.6
(7)	Average maximum gap time (months)	10.0	—
(8)	Average relationship length (months)	5.7	30.0
(9)	... in Manufacturing	5.9	30.6
(10)	... in Wholesale / Transportation	5.7	30.6
(11)	... in Retail	5.9	28.7

¹ Statistics consider only those relationships that last in total for more than 12 months.

bars in the figure show the distribution of value traded in an average quarter by current relationship length, and illustrate that 53% of the value traded in arms' length transactions is accounted for by relationships that have been together for more than 12 months. About 18% is due to pairs that have been together for more than 4 years. The orange bars in Figure 1 display the equally-weighted distribution of buyer-seller associations by length in the average quarter, and show that close to 44% of all importer-exporter pairs observed in an average quarter are new matches. However, such new matches account for only 15% of the value traded.

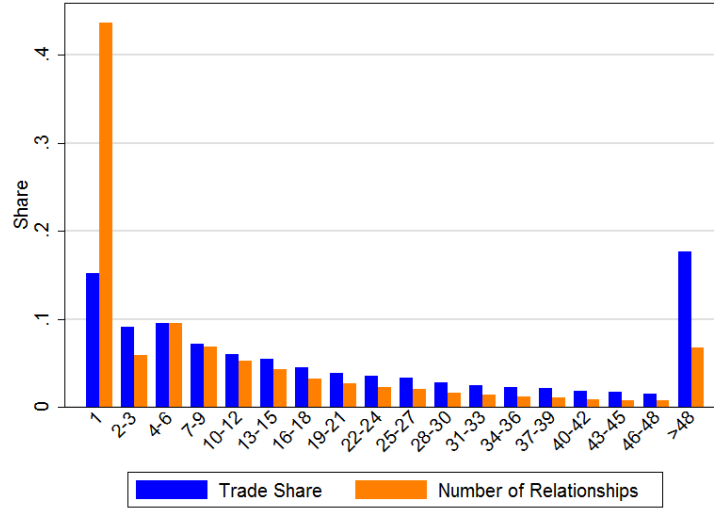
Survey evidence suggests that long-term relationships are also important in the domestic U.S. economy. Table I.15 in Appendix I.2 presents the average length of domestic buyer-seller associations, based on the time passed since the first interaction. The table highlights that the average U.S. relationship is several years old, and relationships with major suppliers can last for decades. This evidence suggests that long-term relationships are not only an international trade phenomenon.

2.3 Reduced-Form Evidence on the Responsiveness of Prices to Shocks

I now turn to the main research question of this paper and examine the connection between relationship length and price flexibility. Barro (1977) and Carlton (1986) suggest that long-term relationships could be an important source of price rigidity due to the use of contracts which specify fixed prices

ship lengths up to 48 months, I drop the first five years for this analysis, up to and including 1996.

Figure 1: Average share of trade and share of relationships by length (in months)



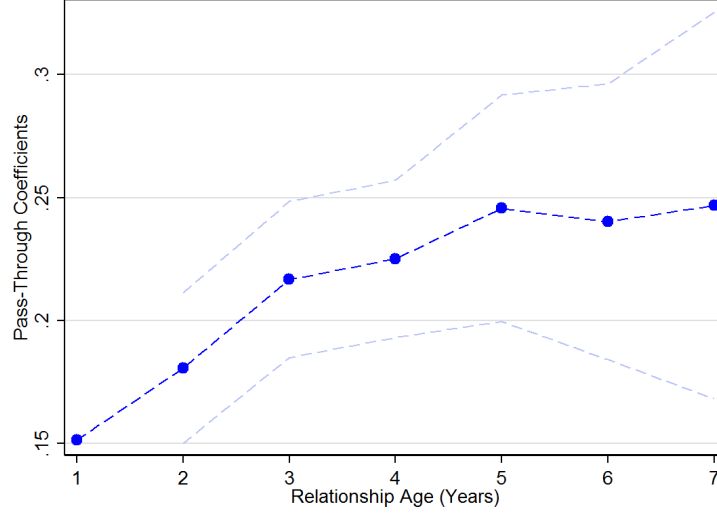
for a period of time. To study this question, I examine how relationships of different length affect firms' price response to an identifiable cost shock. I argue that exchange rate shocks can be used as an easily observable source of exogenous variation in the exporter's costs, following [Berger and Vavra \(2018\)](#). Specifically, I study the share of exchange rate movements since the last transaction of an importer-exporter-product triplet that is passed through into prices at the next transaction. The exchange rates used are obtained from the OECD's Monetary and Financial Statistics database and measured in foreign currency units per U.S. dollar. I supplement these data with rates from Datastream for Eurozone countries.¹⁵ To focus only on relationships which are market-based throughout their life, I apply a more stringent filter from now on and drop all relationships which are ever related at any point.¹⁶ Let m index an importer, x the exporter, c the exporter's country, and h the HS10 product. A relationship is indexed by mx .

To visualize how the responsiveness of prices to shocks varies with relationship age, as a first pass I regress price changes between subsequent transactions of a given relationship on the change in the exchange rate between these transactions and relationship length dummies. I aggregate the transaction-level data at the quarterly level in order to smooth out noise in the unit values, and compute exchange rate shocks for each transaction as the cumulative change in the exchange rate since the last

¹⁵Euro exchange rates are converted into the implied local rate using the conversion rate at the time of the adoption of the Euro to construct consistent time series for each Eurozone country. In total, I have data for 45 countries, presented in Appendix C.

¹⁶This implies that all relationships that switch status at any point are dropped. In future work, I plan to investigate the link between a relationship's features and its probability of making a transition into related party status. There is a large theoretical literature on firms' decisions regarding market-based production vs. integration (see e.g. [Grossman and Helpman \(2002\)](#)). See [Carballo \(2014\)](#) for recent work on this topic using Census export data.

Figure 2: Responsiveness of Price to Exchange Rate Shock



transaction of the same relationship-product triplet. I then run

$$\Delta \ln(p_{mxchi(t)}) = \beta_0 + \beta_1 \Delta \ln(e_{ct}) + \sum_{l=2}^7 \beta_l d_{mxi(t)} + \sum_{l=2}^7 \theta_l d_{mxi(t)} \cdot \Delta \ln(e_{ct}) + \gamma_{mxh} + \omega_t + \varepsilon_{mxchi(t)}, \quad (1)$$

where $\Delta \ln(p_{mxchi(t)})$ is the log nominal price change between transaction i and $i - 1$ for relationship mx trading product h in quarter t , $\Delta \ln(e_{ct})$ is the cumulative exchange rate change since the last transaction of the relationship for that product, $d_{mxi(t)}$ are dummies for the length of relationship mx at transaction i in years (up to seven years), and γ_{mxh} and ω_t are relationship-product fixed effects and time fixed effects, respectively. Standard errors are clustered at the country-level. The analysis is similar to pass-through regressions run for example in [Campa and Goldberg \(2005\)](#), [Gopinath, Itskhoki, and Rigobon \(2010\)](#), or [Berger and Vavra \(2018\)](#), but takes into account the identity of the importer-exporter pair. Figure 2 presents the pass-through coefficients β_1 for year one and the coefficients $\beta_1 + \theta_l$ for the later years, as well as the 95% confidence intervals for θ_l . The results reveal that the response of prices to these shocks significantly increases with relationship age. New relationships exhibit pass-through of about .15, which increases to .25 for relationships of age five years. Overall, the average level of the coefficient is comparable in magnitude to the aggregate exchange rate pass-through for all U.S. imports of around 0.2 documented by [Gopinath, Itskhoki, and Rigobon \(2010\)](#).

Table 2 presents the coefficients of regressions analogous to (1), where the year dummies have been replaced with the length of the importer-exporter relationship in months for better readability. The first column in Table 2 presents the average pass-through in the data, which is about 0.2. Column

(2) presents the specification including relationship length. For each additional month a relationship has lasted, the responsiveness of prices to exchange rate shocks rises by 0.0015. Thus, pass-through in a relationship that is four years old is about 7.2 percentage points higher than pass-through at the point when the relationship was new (a 47% increase). The finding suggests that long-term relationships, which presumably are the most likely to rely on contracts, do not have more rigid prices than new relationships as has been claimed in the literature. In fact, prices become more flexible with relationship length, at least in response to exchange rate shocks. My result aligns well with previous work showing that trade between related partners exhibits higher exchange rate pass-through and less sticky prices than trade between arms' length partners (Neiman (2010)), since related partners can be thought of as having a very close relationship.

The third column of Table 2 shows the same regression but using dummies for relationship length: $d_{med} = 1$ for relationships that are between one and four years old, and $d_{long} = 1$ for relationships that are older than four years. Pass-through in old relationships is almost 80% higher than in new ones. The fourth and fifth column present the regressions only for positive and negative exchange rate shocks, respectively. The positive coefficients in both regressions indicate that prices change in the direction of the shock in both cases. As before, long-term relationships have a higher responsiveness of prices for both types of shocks. Thus, buyers in new relationships participate less in cost increases when the exchange rate appreciates, but also get smaller price reductions when the exchange rate declines. I also find that the response of prices to foreign currency appreciations (increasing costs) is higher (and also more significant) than the response following depreciations. This asymmetry of the price response to cost shocks is consistent with evidence from domestic studies of price setting such as Peltzman (2000).

Column (6) of Table 2 replaces γ_{msh} and ω_t with exporter-HS10-quarter fixed effects. This specification examines whether the price response of a given exporter to an exchange rate movement differs across customers purchasing the same product. I find that pass-through is higher for customers with whom the exporter has a longer relationship.

Since relationships do not necessarily trade in every quarter, the price changes observed could be based on a selected sample. This problem biases the fixed effects estimator if the selection is correlated with the errors in (1). I therefore restrict the dataset to only those importer-exporter-product triplets that trade in every quarter for the duration of their association, and re-estimate the within-relationship regression. The results are very similar to before (column 1 in Table I.16 in Appendix I.2). More formally, I implement a selection model to correct for the selection bias. Given the panel nature of my dataset, pass-through and selection are likely to depend on unobservable heterogeneity at the level of the relationship-product triplet. I therefore apply the selection correction for panel data proposed

Table 2: Pass-Through Regressions

$\Delta \ln(p_{mcxht})$	Within Relationship-Product (mxh)					Within exporter
	Overall	Cont. length	Dummies	Positive	Negative	(xht)
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln(e_{cht})$	.2004*** (.0540)	.1543*** (.0517)	.1521*** (.0463)	.2797*** (.0794)	.0657*** (.0193)	.1428*** (.0673)
$\Delta \ln(e_{cht}) \cdot \text{Months}$		.0015*** (.0002)		.0014*** (.0004)	.0008* (.0004)	.0009*** (.0002)
$\Delta \ln(e_{cht}) \cdot d_{med}$			.0480*** (.0140)			
$\Delta \ln(e_{cht}) \cdot d_{long}$			.1132*** (.0219)			
Fixed effects	mxh, t	mxh, t	mxh, t	mxh, t	mxh, t	xht
Observations	16,902,000	16,902,000	16,902,000	5,700,000	11,202,000	16,902,000

Notes: Superscripts *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Standard errors are clustered at the country-level. Number of observations has been rounded to the nearest 1000 as per U.S. Census Bureau Disclosure Guidelines.

in [Wooldridge \(1995\)](#) to my problem, which approximates the fixed effects using leads and lags of observable variables. I discuss the correction procedure in Appendix B. Column 2 in Table I.16 shows the results from this exercise. The results are similar to the baseline regression, even though the selection term λ is statistically significant.

I conduct a number of additional robustness checks. First, [Gopinath, Itskhoki, and Rigobon \(2010\)](#) document that the responsiveness of import prices is significantly higher when pricing occurs in the foreign currency, rather than in U.S. dollars. Unfortunately, the currency of invoice is not observed in the LFTTD. I therefore construct a group of countries with a relatively high share of local currency pricing, using the countries listed in Table 1 in [Gopinath, Itskhoki, and Rigobon \(2010\)](#). I then run regression (1) for this group of countries and for its complement (columns 3-4 in Table I.16). I find that the level of pass-through is high for the high local currency pricing group but the increase in pass-through with age is only marginally significant, while pass-through is strongly increasing in age for the country group pricing mostly in U.S. dollars. I conduct a similar exercise by sorting transactions into three groups based on the share of local currency pricing within two-digit HS code product categories, using the pricing information in Table 4 of [Gopinath, Itskhoki, and Rigobon \(2010\)](#).¹⁷ The results for the three groups show significantly higher pass-through for long-term relationships in every group (columns 5-7 in Table I.16).

¹⁷The “high” group contains all product groups in which at least 20% of goods are priced in foreign currency, the “medium” group all product groups with foreign currency pricing for 10-19% of the goods, and the “low” group contains the remainder.

I next examine whether pass-through increases with relationship age even when the total length of the relationship is fixed. Column 1 of Table I.17 presents the results from running regression (1) for only the subset of relationships that last for in total between 24 and 35 months. Columns 2 and 3 redo the regression for two different total length groups. My results suggest that there is a time effect on pass-through even when controlling for how long the relationship lasts in total. Columns 4 and 5 aggregate the data at annual or monthly frequency, respectively, to study how aggregation affects the regression results and show that the results are similar

As a final check, I examine whether prices and exchange rates are cointegrated. [Burststein and Gopinath \(2014\)](#) reject the null hypothesis that the U.S. import price index, the nominal exchange rate, and the foreign producer price index are not cointegrated. If cointegration were present, the regression in differences would still yield the correct results for the short-run adjustment, but would miss long-run dynamics. To test for cointegration, I examine whether prices and exchange rates are unit roots. I define a lagged observation as the previous transaction, regardless of how much time has passed since then, since a given cumulative exchange rate movement should have the same effect on prices regardless of the time gap. I drop all relationship-product triplets with fewer than 20 transactions to have sufficiently long time series for each panel. Since the panels contain a heterogeneous number of transactions, I test for unit roots using the test in [Im, Pesaran, and Shin \(2003\)](#). The test strongly rejects the null that all panels contain a unit root for exchange rates ($p < .0001$) (Table I.18). The exchange rate is only observed when the relationship transacts, and therefore the series is not the standard exchange rate process. The null cannot be rejected for prices. Since both series need to be unit roots for cointegration to be present, differencing seems to be a valid approach.

2.4 Further Properties of Relationships

I document a number of additional stylized facts, which will guide me in the development of a theory linking relationships and pass-through. The facts I study are motivated by a large, mostly survey-based management literature on relationships. This literature has suggested that relationships, defined as buyer-seller pairs interacting repeatedly, follow a life cycle and are valuable for firms. I first discuss these findings. I then take these results to the trade data and provide quantitative evidence supporting them for U.S. import transactions. Finally, I will build on this additional evidence to specify my model of a relationship, and use the previous evidence of pass-through dynamics to validate the model.

Management research suggests that relationships follow a life cycle ([Dwyer, Schurr, and Oh \(1987\)](#), [Ring and van de Ven \(1994\)](#)).¹⁸ While the details differ across papers, at its core this work

¹⁸Several authors have since extended their work, e.g. [Wilson \(1995\)](#), [Jap and Anderson \(2007\)](#)

proposes that relationships begin with an *exploration stage*, in which buyers search for partners and run trials by placing small purchase orders with possible suppliers (Egan and Mody (1992)). The relationship is still very loose at that point, and the focus is on selection based on satisfaction with performance and bargaining. In the *build-up and maturity stage*, the benefits of being in the relationship gradually increase as it accumulates specific assets and trust. Commitment to the relationship increases and the partners derive value through lower costs, market access, and information sharing. Informal agreements increasingly replace formal contracts, and the partners work together to solve their problems jointly. In the final *decline* phase, the relationship unravels, for example because of changing product requirements, increased transaction costs, or a breach of trust. Jap and Anderson (2007) test the life cycle theory based on a qualitative survey of 1,540 customers of a U.S. chemicals manufacturer, and confirm its main implications for these relationships.

The trade data provide evidence supporting the survey-based results. I study the path of value traded, relationship prices, and the hazard rate of relationship break-ups and show that they provide quantitative evidence of a life cycle.

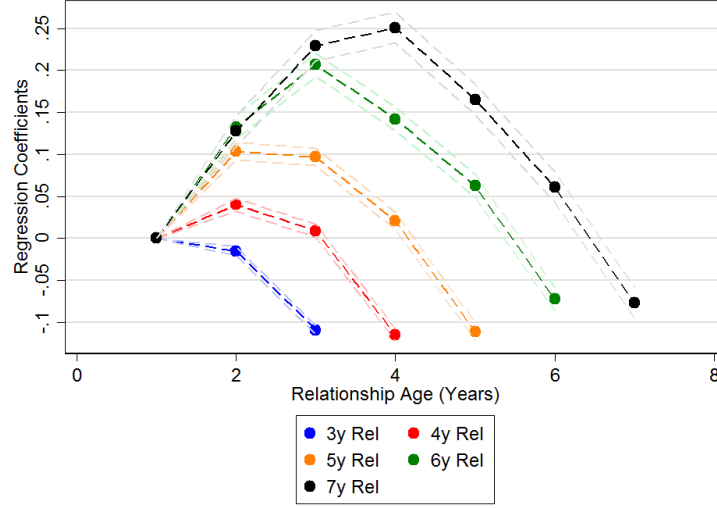
Value and number of products traded

I begin by examining the link between value traded and relationship age. I first sort relationships into groups, based on whether they last for three years but less than four years, four years but less than five years, and so on. I examine the evolution of trade values separately for these groups to ensure that my results are not driven by composition effects. For each relationship, I compute the total value traded within its first 12 months, months 13-24, etc., up to the maximum full number of years for which the relationship is alive, and regress this on dummies indicating the relationship length. Since many relationships do not trade in every year, I apply a smoothing procedure to fill in years with zero trade. Otherwise, since by definition each relationship trades a positive quantity in the first year, I would find a sharp drop in trade from year one to year two. I therefore assume that the value purchased is equally distributed across subsequent years with zero trade.¹⁹ I distribute the last trade of the relationship linearly over a time period corresponding to the average time gap between transactions for that relationship. Letting τ be the age of the relationship in years, and τ^* be the total number of full years the relationship exists, I then run the following regression for $\tau^* = 3, 4, 5, 6, 7$:

$$\ln(y_{m\tau}) = \beta_0 + \sum_{i=2}^{\tau^*} \beta_i d_i + \gamma_{mx} + \varepsilon_{m\tau}. \quad (2)$$

¹⁹This is consistent with a linear inventory policy with repurchase once the inventory level hits zero.

Figure 3: The life cycle of total value traded



Here, $\ln(y_{mxt})$ is the (log of) the total trade value of relationship mx in year τ , d_i are relationship age dummies, and γ_{mx} are relationship fixed effects. Figure 3 plots the β_i coefficients and 95% confidence bands from these regressions, with year one normalized to zero.

The figure is consistent with the life cycle theory of relationships. For all relationships lasting at least four years, the value traded follows a hump-shaped pattern, with the value traded increasing over the first few years and then stabilizing and declining gradually. The effect is quantitatively important: for example, for relationships lasting six years, the value traded in year three is 21% higher than in year one. Trade values in the last year are below the initial starting point, consistent with problems and abandonment of the relationship. There is a very clear ordering based on how long the relationship eventually lasts: relationships that last six years have a stronger increase in trade than relationships lasting only five years, and so on. The patterns could be consistent with two explanations: on the one hand, there could be selection based on persistent shocks to the relationship, such as demand fluctuations. On the other hand, pairs that start out better could actively invest more into their relationship, which therefore survives longer (see e.g., [Ganesan \(1994\)](#)). I will test the latter explanation below, and develop a theory that incorporates both mechanisms.

Figures [L.13a-L.13b](#) in Appendix [L.1](#) show that the number of products traded and the number of transactions per year follow a similar pattern as the total value. My findings are consistent with results by [Fitzgerald, Haller, and Yedid-Levi \(2015\)](#), who examine the growth patterns of exporters selling to a new destination country. My results highlight that the pattern also holds at the level of the individual relationship.

Relationship prices

I next examine the path of prices over the duration of a relationship. I focus on importer-exporter-product triplets because overall relationships may trade several products. For each transaction i in quarter t , I compute the *relative* log price $\ln(\tilde{p}_{mxchi(t)})$ by taking the log transaction price and subtracting the log average price for that product-country combination in that quarter. This removes product- or country-specific price trends. I discard all product-country-quarter cells that do not contain at least five observations.²⁰ I then regress the relative price on dummies measuring how often the triplet has transacted. Let $d_6, d_{11}, d_{16}, d_{21}$, and d_{41} be dummies for whether the triplet has conducted 6-10, 11-15, 16-20, 21-40, or 41-60 transactions, respectively (observations beyond transaction 60 are dropped). I include two additional control variables: first, I include the pair's overall relationship length in months at transaction i , $Months_{mxi(t)}$. This variable captures whether prices are affected by overall relationship length, across all products. Second, I control for whether the relationship has previously been broken up and is now continuing, $Cont_{mxi(t)}$. This variable picks up whether price setting is different in continued relationships compared to ones that are genuinely new. Thus, I run:

$$\ln(\tilde{p}_{mxchi(t)}) = \beta_0 + \sum_j \rho_j d_j + \beta_1 \cdot Months_{mxi(t)} + \beta_2 \cdot Cont_{mxi(t)} + \gamma_{mxh} + \varepsilon_{mxchi(t)}, \quad (3)$$

where γ_{mxh} are fixed effects for the triplet.²¹

The regression shows that the relative price obtained in a relationship declines monotonely up to about 1.3% per purchase by transaction 41-60, with an additional reduction by .03% per relationship month (column 1 in Table 3). The management literature has similarly found evidence that long-term relationships provide price discounts to the buyer (Kalwani and Narayandas (1995), Cannon and Homburg (2001), Claycomb and Frankwick (2005)). This literature suggests that price declines are the result of a *direct effect* due to (possibly required) productivity improvements and learning curve effects (Lyons, Krachenberg, and Henke Jr. (1990), Kalwani and Narayandas (1995), Ulaga (2003)), and an *indirect effect* due to quantity discounts as order volumes rise (Cannon and Homburg (2001), Claycomb and Frankwick (2005)). I will incorporate both of these effects in my model below.

To test whether quantity discounts might be present, I first re-run regression (3), using the log deviation of quantity ordered from the market average for the product as dependent variable (column 2 in Table 3). The results show that the quantity ordered increases with the number of transactions, which may increase the price discount the buyer receives. To investigate this effect, I need to specify

²⁰In order to keep the dataset consistent with the regression involving instruments, discussed below, only transactions from 1997 onwards are used in this regression.

²¹As for the pass-through regressions, I do not need country dummies since these are a linear combination of triplet fixed effects.

Table 3: Price Setting by Transaction Number and Relationship Length

	$\ln(\bar{p}_{mxch})$	$\ln(\bar{q}_{mxch})$	$\ln(\bar{p}_{mxch})$	$\ln(\bar{p}_{mxch})$
	(1)	(2)	(3)	(4)
d_6	-.0036*** (.0002)	.0131*** (.0005)	-.0006*** (.0002)	-.0018*** (.0002)
d_{11}	-.0050*** (.0003)	.0243*** (.0006)	.0003 (.0003)	-.0019*** (.0003)
d_{16}	-.0069*** (.0004)	.0332*** (.0007)	.0002 (.0003)	-.0027*** (.0004)
d_{21}	-.0096*** (.0003)	.0434*** (.0006)	-.0006** (.0003)	-.0043*** (.0004)
d_{41}	-.0131*** (.0004)	.0554*** (.0008)	-.0019*** (.0004)	-.0066*** (.0005)
Length_{mx}	-.0003*** (.0000)	-.0002*** (.0000)	-.0007*** (.0000)	-.0006*** (.0000)
Cont_{mx}	-.0193*** (.0003)	.0035*** (.0006)	-.0314*** (.0003)	-.0264*** (.0004)
$\ln(q_{mxch})$			-.2160*** (.0000)	-.1272*** (.0000)
Instruments	No	No	No	Yes
Fixed effects	mxh	mxh	mxh	mxh
Observations	67,868,000	67,868,000	67,868,000	67,868,000

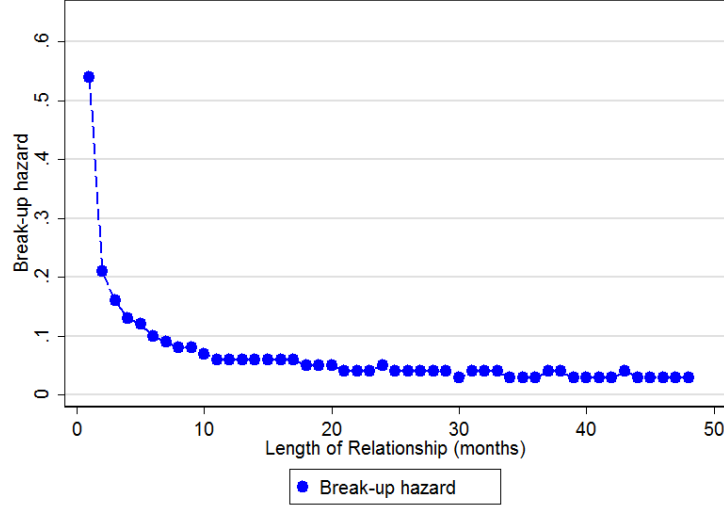
Notes: Superscripts *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Number of observations has been rounded to the nearest 1000 as per U.S. Census Bureau Disclosure Guidelines.

an assumption how prices are set. In my theory below, I will assume that buyers face a downward sloping demand curve and choose the quantity ordered from the seller to maximize profits, taking price as given. Longer relationships enable the buyer-seller pair to reduce marginal costs, for example due to productivity improvements, which lowers the price charged by the seller. In this setup, a regression of price on quantity will suffer from endogeneity bias since the buyer's quantity ordered depends on the price. I therefore need to find an exogenous demand shifter to separate supply curve shifts due to productivity improvements from movements along the supply curve caused by higher quantities ordered.

My demand instrument is the weighted average gross output of the downstream industries of the imported good, where the weights are constructed via the "Use" table of the 2002 input-output table of the BEA.²² The identifying assumption behind this instrument is that when downstream industries' output is high, their demand for inputs is large, and hence importers selling to these industries increase their imported inputs. Since prices are computed relative to the market average, the effect of industry-wide price trends on demand is stripped out. The industry gross output figures are obtained for the period 1997-2011 from the BEA, and matched with the industries recorded in the IO table. Since detailed industry outputs are only available at annual frequency, I also use U.S. GDP as a second

²²I use the most detailed input-output matrix containing 417 industries.

Figure 4: Hazard rate of breaking up a relationship (monthly)



instrument to introduce quarterly variation. I detrend both variables using an HP filter.

The first-stage regression is run for each of 18 broad product categories presented in Appendix C. I regress log quantity on $ProdDown_{1t} - ProdDown_{18t}$ and $GDP_{1t} - GDP_{18t}$, where the transaction's cyclical downstream demand component, $ProdDown_{yt}$, and the cyclical GDP component, GDP_{yt} , are set to their value if the transaction falls into product category y , and are set to 0 otherwise. This specification allows for different cyclical responses by product category. The results from running (3) using the actually observed transaction quantity are shown in column 3 of Table 3, and the results using the instruments are shown in column 4. These results show that prices decline due to a direct effect alone. On average, relative price falls by about 0.7% by transaction 41-60. In Appendix I.2, Table I.20 repeats column 1 of Table 3 for different product categories. Price declines tend to be strongest for differentiated products such as chemicals, metal products, and machinery, and weakest for minerals, leather products, or textiles. While I cannot adjust prices to account for changing quality, these results provide suggestive evidence that a main driver behind the price declines is customization and associated productivity improvements, which cannot be generated for more standardized products.

Hazard rate of breaking up a relationship

I finally analyze the hazard rate of breaking up a relationship at a given age, conditional on having reached that age. Let τ be a relationship's age in months, and $I\{\tau_{mxt} = \tau\}$ be an indicator that is equal to 1 if relationship mx with age equal to τ breaks up in month t . I define ω_{mxt} as the relationship's value traded during the past twelve months, which will be used as a weight for the relationship's importance.

Recall that a relationship ends only when the maximum gap time has elapsed for all its products, and hence a relationship does not need to trade at t to be ongoing. The weighted hazard rate at t is defined as a weighted average over all relationships having that length at t :

$$\{\bar{I}_{mxt} | \tau_{mxt} = \tau\} = \frac{\sum_{mx} \omega_{mxt} I\{\tau_{mxt} = \tau\}}{\sum_{mx} \omega_{mxt}}. \quad (4)$$

The hazard rate for the sample is computed by taking a simple average over the hazard rates in all months. Figure 4 shows that this break up hazard declines very rapidly: from 55% in the first month to 6% in month 12.²³ This result is consistent with findings by [Eaton, Eslava, Jinkins, Krizan, and Tybout \(2015\)](#) and [Monarch \(2015\)](#) who report a high rate of attrition in the first year of a relationship.²⁴ I find that relationships are actually very likely to break up within the first months (usually after the first transaction), but once they clear that hurdle they are likely to continue. The findings align well with the presence of an “exploration phase” of the relationship life cycle. The results also mirror the negative association between job tenure and separation in worker-firm relationships (e.g., [Mincer and Jovanovic \(1979\)](#)). [Pries \(2004\)](#) estimates that the separation hazard for workers is more than 60% in the first year, and falls to less than 10% by year five, somewhat similar to my findings for firms.

2.5 Interview Evidence

I conducted 16 interviews with purchasing managers and executives of 15 companies in Germany, the United States, and Chile to obtain additional qualitative evidence about firms’ relationships with their suppliers.²⁵ More than half of the companies interviewed are well-known, leading players in their industry. Interview partners were found via personal connections, LinkedIn, and via the Yale Career Network. In total, 9 of the respondents are manufacturing firms²⁶, 2 are supermarkets, 2 are apparel retailers, and 2 are grocery wholesalers. The interviews were mostly conducted over the phone, and lasted between 20 and 30 minutes. The detailed interview transcripts are available on request. Table 4 presents a summary of my findings. The “Sample” column indicates with how many interview partners I spoke about this topic. The “Agree” column shows what fraction of respondents agreed

²³ For this analysis, in order to account for relationship lengths up to 48 months accurately, I drop not only the first three years but the first five years, up to 1997.

²⁴ For relationships with Colombian and Chinese suppliers, respectively.

²⁵ I thank Prof. Eduardo Engel for conducting one of the interviews in Chile and for making the other one possible.

²⁶ The firms are based in the following industries: Electrical and optical equipment (4), steel production (1), car manufacturing (1), tobacco (1), pharmaceuticals (1), and cardboard manufacturing (1).

Table 4: Summary of Interview Responses

Fact	Sample: n=16	Sample	Agree
	Most of our transactions are done via long-run relationships	10	100%
1	Over time, we order more from the same supplier	15	87%
	Over time, we customize and develop products together	13	92%
2	We get better prices in relationships due to quantity discounts	6	67%
	Prices may improve due to efficiency gains	5	40%
3	We run a small pilot to find out about new suppliers	12	100%
	We learn in less than 3 months if we want to work with a new supplier	8	75%

with the statement.

As expected, I find that long-run relationships with suppliers are important. The majority of respondents reported that long-term relationships account for 80% to almost all of their supplier relationships. Most firms are aware of a lot of potential suppliers, which they usually get to know via trade fairs, trade magazines, or the internet. Once a supplier has been selected, firms often conduct an initial test run by ordering a small quantity. This aligns well with the exploration phase of the life cycle theory. Learning about the supplier's overall quality is usually quick, and takes only one or at most a few transactions. However, entering into a legal agreement, transferring technology, or setting up the logistics of a relationship may take a long time. Especially manufacturing firms and apparel retailers often conduct a lengthy evaluation involving formal audits and negotiations before starting a long-term relationship with a supplier. This suggests that the main friction is not so much about finding a supplier in general, but rather finding a supplier meeting the company's criteria.

Once the relationship with a supplier has been established, relationships deepen over time. This includes ordering larger quantities from the supplier by allocating him a higher share of production or by growing quantities in line with increasing sales of the final output. Manufacturing firms often also ask for greater customization of the product. If the supplier is good, smaller existing connections may be replaced by this supplier and additional products may be ordered. Several respondents stated that they are able to obtain price reductions from long-term relationships because they order higher quantities. In the manufacturing sector, respondents also mentioned efficiency improvements in the production process. All these facts accord well with the build-up of relationship capital. While firms try to remain aware of alternative suppliers, they rarely switch suppliers once a successful long-term relationship is in place. Interview respondents cited the high costs of building up a new relationship as a key reason not to switch unless there is no other option. One executive in the apparel industry mentioned that following a break-up she lost an entire year of sales of a product due to the time it took to audit a new supplier and to ensure its quality.

3 Model

To rationalize the empirical findings, I develop a model of relationship dynamics under limited commitment. A buyer and a seller firm interact repeatedly, and have the outside option to leave the relationship to search for an alternate partner. Marginal production costs are affected by the pair's level of relationship capital, which represents for example the extent to which the partners have learnt about each other or have built up customized assets. Management research suggests that such customized assets are a key source of value of relationships, signalling commitment and making break-ups less likely (Anderson and Weitz (1992), Parkhe (1993)). In my model, relationship capital accumulates endogenously in proportion to the quantity traded. I show that endogenous capital accumulation together with limited commitment implies that prices fall with relationship capital while quantity traded, mark-ups, and pass-through rise. While each individual relationship follows a life cycle, older relationships on average have more relationship capital through a selection mechanism, and therefore on average set lower prices and display a higher responsiveness of prices to shocks, as in the data.

Section 3.1 first analyzes the case of full commitment to demonstrate the effect of relationship capital accumulation on price setting. Section 3.2 then introduces two-sided limited commitment and illustrates how the model generates increasing pass-through with relationship capital. I analyze two alternative models, based on variable mark-ups in the spirit of Atkeson and Burstein (2008) and based on Nash bargaining, in Section 3.3 and show that they fail to match the empirical patterns. Section 3.4 presents additional moments in the data that are consistent with my theory. I will estimate the model quantitatively in Section 4.

3.1 Full Commitment

Setup

Let time be discrete and indexed by t . A buyer firm desires to purchase a quantity q_t from a seller in each period t . The buyer produces output $y_t = Aq_t$ and faces a demand function for his final output given by

$$y_t = \Lambda(p_t^f)^{-\theta}, \quad (5)$$

where p_t^f is the price charged by the buyer for her final output, $\theta > 1$ is the elasticity of demand, and Λ is a demand shifter. Profit maximization implies that the buyer firm sets its final goods price as a constant mark-up over marginal costs,

$$p_t^f = \frac{\theta}{\theta - 1} \frac{p_t}{A}, \quad (6)$$

where $p_t > 0$ is the seller's price for her good.

The seller produces the buyer's input q_t according to the production function

$$q_t = a_t^\gamma x_t, \quad (7)$$

where x_t is an input or an input bundle used by the seller and a_t is a productivity shifter affecting the seller's marginal costs. I will interpret this variable as relationship capital, in line with the management evidence discussed in Section 2.4, but more broadly an increase in a_t can reflect any process that reduces costs or that raises the amount of quality produced per unit of input. The parameter γ , estimated below, reflects decreasing returns on additional relationship capital, since management research has shown that the most important components of relationship value are created in the early stages (e.g., [Eggert, Ulaga, and Schultz \(2006\)](#)). The seller's input is purchased at exogenous cost w_t which follows a stochastic process on an interval $[\underline{w}, \infty)$, $\underline{w} > 0$. Below, I will associate changes in production costs with fluctuations in exchange rates. From the buyer firm's demand (5) and the final goods price (6), the quantity sold q_t can be expressed as

$$q(p_t) = \left(\frac{\theta}{\theta - 1} \right)^{-\theta} p_t^{-\theta} A^{\theta-1} \Lambda, \quad (8)$$

and the seller's profits in period t are $\Pi^s(a_t, w_t) = (p_t - w_t/a_t^\gamma)q(p_t)$.

At the beginning of a relationship, relationship capital a_0 is drawn from a continuous distribution $G(a)$ with support on $(0, \infty)$. Based on the interview evidence showing that buyers learn the quality of their supplier quickly, I assume that both partners have full information about a at this point. Relationship capital evolves from one period to the next in two steps. In the first step, it depreciates at rate δ , reflecting physical wear and tear of customized machines or staff turnover that breaks personal bonds. In addition to that, capital is added in proportion to the quantity sold q_t , for example because a larger trading volume makes investment into specialized machines more worthwhile. Empirically, this feature reflects the fact that relationships that increase their trading volume substantially in early years last longer (Figure 3), which as described below is correlated in my model with higher levels of relationship capital. Capital thus accumulates according to

$$\tilde{a}_{t+1} = (1 - \delta)a_t + \rho q_t(p_t), \quad (9)$$

where ρ is a proportionality constant. The dependence of the speed of relationship capital accumula-

tion on the quantity traded generates a trade-off for sellers between maximizing profits in the current period and setting a lower price in order to sell more and to build up relationship capital quickly.

After the quantity decision has been made, in the second step the new capital level $\tilde{a}_{t+1}$ experiences an additive random shock $\varepsilon_{t+1} \sim N(0, \sigma_\varepsilon^2)$ that capture disagreements between partners, etc. These shocks introduce heterogeneity in the life cycle profiles of firms starting at the same level of capital. The final level of relationship capital in the next period is thus

$$a_{t+1} = \tilde{a}_{t+1} + \varepsilon_{t+1}. \quad (10)$$

I assume that the seller sets prices. Thus, given a state (a_t, w_t) in period $t \geq 0$, she chooses a price sequence $\{p_s\}_{s=t}^\infty$ to solve

$$J(a_t, w_t) = \max_{\{p_s\}_{s=t}^\infty} \left\{ \left(p_t - \frac{w_t}{a_t^\gamma} \right) q(p_t) + E \sum_{s=t+1}^\infty \beta^{s-1} \left[\left(p_s - \frac{w_s}{a_s^\gamma} \right) q(p_s) \right] \right\}. \quad (11)$$

Note that the seller's value is strictly increasing in relationship capital a , since an increase in current capital raises current and expected future profits even without re-optimizing prices to account for the change. Conversely, the seller's value declines in costs.

Characterization

Since next period's relationship capital a_{t+1} is a function of the current period price p_t , the seller's problem (11) can be transformed into a problem with choice variables $\{\tilde{a}_{s+1}^*\}_{s=t}^\infty$ instead of $\{p_s\}_{s=t}^\infty$. This problem setup resembles a standard growth problem where firms choose next period's capital. I make the following assumption.

Assumption 1. $\gamma < 1/\theta$

Assumption 1 implies that the returns to relationship capital are sufficiently concave so that there exists a threshold level of capital $\bar{a}$ such that the seller optimally plans to reduce capital and sets $\tilde{a}_{t+1} < a_t$ whenever $a_t > \bar{a}$.²⁷ I prove in Appendix D.1 that under this assumption the sequence problem (11) can be written recursively and an optimal policy exists. The recursive problem formulation is

$$J(a, w) = \max_p \left(p - \frac{w}{a^\gamma} \right) q(p) + \beta E J(a', w'), \quad (12)$$

²⁷See Lemma 2 in Appendix D.1. Due to the stochastic shocks to capital, it is possible that $a_t > \bar{a}$. Since the mean of the shocks is zero and their variance is finite and since the seller chooses $\tilde{a}_{t+1} < \bar{a}$ whenever $a_t > \bar{a}$, the probability that capital exceeds some upper bound $a'' \gg \bar{a}$ goes to zero for sufficiently large a'' .

where primes indicate the next period. Appendix D.2 shows that the static profit function $\Pi^s(a, w)$ is strictly concave in both a and in next period's choice of capital $\tilde{a}'$ for all parameter values. It is jointly concave in both arguments as long as $p > \frac{\gamma\theta}{1+\gamma} \frac{\theta}{\theta-1} \frac{w}{a^\gamma}$, and hence for such cases the solution is a unique policy function. Note that this condition covers a range of prices below the static optimum in particular when γ is small. I will verify this condition in the simulations below. Taking the first-order condition of problem (12), using (8) and (9), I obtain an implicit expression for the optimal price charged by the seller

$$p = \frac{\theta}{\theta-1} \left[\frac{w}{a^\gamma} - \beta \rho EJ_a(a', w') \right], \quad (13)$$

where $EJ_a(a', w')$ is the derivative of the expected value function with respect to relationship capital. The equation highlights that the seller charges a lower mark-up compared to the standard monopolistic price setting, trading off reduced profits in the current period with the benefits of higher relationship capital in the future. I prove in Appendix D.3 that the seller's choice of next period's capital $\tilde{a}'$ is strictly increasing in a . Since $J(a, w)$ is concave in a and ε is mean zero, the price thus becomes closer to the monopoly price as the level of current capital increases.

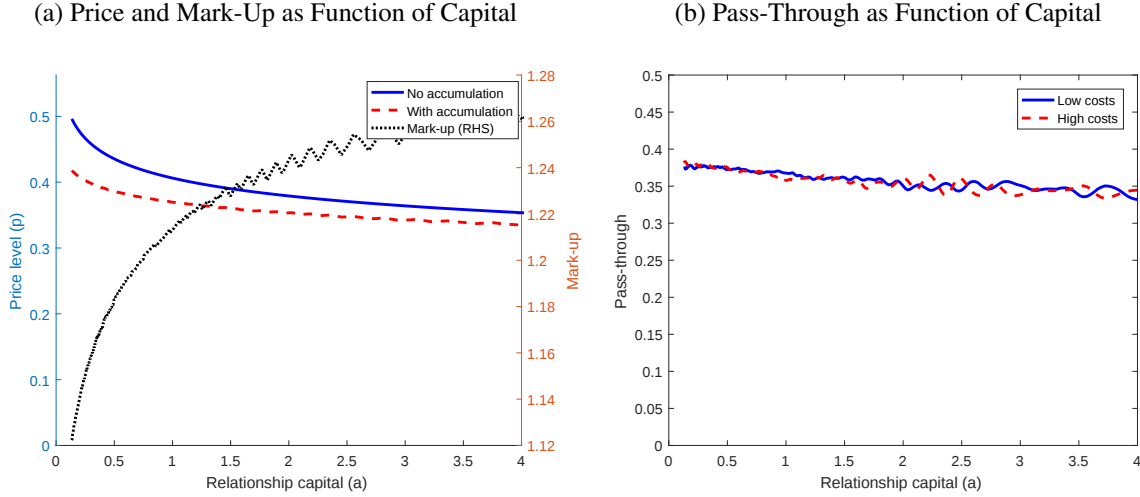
In Appendix D.4, I show that the price is decreasing with the level of relationship capital. Hence, in equation (13) the direct effect of higher relationship capital on marginal costs always outweighs the indirect effect stemming from a lower marginal value of additional capital in the future. A typical pricing schedule as a function of capital is depicted by the dashed line in Figure 5a. For comparison, the solid line presents the optimal price when $\rho = 0$ and hence when there is no incentive to accumulate capital. The seller charges a lower price than under static profit maximization since she internalizes the positive effects on future relationship capital, and the price declines in a due to lower marginal costs. As I will show below, older relationships on average have more relationship capital, and thus the model implies declining prices with relationship age, as documented in the empirical section and in the management literature (e.g., Kalwani and Narayandas (1995)).

The seller's price consists of marginal costs times a mark-up $\mu = p/(w/a^\gamma)$. Differentiating (12), applying the envelope condition, and substituting into (13), I obtain

$$\mu = \frac{\theta}{\theta-1} \left[1 - \beta \gamma \sum_{j=1}^{\infty} [\beta(1-\delta)]^{j-1} E \left[\frac{w_j/(a_j)^\gamma}{w/a^\gamma} \right] \left[\frac{\phi(a_j)}{a_j} - (1-\delta) \right] \right], \quad (14)$$

where j indexes the number of periods after the current period (e.g., $a_2 \equiv a''$), and $\phi(a)$ is the policy function that gives $\tilde{a}'$ as a function of a . Since $\phi(a_j) \geq (1-\delta)a_j$, the mark-up is smaller than under static profit maximization. Whether the mark-up rises or falls with the level of relationship capital depends on the relative change of the two terms in brackets in the expectation. If the seller's incentives to invest into additional relationship capital decline sufficiently strongly with a , then the

Figure 5: Full Commitment



mark-up increases with relationship capital. This outcome is depicted by the dotted line in Figure 5a. Intuitively, as the seller's incentives to build up more relationship capital decline, she sets mark-ups that are closer to the static optimum. Thus, while the seller lowers her overall price in relationships with more capital due to higher productivity, she is also able to increase her share of the joint profits by raising her mark-up, thus participating in the gains from the relationship. This feature of the model reflects the idea that relationships expand the joint “pie”, and that both parties are able to participate (e.g., Jap (1999)).

There exists a substantial literature on sellers charging low introductory prices and then increasing mark-ups as implied by my setup, see Fudenberg and Villas-Boas (2007) for a summary. This literature has suggested that firms may charge low initial mark-ups to customers that shop repeatedly in order to for example signal their costs (e.g., Bagwell (1987)), or to poach customers from rivals (e.g., Fudenberg and Tirole (2000)). I provide an additional reason for the case of firm-to-firm transactions, which is that lower initial prices allow the seller to build up relationship capital more quickly by transacting more. Empirically, Doney and Cannon (1997) document that firms' choice of new suppliers is significantly influenced by a competitive price, but that the importance of price declines over time as the relationship builds up trust and experience. Jap (1999) show that long-term relationships lead to higher profits for both the buyer and the seller. Lewis (2005) shows in the newspaper subscription market that the seller's optimal pricing strategy consists of a series of decreasing discounts (and hence rising mark-ups) based on customer tenure, as implied by my model.

The following proposition shows how the seller's price is affected by the model parameters.

Proposition 1. *a) $dp/d\rho < 0$, b) $dp/d\delta > 0$, c) $dp/d\gamma < 0$ for $a < 1$ and $dp/d\gamma > 0$ for $a > 1$.*

Proof. See Appendix D.5. □

The seller sets lower prices if an additional unit sold leads to a stronger capital accumulation, while a higher depreciation rate reduces the seller's incentives to build up relationship capital. A less concave relationship between output and relationship capital reduces underpricing when a is low, but increases underpricing for high capital levels.

From equation (13), pass-through is given by

$$\frac{d \ln(p)}{d \ln(w)} = \frac{\left(\frac{\theta}{\theta-1}\right) \frac{w}{a^\gamma}}{p} \left[1 - \beta \rho a^\gamma E \left(J_{aa}(a', w') \frac{d\tilde{a}'}{dw} + J_{aw}(a', w') \right) \right], \quad (15)$$

where $J_{aw}(a', w')$ is the cross-partial derivative with respect to both arguments of J . Since p is less than the monopoly price, the term outside of the brackets is greater than one. Therefore, pass-through exceeds one unless the indirect effect is strong enough. In Appendix D.6, I show that $d\tilde{a}'/dw < 0$ and $J_{aw}(a', w') < 0$, and hence the first term in parentheses is positive and the second term is negative. From the term $J_{aa}(a', w') \frac{d\tilde{a}'}{dw}$, incomplete pass-through only occurs when the reduction in investment caused by the rise in costs leads to a sharply increased marginal value of investment, and hence the term is large. For my preferred calibration of the model, Figure 5b shows that pass-through is larger than one and slightly decreasing, at odds with the data. I introduce limited commitment in the next section and show that it naturally generates increasing pass-through. It also allows for relationship termination and therefore a relationship life cycle.

3.2 Limited Commitment

I now allow both partners to leave the relationship at the beginning of each period after the state (a, w) has been revealed. Let the buyer have an outside option of $U(w) > 0$, reflecting her ability to search for a new seller and to start a new relationship. I assume that $\frac{dW(a, w)}{dw} < \frac{dU(w)}{dw}$, and hence the buyer's inside value is more responsive to cost fluctuations than the outside option, for example due to the buyer's ability to switch to a different country with a different exchange rate. Based on the limited commitment assumption, I assume that the buyer also cannot commit to charge a specific final goods price p^f when transacting with the seller. The seller's outside option value is $V(w) > 0$. Note that neither outside option depends on a , and thus capital is fully specific to the relationship. I assume that the seller cannot search for an alternate partner in the first period of a newly established relationship due to the time needed to set up the production in that period, and hence her outside option is that period is zero.

The buyer's per period profits are $\Pi^b(a, w) = (p^f - p/A)y(p^f)$, and hence her value from a relationship that is continued in the current period is

$$W(a, w) = (p^f - p/A)y(p^f) + \beta E [I'W(a', w') + (1 - I')U(w')]. \quad (16)$$

Here, $I' \equiv I(a', w')$ is an indicator that is equal to one if the relationship is continued in state (a', w') . The seller's value function in each period is now a modified version of (12)

$$J(a, w) = \max_p \left(p - \frac{w}{a^\gamma} \right) q(p) + \beta E \left\{ \max [J(a', w'), V(w')] \right\}. \quad (17)$$

The seller's problem is to maximize (17), subject to (5), (6), (8), and $W(a, w) \geq U(w)$. Since $J(a, w)$ is a maximized value, the seller must always be better off terminating the relationship if her participation constraint becomes binding, and hence $I' = 0$ if and only if $J(a, w) < V(w)$.²⁸ The seller's value is increasing in a and decreasing in w , as argued before, and hence the seller's constraint will become binding if capital falls below a lower bound given costs, $a < \underline{a}(w)$. This bound is increasing in w . The buyer's constraint is also more likely to bind for a low level of relationship capital, since the seller's price falls with a therefore $\partial W(a, w)/\partial a > 0$.

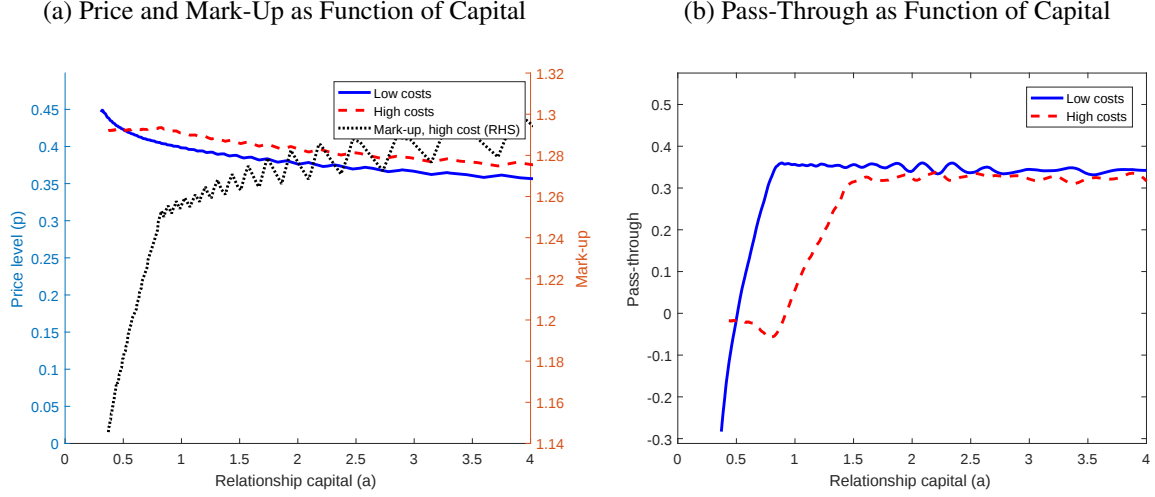
In Appendix D.7, I derive the first-order condition of the pricing problem

$$p = \frac{\theta}{\theta - 1 + \lambda} \left\{ \frac{w}{a^\gamma} - \beta \rho E \left\{ I' [J_a(a', w') + \lambda W_a(a', w')] + \lambda \left[\frac{\partial I'}{\partial a'} \{W(a', w') - U(w')\} \right] \right\} \right\}, \quad (18)$$

where λ is the Lagrange multiplier on the buyer's participation constraint. The equation shows that when the buyer is constrained ($\lambda > 0$), the seller lowers the price by more than in the full commitment case, via three channels. First, there is a direct reduction in the mark-up to provide a higher surplus to the buyer, which is independent of the endogenous capital accumulation channel. Second, the first set of brackets shows that underpricing is particularly severe when the slope of the buyer's value function $W_a(a', w')$ is high, since in that case small increases in a allow the seller to leave the buyer's constrained region quickly. Finally, the second set of brackets shows that the seller lowers the price by more if additional relationship capital strongly affects the likelihood of continuing the relationship, in particular if the relationship is relatively valuable. While in the model the seller is the price setter, the value of the buyer's outside option determines the share of the profits obtained by the two partners, and hence the transaction price may be well below the monopoly price if the buyer has a good outside

²⁸Note that if $J(a, w) < V(w)$ and $W(a, w) > U(w)$, the buyer would like to make a side payment to the seller to incentivize her to maintain the relationship. However, since the buyer cannot commit to the final goods price by assumption, the seller anticipates that the buyer will modify p^f to account for this side payment once the transaction is agreed on, selling a different quantity to consumers. This has the same effect as if the seller set a different, non-profit-maximizing price ex-ante.

Figure 6: Limited Commitment Case



option.

Using the condition $W(a, w) = U(w)$ and re-arranging, I find that when the buyer is constrained the seller sets the price

$$p = \left[\frac{1}{U(w) - \beta E [I'W(a', w') + (1 - I')U(w')]} \left(\frac{1}{\theta - 1} \right) \left(\frac{\theta}{\theta - 1} \right)^{-\theta} A^{\theta-1} \Lambda \right]^{1/(\theta-1)}. \quad (19)$$

Since $W(a', w')$ is increasing in a' , and hence in a , a higher level of relationship capital increases the price in the constrained region. Intuitively, a higher level of capital relaxes the buyer's constraint, allowing the seller to reduce her underpricing. On the other hand, since $\frac{dW(a, w)}{dw} < \frac{dU(w)}{dw}$, an increase in w makes the buyer's outside option more binding and therefore forces the seller to lower the price. Intuitively, in order to compensate the buyer for the drop in the relationship's future value due to higher costs going forward (due to the persistence of w), the seller has to cut the price in the current period by reducing her mark-up. Figure 6a shows the seller's price as a function of relationship capital both for a high w for which the buyer is constrained at low levels of capital and for a low w at which she is always unconstrained. Note that in the constrained case, the seller terminates the relationship for low capital values.

Based on the previous discussion, pass-through falls into one of three regions. First, if the buyer is constrained for both w_1 and $w_2 > w_1$, then pass-through is negative since the seller has to lower the price to maintain the relationship. The extent of negative pass-through is determined by the elasticities of the inside option and the outside option with respect to costs. If the two elasticities are relatively similar, then the response of the price to the shock is small and pass-through is close to zero. The

frequency of negative pass-through is affected by the tightness of the seller’s outside option. If the seller always terminates the relationship once the buyer becomes repeatedly constrained, then negative pass-through will not occur. I will examine the extent of negative pass-through in the data below. On the other extreme, if the buyer is unconstrained at both cost levels, then pass-through corresponds to the case with full commitment discussed above, and is generally greater than one. Finally, in an intermediate range in which the buyer switches from being unconstrained to being constrained, the seller cannot increase the price as much as without the constraint and hence pass-through falls into an intermediate range. Figure 6b shows the pass-through as a function of relationship capital.

The model generates the relationship life cycle observed in the data via a selection mechanism. New relationships draw a level of capital that is frequently close to the separation bound and thus have a high separation hazard. They have high production costs and therefore set elevated prices and transact low quantities. The seller chooses low mark-ups to build up relationship capital and to leave the constrained region quickly. Relationships that are subject to good idiosyncratic shocks manage to build up relationship capital and experience declining production costs. They therefore trade more, set lower prices, and become less likely to break up. Since additional relationship capital becomes less valuable and the buyer is less frequently constrained, mark-ups and pass-through rise. On the other hand, bad shocks to relationship capital decrease the quantity traded, and lead to endogenous separation if the level of relationship capital becomes sufficiently low. Each relationship follows this life cycle of trade. However, since old relationships on average have a high level of relationship capital, unconditionally they have higher pass-through and lower prices. I confirm empirically that pass-through rises with a relationship’s value traded and falls again before a relationship ends in Section 3.4 below.

3.3 Alternative Models

I briefly discuss two alternative models and show that they fail to generate the increase in pass-through with relationship age delivered by the baseline model.

First, consider a setup with variable mark-ups in the spirit of Atkeson and Burstein (2008). In this model, foreign sellers respond to foreign cost shocks by adjusting their mark-ups, leading to incomplete pass-through into foreign prices. In Appendix E I develop a simple partial equilibrium model with a continuum of U.S. sectors which are each populated by a small number K of domestic and foreign sellers, respectively. Sellers face an elasticity of demand η across goods within their sector and a demand elasticity $\theta > \eta$ across sectors. I assume that a now represents the seller’s productivity, rather than relationship capital, and evolves stochastically over time according to an

exogenous process, $a_{t+1} = (1 + \varepsilon)a_t$, where $\varepsilon \sim (\mu, \sigma^2)$ are independent shocks across sellers. The stochastic input cost w is assumed to differ across domestic and foreign firms but is identical across sectors and for all firms of a given origin. Sellers face a fixed cost of operation F and exit the market if their profits fall below this threshold. They are then replaced by a new seller.

The evolution of productivity in this model generates life cycle dynamics for sellers, similar to the relationship life cycle before. Furthermore, older sellers have on average received better shocks to productivity, which implies that they on average have higher market shares. I can derive a similar expression as equation (25) in [Atkeson and Burstein \(2008\)](#), which relates price changes to shocks,

$$\hat{p} = \frac{1}{1 + (\eta - 1)\Gamma(s)} [\hat{w} - \gamma\hat{a}] + \frac{(\eta - 1)\Gamma(s)}{1 + (\eta - 1)\Gamma(s)} \hat{p}(k), \quad (20)$$

where hats indicate deviations from steady state, and $\hat{p}(k)$ is the change in the price index of the firm's sector. The variable $\Gamma(s)$ is the elasticity of the mark-up with respect to the market share, which satisfies $\Gamma'(s) > 0$.

Consider a change in the exchange rate, $\hat{w} > 0$, while sellers' productivity remains unchanged, $\hat{a} = 0$. Since the sectoral price index contains domestic firms which are not directly exposed to the exchange rate shock, it is typically the case that $\hat{w} > \hat{p}(k)$. It follows from (20) that since $\Gamma'(s) > 0$, older sellers (which on average have higher productivity and market shares) price more to market and adjust their U.S. price by *less* than new sellers in response to an exchange rate shock. [Berman, Martin, and Mayer \(2012\)](#) confirm empirically that more productive exporters adjust their mark-ups by more than less productive ones in response to an exchange rate shock, leading to a lower pass-through into the *import* price observed by the buyer (or equivalently, higher pass-through into the export price in foreign currency). In the case of $\hat{a} > 0$, idiosyncratic productivity shocks introduce additional noise which weaken the relationship between exchange rate shocks and prices, but the overall relationship remains the same. Thus, the standard variable mark-up model is at odds with the data.

The second model I examine is price setting based on Nash bargaining. In [Appendix F](#) I solve a Nash bargaining model with endogenous capital accumulation and free entry on the buyer side, where prices are set by maximizing the Nash product. Here, firms choose in each period the quantity which maximizes the surplus of the relationship, and then implement a transfer which splits the surplus according to the fixed bargaining shares. The relationship is terminated whenever the surplus becomes negative and hence both outside options bind. Since the price always splits the surplus in fixed proportions and separate when outside options become binding, the baseline model's mechanism to generate low pass-through via limited commitment is not present in this setup. Instead, since the surplus is always split in fixed proportions, the model generates basically constant pass-through.

3.4 Empirical Tests of Model Implications

I now present additional evidence supporting my model. First, I examine different channels affecting the buyer's outside option, as changes to the outside option affect pass-through in my model. Second, I examine several implications of the life cycle.

Outside Options and Pass-Through

A key model prediction is that relationships that have more binding buyer outside options when they start out should exhibit low pass-through at that time. As relationship capital is built up, the outside option becomes less binding and pass-through rises. On the other hand, pass-through should be relatively constant over the life of the relationship if the buyer's outside option never binds. I can test this implication using size as a proxy for bargaining power. Small sellers should have relatively little bargaining power when dealing with a given U.S. importer compared to large foreign suppliers. Therefore, pass-through should increase relatively more with relationship age for small sellers as the relationship is built up and accumulates relationship capital such as customized equipment.

To examine this implication, I compute the exporter's size as the sum of its total real exports in the dataset. I then run the following specification:

$$\begin{aligned} \Delta \ln(p_{mxchi(t)}) = & \beta_0 + \beta_1 \Delta \ln(e_{ct}) + \beta_2 \ln(Size_m) + \beta_3 \ln(Size_x) + \beta_4 Months_{mxi(t)} \\ & + \beta_5 \Delta \ln(e_{ct}) \cdot \ln(Size_x) \cdot Months_{mxi(t)} + \kappa \chi_{xcht} + \gamma_c + \xi_h + \omega_t + \varepsilon_{mxchi(t)}, \end{aligned} \quad (21)$$

where the variables are defined as in Section 2.3, $Size_x$ is the size of the exporter based on its total real exports to the U.S., $Size_m$ is the size of the importer based on its total real imports, and χ_{xcht} is a vector containing all three combinations of interactions between $\Delta \ln(e_{ct})$, $\ln(Size_x)$, and $Months_{mxi(t)}$. The specification examines pass-through controlling for country, product, and quarter fixed effects and the size of the importer across exporters of different size. Coefficient β_5 is the coefficient of interest. Standard errors are clustered at the country-level. Column 1 of Table 5 presents the results. The negative coefficient on $\Delta \ln(e_{cht}) \cdot \ln(Size_x)$ shows that the average level of pass-through is declining with the size of the exporter, as documented previously by [Berman, Martin, and Mayer \(2012\)](#) and [Chatterjee, Dix-Carneiro, and Vichyanond \(2013\)](#). Larger sellers exhibit overall lower pass-through, for example because they price more to market. The coefficient of interest for my model is $\Delta \ln(e_{cht}) \cdot \ln(Size_x) \cdot Months_{mxi(t)}$. As predicted, I find that when the seller is larger pass-through rises less quickly with relationship age. Quantitatively, a seller supplying a total of \$1 million in exports to the U.S. exhibits an increase in pass-through by 3.5pp (20.3%) over the first year of a given relationship, from 0.173 to 0.208. By contrast, a seller supplying a total of \$100 million of the same product to a buyer

Table 5: Responsiveness of Prices to Exchange Rate Shocks, by Size

$\Delta \ln(p_{mxht})$	All	Positive	Negative
	(1)	(2)	(3)
$\Delta \ln(e_{cht})$	.4707*** (.1304)	.7428*** (.1423)	.2120*** (.0727)
$\Delta \ln(e_{cht}) \cdot \ln(\text{Size}_x)$	-.0218*** (.0068)	-.0340*** (.0094)	-.0090** (.0039)
$\Delta \ln(e_{cht}) \cdot \ln(\text{Months}_{mxt})$	.0101*** (.0016)	.0078*** (.0032)	.0069*** (.0023)
$\Delta \ln(e_{cht}) \cdot \ln(\text{Size}_x) \cdot \ln(\text{Months}_{mxt})$	-.0005*** (.0001)	-.0003* (.0002)	-.0004*** (.0001)
Fixed effects	c, h, t	c, h, t	c, h, t
Observations	16,902,000	11,202,000	5,700,000

Notes: Superscripts *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Standard errors are clustered at the country level. Number of observations has been rounded to the nearest 1000 as per U.S. Census Bureau Disclosure Guidelines.

of the same size increases pass-through by only 1pp (14.0%), from 0.07 to 0.08. The results hold separately for both positive and negative exchange rate shocks (Columns 2-3).

Pass-Through and the Relationship Life Cycle

I test three additional implications of the life cycle model in the data, and show that they are not rejected. First, the model predicts that pass-through is higher for those relationships which have more relationship capital. Since relationship capital is correlated in my model with the observed trade value, I can test this implication. I run a regression of the form given in (1), where I replace the relationship length dummies with dummies for value traded. To eliminate cross-sectional effects, I normalize the value traded in the first year of a relationship to one, and examine whether pass-through is positively correlated with trade relative to year one. Define $d_{mx,i(t)}^{med}$ as a dummy that is equal to one if the relationship trades 25%-50% more in the year associated with transaction i than in year one, and $d_{mx,i(t)}^{high}$ be a dummy that is one if the relationship trades more than 50% more than in the first year. I then run

$$\begin{aligned} \Delta \ln(p_{mxchi(t)}) = & \beta_0 + \beta_1 \Delta \ln(e_{ct}) + \beta_2 d_{mx,i(t)}^{med} + \beta_3 d_{mx,i(t)}^{med} + \beta_4 \Delta \ln(e_{ct}) \cdot d_{mx,i(t)}^{med} \\ & + \beta_5 \Delta \ln(e_{ct}) \cdot d_{mx,i(t)}^{high} + \gamma_{mxh} + \omega_t + \epsilon_{mxchi(t)}. \end{aligned} \quad (22)$$

Table 6: Pass-through model implications

$\Delta \ln(p_{mcxht})$	Value	Products	Last year	Quadratic	Total length	Total length
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln(e_{cht})$	.1904*** (.0053)	.1968*** (.0051)	.2188*** (.0056)	.1407*** (.0085)	.1149*** (.0107)	.1060*** (.0110)
d_{med}	.0266* (.0150)	0.0003 (.0172)				
d_{high}	.0310*** (.0093)	.0183* (.0101)				
d_{first}			-.0621*** (.0094)			
d_{last}			-.0176* (.0093)			
<i>Months</i>				.0022*** (.0004)		
<i>Months</i> ²				-.0000** (.0000)		
<i>Totmonths</i>					.0005[†] (.0003)	
$d_{med,tot}$						.0372** (.0148)
$d_{high,tot}$						.0462* (.0272)
Fixed effects	<i>mxh,t</i>	<i>mxh,t</i>	<i>mxh,t</i>	<i>mxh,t</i>	<i>mxh,t</i>	<i>mxh,t</i>
Observations	16,902,000	16,902,000	16,902,000	16,902,000	16,902,000	16,902,000

Significance levels:*** : 99% level, ** : 95% level, * : 90% level, [†] : 89% level

Column 1 of Table 6 shows that pass-through is increasing in value traded. Relationships trading more than 50% more than in the first year exhibit pass-through that is about 3.1 percentage points higher than in that year. The effect is smaller but significant for relationships with a moderate increase in trade value.

As an alternative specification, I run the same regression using the number of products traded instead of value. While in my model all relationships trade only one product, it seems plausible that relationships that increase the number of products traded are good relationships that have increased specific assets. Column 2 of Table 6 documents that a higher number of products compared to the first year is associated with higher pass-through, although the effect is small.

The second prediction I examine is that relationships close to separation have a low level of specific assets. Such relationships should therefore have diminished pass-through. To test this implication, I run the pass-through regression (1) with dummies for whether the relationship is in its first or in

its last year. The regression coefficients are only identified for relationships lasting at least three years. Column 3 of Table 6 shows that pass-through is diminished in the last year of a relationship, as predicted. Pass-through is about 1.8% lower in the last relationship year than in the years in the middle of the relationship. Since value traded increases at a diminishing rate in my model and in the data (see Figure 3), another test of the model fit is to introduce a quadratic term into the baseline pass-through regression and to examine its significance. I find that indeed the increase in pass-through with relationship length is a quadratic (Column 4).

A third implication of the model is that relationships that start out with a higher level of relationship capital last longer, since they are further away from the termination threshold. Such relationships should be characterized by high pass-through. To test this implication, I calculate for each relationship the total number of months it exists. I then examine whether a given importer exhibits higher pass-through in the first year for those of his relationships that last longer by running

$$\Delta \ln(p_{mxchi(t)}) = \beta_0 + \beta_1 \Delta \ln(e_{ct}) + \beta_2 Totmonths_{mx} + \beta_3 \Delta \ln(e_{ct}) \cdot Totmonths_{mx} \quad (23)$$

$$+ \ln(AvgSize_x) + \gamma_c + \xi_{mh} + \omega_t + \varepsilon_{mxchi(t)},$$

where $Totmonths_{mx}$ is the total length of the relationship in months, and $AvgSize_x$ controls for the average size of the exporter in the relationship by calculating the sum of his total export value divided by the number of quarters the exporter is in the data. Furthermore, ξ_{mh} are importer-product fixed effects. I use average size rather than total size of the exporter because an exporter with longer relationships has by definition a higher export value. I therefore normalize this figure by the number of quarters the exporter is active. I run the regression only for transactions in the first year of a relationship, and consider only pass-through based on price changes that occur between subsequent quarters, since the asset level could have changed significantly over a longer time horizon. The coefficient of interest is identified by comparing cases where the same importer buys the same product in the same quarter from two exporters of the same size located in the same country, where the relationships with the two last for a different number of months. Columns 5 in Table 6 highlights that higher pass-through in the first year is indeed associated with a longer relationship. A relationship lasting one month longer has pass-through in the first year that is about .05% higher. Column 6 repeats the regression using dummies for relationships that last in total one to four years and more than four years. These findings lend additional support to the relationship life cycle theory.

4 Quantitative Analysis

I now structurally estimate the model. To derive aggregate implications, I extend the model to a continuum of trade relationships selling differentiated varieties to a representative household and parametrize the outside options. The analysis has two purposes: first, I show that the model with relationship capital accumulation is capable of quantitatively matching the relationship life cycle and the increase in pass-through with relationship age observed in the data. Second, I use the estimated model to provide intuition on how changes in the distribution of relationships may affect aggregate inflation, pass-through, and mark-ups. I relate this analysis to the 2008-09 recession, when the number of import relationships of age less than one year fell by one fifth.

4.1 Setup

Let a time period correspond to one quarter. There is a unit mass of buyer firms indexed by j with the production technology described before, each selling a differentiated variety to a representative household. The household aggregates varieties according to a Dixit-Stiglitz aggregator

$$Y = \left(\int_0^1 y(j)^{(\theta-1)/\theta} dj \right)^{\theta/(\theta-1)}, \quad (24)$$

where $y(j)$ is the quantity sold. The demand equation (5) then holds with $\Lambda = P^\theta Y$, where $P = (\int p^f(j)^{1-\theta} dj)^{1/(1-\theta)}$. I set aggregate demand Y exogenously by fixing the household's total income M .

Each buyer searches in a frictional market for a foreign supplier to obtain an input for production. Suppliers are of mass $k > 1$ and homogeneous, and each supplier is able to produce input for any buyer with whom she is matched. To match the level of pass-through in the data, I assume that the seller's input bundle is combined from two primary inputs according to $x = l^\alpha z^{1-\alpha}$, where l is a traded input and z is a local input unaffected by exchange rate shocks (e.g., services). Using the notation from above, the seller's input cost w is then given by $w = (\omega_F)^\alpha (\omega_D)^{1-\alpha}$, where ω_F is the cost of the traded input and ω_D is the price of the local input.²⁹ Let the cost of the traded input evolve according to an AR(1) in logs,

$$\ln(\omega'_F) = \phi \ln(\omega_F) + \xi \quad (25)$$

with $\xi \sim N(0, \sigma_\xi^2)$ independent across sellers. The independence assumption here is not necessary

²⁹I rescale the local input cost to absorb the scaling constant $\alpha^{-\alpha}(1-\alpha)^{\alpha-1}$.

and is made for simplicity.³⁰ I assume that local costs are constant. The presence of a local cost component has been extensively noted in the literature (e.g., [Goldberg and Verboven \(2001\)](#)). I will use the parameter α to match the average degree of pass-through of exchange rate shocks in the data.

Unmatched buyers have probability π_b to meet a new seller in the next period. I will target this probability directly in the estimation. An extension incorporating a matching function generating endogenous matching probabilities as in [Mortensen and Pissarides \(1994\)](#) is discussed in Appendix G.³¹ Buyers search across all countries, and hence their outside option does not depend on costs of any particular seller, $U(w) \equiv U$. I assume that the mass of available sellers is large, so that the distribution of sellers from which unmatched buyers sample is equal to the ergodic distribution of w . Unmatched buyers can produce inputs in-house with marginal cost χ , obtaining a profit of $\Pi_u^b = (1/(\theta - 1))(\theta/(\theta - 1))^{-\theta}(\chi/A)^{1-\theta}P^\theta Q$. This assumption ensures that the full set of varieties is always produced and there is no extensive margin based on the fraction of buyers that is matched. A buyer's outside option is then given by

$$U = \Pi_u^b + \beta[\pi_b EJ(a, w') + (1 - \pi_b)U]. \quad (26)$$

The seller's probability of meeting an unmatched buyer is denoted by π_s . In contrast to the buyer's outside option, the seller's outside value depends on the evolution of her own costs,

$$V(w) = \beta[\pi_s EW(a, w') + (1 - \pi_s)EV(w')], \quad (27)$$

where the per-period profit of being unmatched is normalized to zero.

Initial relationship capital is drawn from a lognormal distribution with parameters (μ_a, σ_a) . Each relationship then evolves as described above. A steady state equilibrium consists of a set of value functions $J(a, w), W(a, w), V(w)$, and U , prices $p(a, w)$ and $p^f(a, w)$, break-up policies $I(a, w)$, a distribution of relationships across states $\Gamma(a, w)$, and a fraction u of unmatched buyers such that buyers choose prices $p^f(a, w)$ to maximize profits, taking as given the intermediate goods price, sellers choose prices $p(a, w)$ and separation policies $I \equiv I(a, w)$ to maximize their value function subject to the buyer's participation constraint, taking as given (a, w) , and the goods market clears.

³⁰Modelling the importance of each country in the representative household's consumption basket and the correlation of each country pair's exchange rates would be an interesting extension, which is beyond the scope of this paper.

³¹This approach also requires two parameters to be estimated (a search cost and a matching function parameter), which would be set to target the empirically observed matching probabilities. Since only these probabilities are needed for the performance of the model, I opt for a more parsimonious route and target them directly.

4.2 Estimation and Identification

Estimating the Parameter Values

I set several parameters of the model exogenously. First, I set the quarterly discount factor to $\beta = 0.992$. I choose an elasticity of substitution of $\theta = 4$ as in [Nakamura and Steinsson \(2008\)](#), which delivers a mark-up of buyers for their final goods close to estimates by [Berry, Levinsohn, and Pakes \(1995\)](#). I estimate the buyer's matching probability π_b using plausibly exogenous break-ups, since after such break-ups buyers seek to replace their lost supplier as quickly as possible. In [Section H](#) in the Appendix, I present a strategy for identifying exogenous supplier deaths, using cases where a supplier suddenly stops trading with at least three independent customers simultaneously and disappears forever from the dataset. I show that such break-ups lead to significant output and employment losses for the importer following the separation, which suggests that buyers seek to replace the lost seller as quickly as possible. The analysis highlights that a buyer that needs to find a new supplier after such a plausibly exogenous break-up takes on average 10.7 months longer to obtain the good than the usual time period between transactions. I therefore set $\pi_b = 0.28$ based on the quarterly period length. For the seller's matching probability π_s , I use the average time passed between the first transaction with a new buyer to the next time the seller meets a new customer, which in the data is about 14 months. Thus, I set $\pi_s = 0.22$. While a higher π_s implies a better outside option for the seller, determining the matching probability accurately is not crucial because the distribution of initial relationship capital is chosen in the estimation step to generate the correct separation rate. When the seller's probability of finding a buyer increases, the distribution shifts to the left so that separation stays the same as before.

I discretize the exchange rate process [\(25\)](#) using the methodology by [Tauchen \(1986\)](#) on a six-state Markov chain. I treat these costs as numeraire and set the mean of the cost process in logs to zero. I set σ_w by calculating in the data the average quarterly standard deviation of exchange rate innovations, across all currencies used. This standard deviation is 6.8%, and thus $\sigma_w = .068$. Similarly, I set ϕ by computing the average quarterly first-order autocorrelation of the log exchange rate processes across all currencies. This procedure yields $\phi = 0.94$. Finally, I fix the total household income to $M = 1$.

Eight parameters remain to be estimated: the mean and standard deviation of the initial distribution of relationship capital, μ_a and σ_a , the depreciation rate δ , the curvature of relationship capital γ , the standard deviation of the idiosyncratic shocks σ_ϵ , the share of traded costs α , the parameter governing the buyer's profits from internal production χ , and aggregate productivity A . I estimate these parameters using 18 moments. First, I choose eight data points from the life cycle of values traded that reflect the overall shape of the relationship life cycle. I target the value traded in the second year of three-year relationships, in the second and third year of four- and five-year relationships, and in the second, third, and fourth year of six-year relationships. Value traded in the model corresponds to pq .

Second, I seek to match the average price decline over time. Since an average relationship trades twice per month, based on the results in Table 3 I target a price decline from the first to the fourth quarter of about 0.9%, from the first to the eighth quarter of about 1.9%, and from the first to the twelfth quarter of about 2.8%. Third, I choose three data points from the quarterly hazard rate of relationship destruction. I target the break-up probability in the first and second quarter to match the high initial rate of destruction, and after 16 quarters to capture the break-up probability of long-term relationships. Fourth, I target the cross-sectional share of value traded by relationships that are one and two quarters old to match the share of young relationships in the data, and the share of relationships that are more than 16 quarters old to match the share of old relationships. Finally, based on the pass-through regressions I target an average pass-through level of 0.2.

Identification

The mean of the initial relationship capital distribution μ_a is identified from the probability of break-ups after the first transaction. If μ_a is low, the average new relationship makes low initial profits, which increases the initial separation probability. The parameter σ_a is identified from the life cycle of values traded, in particular from the path of the life cycle after the peak. If σ_a is high, relationships that survive after the first period on average received larger positive shocks. They are therefore on average further away from termination, leading to large declines in value traded before they terminate.

The depreciation rate of relationship capital δ , the curvature of relationship capital γ , and the standard deviation of the shocks to assets σ_ε are identified from the entire life cycle profile of values, the cross-sectional age distribution, and the hazard rate of break-ups. A higher value of δ implies a flatter profile of values traded, since any positive shock has a smaller impact. Higher depreciation also means that the cross-sectional distribution is more concentrated at younger ages, and the break-up hazard is higher. On the other hand, increasing γ leads to a slower accumulation of relationship capital for $a < 1$ and a faster accumulation for $a > 1$, as per Proposition 1. It therefore leads to a stronger (weaker) increase in quantity traded and stronger (weaker) price declines for relationships with low (high) relationship capital, making it distinct from δ . Lastly, a larger σ_ε steepens the quantity and price profile, since those relationships that survive on average received larger positive shocks. On the other hand, it also makes the break-up hazard flatter, since even relationships that start out with a high level of initial assets may be destroyed quickly. The parameter σ_ε affects all years of the relationship life cycle, thus differing from the initial distribution parameter σ_a , which affects only the starting point.

The buyer's costs in internal production χ are identified from the probability of break-ups and from the average level of pass-through. When χ is low, the set of states in which the buyer's outside option binds while the seller's outside option does not bind increases, lowering the average level of

Table 7: Estimated Simulation Parameters

Parameter	Value
Mean of initial capital (μ_a)	-0.13
Standard dev of initial capital (σ_a)	0.36
Depreciation (δ)	0.11
Curvature of capital (γ)	0.2
Standard dev of shocks (σ_ε)	0.17
Unmatched buyer costs (χ)	0.97
Tradeable share (α)	0.40
Productivity (A)	1.65

pass-through. Note that this feature generates increasing pass-through with relationship capital, but this moment is not explicitly targeted in the estimation. At the same time, a lower χ reduces the value of new relationships, increasing the level of relationship capital at which break-up occurs. Since the outside options depend recursively on the value of a relationship and since the matching probabilities are fixed, χ provides an independent variable to scale the seller's outside option to match the right level of break-ups of young relationships. The trade-off is that in the region in which the buyer is constrained, the price rises with relationship capital, which counterfactually generates higher prices in older relationships. The parameter α is used to target the overall level of pass-through. When α is higher, the share of costs that is affected by cost shocks rises, leading to a larger response of the price to the shock and hence higher pass-through.

Finally, the productivity parameter A scales the overall level of profits, quantities traded, and prices in the model. When A is high, firms make high profits when they are in a relationship and therefore the separation rate is low. At the same time, quantity traded increases rapidly with relationship capital while the price falls.

I estimate the model via simulated method of moments, following the MCMC procedure by [Chernozhukov and Hong \(2003\)](#). The simulations are conducted with 5,000 firms for 300 periods, where I discard the first 50 periods as burn-in. Table 7 shows the estimated parameter values.

4.3 Performance and Aggregate Implications

The upper panel of Table 8 compares the model moments to the data. Columns 1 and 3 present the data moments, and columns 2 and 4 the model moments. To visualize the model's performance, Figure 7 shows the model-generated life cycle of value traded (top left), the price as a function of relationship age (top right), the hazard rate of break-ups (bottom left), and the cross-sectional distribution of re-

Table 8: Data Moments Versus Model Moments

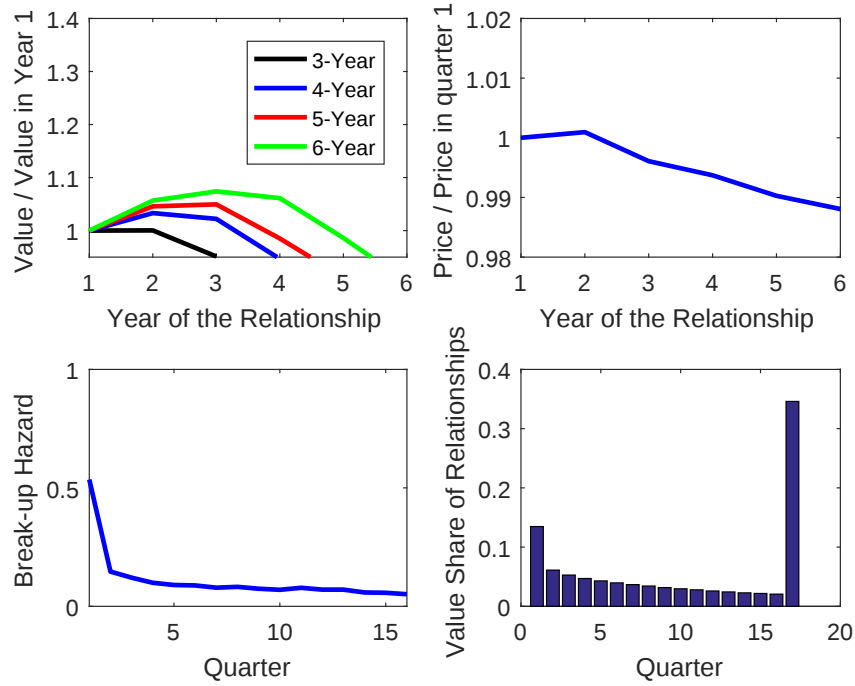
	Data	Model		Data	Model
	(1)	(2)		(3)	(4)
Increase in value year 1-2 (3y rels)	-0.015	0.004	Quarterly break-up hazard in Q1	0.695	0.535
Increase in value year 1-2 (4y rels)	0.040	0.033	Quarterly break-up hazard in Q2	0.311	0.147
Increase in value year 1-3 (4y rels)	0.009	0.022	Quarterly break-up hazard in Q16	0.087	0.051
Increase in value year 1-2 (5y rels)	0.104	0.046	Cross-sectional value in rels $\leq 3m$	0.243	0.135
Increase in value year 1-3 (5y rels)	0.097	0.050	Cross-sectional value in rels 3 – 6m	0.095	0.061
Increase in value year 1-2 (6y rels)	0.133	0.057	Cross-sectional value in rels $> 48m$	0.177	0.346
Increase in value year 1-3 (6y rels)	0.207	0.074	Average pass-through	0.200	0.266
Increase in value year 1-4 (6y rels)	0.142	0.061			
Change in price quarter 1-4	-0.009	0.001			
Change in price quarter 1-8	-0.019	-0.004			
Change in price quarter 1-12	-0.028	-0.006			
J (objective)	0.689				

lationship value by relationship age (bottom right). Overall, the model fits the data well. The model generates a life cycle of value traded and a declining price path, as well as a sharply decreasing separation hazard. The last row of the table provides the value of the objective function J , where a value closer to zero indicates a better model fit. The main shortcoming of the model is that the life cycle is compressed.

The setup overstates the increase in value traded for short relationships, and understates the increase for long relationships. For example, in the data the value traded in 4-year relationships increases by 0.9% between years one and three, and by 20.7% for 6-year relationships. In the model, the corresponding values are 9.3% and 12.7%, respectively. The reason the model has trouble matching this fact is that it generates a higher dispersion across cohorts only via a larger variance of asset shocks σ_ε . However, a higher shock variance also increases the fraction of relationships that get destroyed early, raising the fraction of young relationships and flattening the break-up hazard, which are matched relatively well. One possibility to generate a more dispersed profile would be to introduce heterogeneity in δ or σ_ε for different levels of specific assets, as this would weaken the link between break-ups and the dispersion of the life-cycle.

The solid blue line in Figure 8a presents the coefficients from running specification (1) in the simulated data. I do not include time fixed effects since there is no aggregate trend in the simulation, and plot the coefficients on quarter dummies interacted with the change in $\ln(\omega_F)$. Comparing the regression coefficients from the simulation to the coefficients from the empirical estimation (black solid line), the model overall captures the increase in pass-through with relationship age well. Pass-

Figure 7: Model-Generated Moments

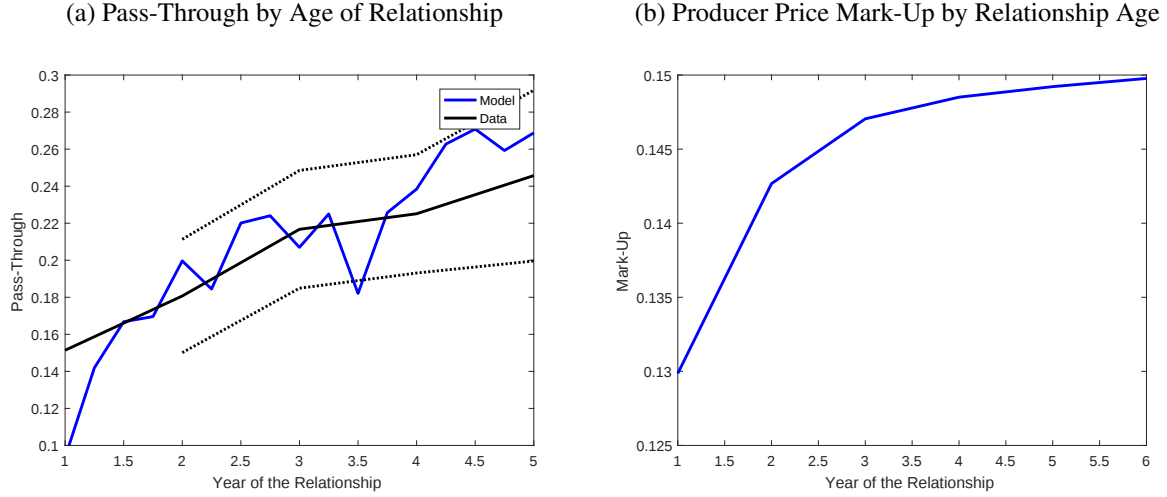


through is within the 95% confidence bands of the empirical estimation throughout years two through five, although it is a bit too low in the first year. In both the model and the data pass-through increases most strongly during the first years and becomes flatter after that, matching the model intuition that pass-through is the same once the buyer constraint is no longer binding. Matching the increase in pass-through is a significant success of the model, as it depends on non-trivial objects such as the value of the Lagrange multiplier. Furthermore, this moment was not part of the estimation.

Figure 8b presents the average producer price mark-up μ by relationship age. Since older relationships on average have more relationship capital, the seller sets a larger mark-up over her input cost (w/a^γ). The mark-up increases from about 13% in the first year to 15% by year six in my simulation. The total mark-up of the consumer price p^f over the original input cost (w/a^γ) is the product of μ and the buyer firm's mark-up $\theta/(\theta - 1)$ charged to the household. Since $\theta = 4$ in the simulation, it rises from about 50% to 53%. Note that despite a larger mark-up in older relationships, overall prices are lower when firms have a longer relationship, as shown in the top right panel in Figure 7, since the decline in marginal costs dominates the increase in mark-ups.

I now use the estimated model to show that changes in the average length of relationships can affect aggregate pass-through and mark-ups. Berger and Vavra (2018) document using import price data from the Bureau of Labor Statistics that pass-through during recessions is significantly higher

Figure 8: Pass-Through and Mark-Ups

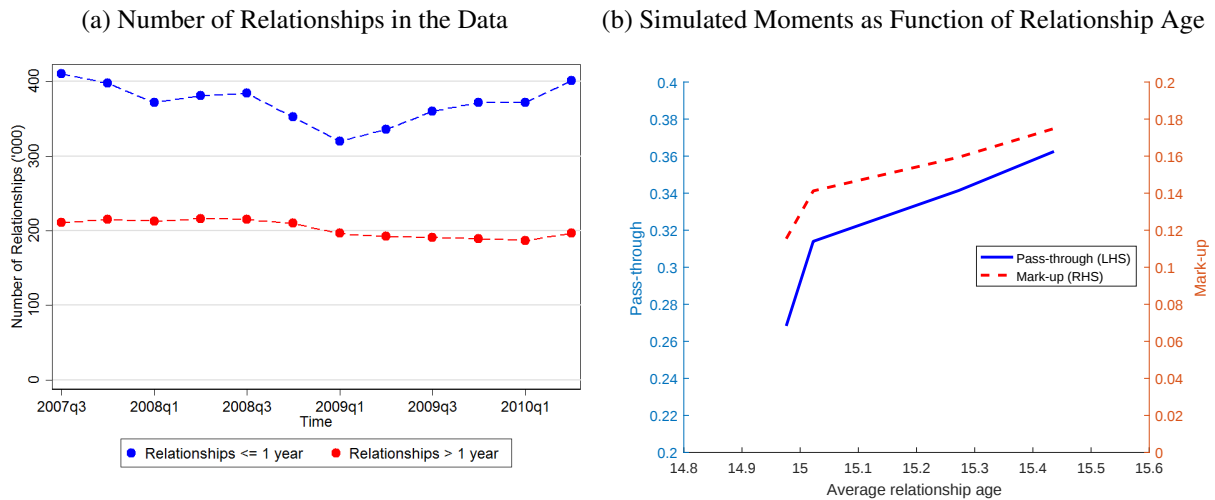


than in expansions, rising from 0.2 to 0.4 during the 2008-09 recession. Similarly, [Rotemberg and Woodford \(1999\)](#) provide evidence that mark-ups are countercyclical. My framework generates both of these effects via a novel mechanism: cyclical variation in the average relationship length in the economy. In the data, I find that during the most recent recession in 2008-09, the number of U.S. import relationships of age less than one year fell by about 20%, compared to a significantly smaller drop in the number of older relationships (Figure 9a). Using the model, I can estimate the effect of an increase in the average age of relationships on pass-through and mark-ups. I compare several steady states with different average relationship length, where I construct these steady states by shifting the mean of the distribution of new relationships μ_a and by adjusting the buyer's marginal cost χ to hold the seller's policy function approximately constant. Figure 9b shows that an increase in the average age of relationships in the economy by one month increases pass-through by about one third and the producer price mark-up by about one half. Given $\theta = 4$, this implies an increase in the consumer price mark-up by about 16%. Since the average age of relationships is countercyclical, my model suggests that variation in the average relationship length in the economy generates countercyclical movements in the responsiveness of prices to shocks and in aggregate mark-ups.

5 Conclusion

This paper argues that the average length of relationships in the economy affects the aggregate responsiveness of prices to shocks and aggregate mark-ups. Using transaction-level trade data, I show that a relationship's price become more responsive to exchange rate shocks as the relationship ages. This

Figure 9: Cyclical Properties of Relationships



effect is large: a four-year relationship exhibits exchange rate pass-through that is about 50% higher than a new relationship. To understand how old relationships differ from new ones, I document a set of stylized facts about the dynamic evolution of relationships and show that they follow a life cycle. Relationships begin by trading little and initially have a high break-up probability. As the relationship ages, the value of trade rises and the price relative to the market falls. Trade declines again near the end of the relationship.

To rationalize my empirical findings, I develop a model in which a buyer and a seller firm interact repeatedly under limited commitment and accumulate relationship capital in proportion to the quantity traded to lower production costs. I show that this model generates the relationship life cycle through a combination of idiosyncratic shocks to relationship capital and endogenous separation when capital is low. Furthermore, the model generates increasing pass-through and mark-ups with relationship age. In a new relationship, relationship capital is low on average, and the seller responds little to shocks and sets low mark-ups to incentivize the buyer to maintain the association and to build up relationship capital more quickly. Older relationships on average have a higher level of relationship capital, weakening these incentives and therefore raising mark-ups and pass-through. Since the average age of relationships increases in recessions, the model predicts a countercyclical responsiveness of prices to shocks and countercyclical mark-ups. Quantitative simulations suggest that an increase in the average age of relationships in the economy by one month could increase pass-through by about one third and the consumer price mark-up by about 16%.

This work forms the beginning of a broader research agenda aimed at understanding how long-term relationships affect the U.S. economy. In related work, I investigate how uncertainty about trade policy may affect firms' desire to form long-term relationships with suppliers (Heise, Pierce,

[Schaur, and Schott \(2017\)](#)). This work has shown that when the probability of a trade war is high, importers are reluctant to form long-term relationships with suppliers since they may be forced to end the relationship soon, which may raise consumer prices.

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Appendix

A Construction of the Dataset

This section describes in detail the preparation of the dataset. The first task is to ensure consistency of the importer identifiers. The alpha variable in the LFTTD identifies the U.S. importer at the firm level, and is analogous to the firm ID in other Census datasets, such as the LBD. However, in 2002, the Census Bureau changed the firm identification codes for single unit firms, making these identifiers inconsistent over time. For single unit firms, I therefore map the alphas in the LFTTD to the Census File Numbers (CFNs) in the LBD, and use these to obtain time-consistent firm identifiers from the LBD. For multi-unit firms, I retain the original identifiers. As a robustness check of these identifiers, I use the Employer Identification Numbers (EINs), which are also reported in the LFTTD, as an alternative identifier. These are tax IDs defined at the level of a tax unit. Consequently, a given firm may have several EINs, and an EIN may comprise several plants. Using this variable yields nearly identical results to my analyses using the firm ID variable. The main difference is that relationships based on the EIN are shorter.

The foreign manufacturer ID (or “exporter ID”) combines the name, the address, and the city of the foreign supplier.³² [Monarch \(2015\)](#) and [Kamal, Krizan, and Monarch \(2015\)](#) conduct a variety of robustness checks of this variable, and find that it is a reliable identifier of firms both over time and in the cross-section. Importantly, importers are explicitly warned by the U.S. CBP to ensure that the manufacturer ID reflects the true producer of the good, and is not an intermediary or processing firm. For the HS10 codes, I use the concordance by [Pierce and Schott \(2012\)](#) to ensure the consistency of the codes, since some of them change over time. With regard to the date, I use the date of the shipment from the foreign country as the date of the transaction, rather than the arrival date in the U.S.. The export date is the date at which the foreign supplier completed the transaction, and based on which the transaction terms should be set. I aggregate all transactions between the same partners in the same HS10 code on the same day into one by summing over the values and quantities of that day. Further aggregation is done on a monthly or quarterly basis when needed.

Several additional data cleaning operations are performed. First, I remove all transactions that do not include an importer ID, exporter ID, or HS code. I also remove all observations for which the recorded date is erroneous, and drop observations for which the exporter ID does not start with a letter (since it should start with the country name) or has fewer than three characters. I also remove observations which are missing a value or a quantity. Note that due to the cleaning operations and the removal of related party transactions, the aggregate value of trade based on my sample is significantly lower than the total value of trade recorded in official publications. In order to remove the general effect of inflation, I deflate the transaction values using the quarterly GDP deflator from FRED. I keep only imports used for consumption by dropping warehouse entries.

³²Specifically, it contains the ISO2 code for the country’s name, the first three letters of the producer’s city, six characters taken from the producer’s name and up to four numeric characters taken from its address. See [Monarch \(2014\)](#) for details.

B Correcting the Pass-Through Regressions for Selection

I re-write regression specification (??) as

$$\Delta \ln(p_{mxcht}) = z_{mxcht}^1 \beta + \gamma_{mxh} + \omega_t + \tilde{\varepsilon}_{mxcht}, \quad (28)$$

where z_{mxcht}^1 is a $1 \times K$ vector of regressors used in the pass-through regression and includes unity, β is a $1 \times K$ vector of parameters, γ_{mxh} accounts for relationship-product specific unobserved heterogeneity, ω_t captures unobserved time-varying effects, and $\tilde{\varepsilon}_{mxcht}$ is an error term. I drop the explicit reference to the transaction number i and use only the time index t to denote the transaction. The selection equation is specified as

$$s_{mxcht} = 1 [z_{mxcht} \delta + \xi_{mxh} + \rho_t + \tilde{a}_{mxcht} > 0], \quad (29)$$

where s_{mxcht} is a selection indicator, $z_{mxcht} = [z_{mxcht}^1 \ z_{mxcht}^2]$ is a vector of regressors, ξ_{mxh} is relationship-product specific unobserved heterogeneity, ρ_t is time-dependent unobserved heterogeneity, and $\tilde{a}_{mxcht}$ is a normally distributed error term.

If firms choose not to trade for unobservable reasons, then $E[\tilde{\varepsilon}_{mxcht} | z_{mxcht}^1, \gamma_{mxh}, \omega_t, s_{mxcht} = 1] \neq 0$, and the standard fixed effects estimator produces inconsistent estimates. While differencing equation (28) could remove the triplet-fixed effect and eliminate the selection problem, this approach only works if

$$E[\Delta \tilde{\varepsilon}_{mxcht} | z_{mxcht}^1, z_{mxcht-1}^1, \omega_t, \omega_{t-1}, s_{mxcht} = s_{mxcht-1} = 1] = 0.$$

This equation does not hold if for example selection is time-varying. In such cases, the estimation needs to take the selection process into account. A standard approach in the literature to estimate a selection model in panel data is based on [Wooldridge \(1995\)](#). This approach parametrizes the conditional expectations of the unobservables via a linear combination of observed covariates.

To simplify, I assume that the time-varying unobservables depend linearly on U.S. GDP according to

$$\omega_t = GDP_t \phi_1 + e_1 \quad (30)$$

and

$$\rho_t = GDP_t \phi_2 + e_2. \quad (31)$$

I define $\varepsilon_{mxcht} = \tilde{\varepsilon}_{mxcht} + e_1$ and $a_{mxcht} = \tilde{a}_{mxcht} + e_2$. Then, the problem can be written as

$$\Delta \ln(p_{mxcht}) = z_{mxcht}^1 \beta + GDP_t \phi_1 + \gamma_{mxh} + \varepsilon_{mxcht}, \quad (32)$$

with

$$s_{mxcht} = 1 [z_{mxcht} \delta + GDP_t \phi_2 + \xi_{mxh} + a_{mxcht} > 0]. \quad (33)$$

I now apply the approach of [Wooldridge \(1995\)](#) to my problem. The method is based on four main assumptions. I follow the discussion in [Dustmann and Rochina-Barrachina \(2007\)](#), and let bold letters indicate vectors or matrices that include all periods.

Assumption 1. The conditional expectation of ξ_{mxh} given $(z_{mxch1}, \dots, z_{mxchT})$ is linear.

Based on this assumption, the selection equation (33) can be written as

$$s_{mxcht} = 1 [\psi_0 + z_{mxch1}\psi_1 + \dots + z_{mxchT}\psi_T + GDP_t\phi_2 + v_{mxcht} > 0], \quad (34)$$

where v_{mxcht} is a random variable. Thus, selection is assumed to depend linearly on all leads and lags of the explanatory variables.

Assumption 2. The error term v_{mxcht} is independent of the entire matrix of observables $[z_{mxch} \quad \mathbf{GDP}]$ and is distributed $v_{mxcht} \sim N(0, 1)$.

Assumption 3. The conditional expectation of γ_{mxh} given z_{mxch} and v_{mxcht} is linear.

Under this assumption,

$$E[\gamma_{mxh} | z_{mxch}, v_{mxcht}] = \pi_0 + z_{mxch1}\pi_1 + \dots + z_{mxchT}\pi_T + \phi_t v_{mxcht}. \quad (35)$$

While the Wooldridge approach allows ϕ_t to be time-varying, I make the assumption that it is constant.

Assumption 4. The error term in the main equation satisfies

$$E[\varepsilon_{mxcht} | z_{mxch}, \mathbf{GDP}, v_{mxcht}] = E[\varepsilon_{mxcht} | v_{mxcht}] = \rho v_{mxcht}. \quad (36)$$

I additionally apply the simplification by [Mundlak \(1978\)](#) and assume that γ_{mxh} and ξ_{mxh} depend only on the time averages of the observables $\bar{z}_{mxch}$, rather than on the entire lead and lag structure. [Dustmann and Rochina-Barrachina \(2007\)](#) also use this assumption in their application. The assumption is necessary here since the dataset is extremely large, and therefore estimating the coefficients on all leads and lags is computationally infeasible. Under these assumptions, I can re-write the main equation as

$$\Delta \ln(p_{mxcht}) = z_{mxcht}^1 \beta + \bar{z}_{mxch} \pi + GDP_t \phi_1 + \mu \lambda [z_{mxcht} \rho + \bar{z}_{mxch} \eta + GDP_t \phi_2] + \varepsilon_{mxcht}, \quad (37)$$

where $\lambda(\cdot)$ denotes the inverse Mill's ratio. The selection equation is given by

$$s_{mxcht} = 1 [z_{mxcht} \rho + \bar{z}_{mxch} \eta + GDP_t \phi_2 + v_{mxcht} > 0]. \quad (38)$$

While it would be desirable to estimate the equation on a fully squared dataset that records a missing observation in every quarter between 1995 and 2011 in which a relationship-product triplet does not trade, such a dataset

would be considerably too large for estimation, in particular since many relationships trade only a few times. To operationalize the estimation, I therefore assume that new relationships are randomly formed. This assumption is supported by the high hazard rate of separation after the first transaction observed in the data. More strongly, I assume that there is no selection problem regarding the start of a relationship-product triplet, which allows me to exclude all missing trades before the start of a triplet from the selection problem. Furthermore, I retain missing trades after the last transaction of a relationship-product triplet for only four quarters, and interpret this as relationship partners “forgetting” their transaction partner for that product after that time. While these assumptions are obviously stylized, they allow me to reduce the dataset to a manageable size. Given these assumptions, for each triplet the time averages $\bar{z}_{mxch}$ are only taken over the relevant period.

As in the main text, z_{mxcht} contains the cumulative exchange rate change $\Delta \ln(e_{ct})$, the length of the relationship in months $Months_{mxt}$, and the interaction of the two. I add several variables that should predict selection. I include the level of the exchange rate, the log real value traded at the last transaction, the time gap in quarters since the last transaction of the triplet, and the average time gap since the last transaction across all U.S. importers. A higher value traded at the last transaction should diminish the probability to transact again, while this probability should increase with the time gap since the last transaction. On the other hand, a larger average time gap across all exporters implies that this is a product that is less frequently traded, which should reduce the probability of trade in a given quarter. My exclusion restriction is that the average time gap at the product level is unrelated to pass-through, and therefore does not enter the main equation (37). Thus, z_{mxcht}^1 includes all regressors except this variable. If I impose the strong assumption that ε_{mxcht} is normally distributed, I can estimate the system via Maximum Likelihood in the same way as a Heckman selection model.

C Product and Country Categories

Table 9: List of product categories

Product category	HS 2 code	Product category	HS 2 code
Animal products	01 - 05	Textiles	50 - 63
Vegetables	06 - 14	Footwear	64 - 67
Fats	15	Stones and ceramics	68 - 70
Food	16 - 24	Jewelry	71
Mineral products	25 - 27	Metals and metal products	72 - 83
Chemicals	28 - 38	Machinery	84 - 85
Plastics	39 - 40	Transportation	86 - 89
Leather products	41 - 43	Optical products	90 - 92
Wood products	44 - 49	Arms	93

Table 10: List of countries

Australia	Czech Republic	India	Mexico	South Africa
Austria	Denmark	Indonesia	Netherlands	South Korea
Belgium	Estonia	Ireland	New Zealand	Spain
Brazil	Finland	Israel	Norway	Sweden
Canada	France	Italy	Poland	Switzerland
Chile	Germany	Japan	Portugal	Taiwan
China	Greece	Latvia	Russia	Thailand
Colombia	Hungary	Lithuania	Slovak Republic	Turkey
Costa Rica	Iceland	Luxemburg	Slovenia	United Kingdom

D Proofs

D.1 Existence of Recursive Representation

Denote by $A \in \mathbb{R}$ the set of values that a can take. Furthermore, let $H(a_t)$ denote the constraint correspondence mapping a_t into possible values for $\tilde{a}_{t+1}$. Following Acemoglu (2009), Chapter 6.3, Theorems 6.1- 6.3, if the conditions listed in the following hold, then for any $a \in A$ and $w \in [\underline{w}, \infty)$ any solution to the sequence problem (11) is also a solution to the recursive formulation of the problem, the solutions to the two problems are identical, and an optimal plan $\tilde{a}^*$ exists.

1. A is a compact subset of $\mathbb{R}$
2. The correspondence $X(a_t)$ is non-empty for all $a_t \in A$, compact, and continuous
3. $\Pi^s(a_t, w_t)$ is continuous in both a_t and $\tilde{a}_{t+1}$ and finite for all $a_t \in A$ and w_t

To prove these statements, I first show the following two Lemmas.

Lemma 1. *The seller's profit function $\Pi^s(a_t, w_t)$ is strictly concave in the choice variable $\tilde{a}_{t+1}$ for all (a_t, w_t) and all t and attains a positive maximum for some $\tilde{a}_{t+1}^*$, given (a_t, w_t) .*

Proof. Using equation (8) in (9) and re-arranging, the seller's price can be expressed as

$$p_t = \left[\frac{\left(\frac{\theta}{\theta-1}\right)^\theta}{\rho A^{\theta-1} \Lambda} (\tilde{a}_{t+1} - (1-\delta)a_t) \right]^{-1/\theta}.$$

Therefore, the seller's profits in period t are

$$\Pi^s(a_t, w_t) = \left[\left[\frac{\left(\frac{\theta}{\theta-1}\right)^{-\theta} \rho A^{\theta-1} \Lambda}{(\tilde{a}_{t+1} - (1-\delta)a_t)} \right]^{1/\theta} - \frac{w_t}{a_t^\gamma} \right] \frac{1}{\rho} (\tilde{a}_{t+1} - (1-\delta)a_t). \quad (39)$$

The second derivative with respect to $\tilde{a}_{t+1}$ is

$$-(\theta-1) \frac{\left[\frac{\rho(\theta/(\theta-1))^{-\theta} A^{\theta-1} \Lambda}{(\tilde{a}_{t+1} - (1-\delta)a_t)} \right]^{1/\theta}}{\theta^2 \rho (\tilde{a}_{t+1} - (1-\delta)a_t)} < 0.$$

Therefore, profits are strictly concave in $\tilde{a}_{t+1}$ and are maximized at the FOC. The maximizer is $p_t^* = (\theta/(\theta-1))w_t/a_t^\gamma$, which yields the static optimum of profits of

$$(\Pi^s)^*(a_t, w_t) = \left(\frac{1}{\theta-1} \right) \left(\frac{\theta}{\theta-1} \right)^{-2\theta} w_t^{1-\theta} a_t^{\gamma(\theta-1)} A^{\theta-1} \Lambda > 0. \quad (40)$$

□

Lemma 2. *There exists an upper bound on the capital choice $\bar{a}$ such that $\tilde{a}_{t+1} < a_t$ for any $a_t > \bar{a}$ and for all w_t .*

Proof. Assume that given state (a_t, w_t) , the seller sets next period's capital to the current capital level, $\tilde{a}_{t+1} = a_t$. At this capital choice, from equation (39), the seller's static profits are

$$\Pi^s(a_t, w_t)|_{\tilde{a}_{t+1}=a_t} = \frac{\delta}{\rho} a_t^{(\theta-1)/\theta} \left\{ \left[\rho \left(\frac{\theta}{\theta-1} \right)^{-\theta} A^{\theta-1} \Lambda \right]^{1/\theta} \delta^{-1/\theta} - w_t a_t^{1/\theta-\gamma} \right\}.$$

Since by Assumption 3.1 $\gamma < 1/\theta$, the term in parentheses becomes negative once a_t exceeds a threshold value that sets the term equal to zero. Call this value $\hat{a}(w_t)$. The first derivative of profits, evaluated at $\tilde{a}_{t+1} = a_t > \hat{a}(w_t)$, is

$$\begin{aligned} \frac{d\Pi^s(a_t, w_t)}{d\tilde{a}_{t+1}} \Big|_{\tilde{a}_{t+1}=a_t > \hat{a}(w_t)} &= \frac{\delta}{\rho} \left(\frac{\theta-1}{\theta} \right) a_t^{-1/\theta} \left\{ \left[\rho \left(\frac{\theta}{\theta-1} \right)^{-\theta} A^{\theta-1} \Lambda \right]^{1/\theta} \delta^{-1/\theta} - w_t a_t^{1/\theta-\gamma} \right\} \\ &\quad - \frac{\delta}{\rho} \left(\frac{1}{\theta} - \gamma \right) w_t a_t^{-\gamma} < 0. \end{aligned}$$

Therefore, since the seller's profit function is strictly concave in $\tilde{a}_{t+1}$ by Lemma 1 and attains a positive maximum, setting $\tilde{a}_{t+1} > a_t$ whenever $a_t > \hat{a}(w_t)$ gives the seller a strict loss in the current period. Furthermore, for any two values a_t^1 and a_t^2 satisfying $\hat{a}(w) < a_t^1 < a_t^2$,

$$0 > \Pi^s(a_t^1, w_t)|_{\tilde{a}_{t+1}=a_t^1} > \Pi^s(a_t^2, w_t)|_{\tilde{a}_{t+1}=a_t^2},$$

and hence the smallest possible loss from choosing $\tilde{a}_{t+1} \geq a_t$ become larger and larger as a_t grows, and $\Pi^s(a_t^1, w_t)|_{\tilde{a}_{t+1}=a_t}$ goes to negative infinity as $a_t \rightarrow \infty$.

It remains to show that the seller's additional expected value from future periods obtained by setting $\tilde{a}_{t+1} \geq a_t$ is not sufficient to offset these losses. From equation (40), the seller's profits at the static profit maximizing price are strictly concave in a_t , since by Assumption 3.1, $\gamma < 1/(\theta-1)$. Furthermore, $\lim_{a_t \rightarrow \infty} (d(\Pi^s)^*(a_t, w_t)/da_t) = 0$. Therefore, the marginal value of additional capital falls, and the seller's incentive to deviate from the profit-maximizing price diminishes as $a_t \rightarrow \infty$. Since the current period loss from increasing the expected value of a_t is growing to infinity with the level of capital while the marginal benefit of increasing a_t declines and approaches zero, it must be the case that there is a threshold level $\bar{a}$ at which the marginal benefit of adding an extra unit of capital is smaller than the marginal cost for any $w_t > \underline{w}$ (and equal for $\underline{w}$).

□

I now prove that the three conditions hold.

1. A is a compact subset of $\mathbb{R}$

By Lemma 2, the seller chooses $\tilde{a}_{t+1} < \bar{a}$ whenever $a_t > \bar{a}$, and hence if there were no stochastic shocks to capital

then capital would never exceed $\bar{a}$ for any process with $a_0 < \bar{a}$. As stated in Footnote 27, due to the stochastic shocks it is possible that $a_t > \bar{a}$ for a sequence of very good shocks. However, since the mean of the shocks is zero and their variance is finite and since the seller chooses $\tilde{a}_{t+1} < \bar{a}$ whenever $a_t > \bar{a}$, the probability that capital exceeds some upper bound $a'' \gg \bar{a}$ goes to zero for sufficiently large a'' . Under the technical assumption imposed by Footnote 27 that the capital evolution process is bounded above by some very large a'' , $A = [0, a'']$ is a compact subset of $\mathbb{R}$.

2. The set $X(a_t)$ is non-empty for all $a_t \in A$, compact, and continuous

Since $p_t \geq 0$ by assumption, it follows that the choice set $X(a_t)$ satisfies $\tilde{a}_{t+1} \in [(1 - \delta)a_t, a'']$ for all t . This set is non-empty, compact, and continuous.

3. $\Pi^s(a_t, w_t)$ is continuous in both a_t and $\tilde{a}_{t+1}$ and finite for all $a_t \in A$ and w_t

From the expression in (39), $\Pi^s(a_t, w_t)$ is clearly continuous for all $\tilde{a}_{t+1} \geq (1 - \delta)a_t$. Furthermore, from equation (40), $\lim_{a \rightarrow 0} (\Pi^s)^*(a, w) = 0$ (given $w > 0$), and $(\Pi^s)^*(a'', w)$ is finite for all w . Therefore, the maximum possible profits the seller can obtain in any given state are finite, and hence $\Pi^s(a_t, w_t)$ must be finite.

D.2 Concavity of the Value Function

Following Acemoglu (2009), Theorem 6.4, the value function $J(a, w)$ is strictly concave in a if the profit function $\Pi^s(a, w)$ is concave and if the constraint correspondence $X(a)$ is convex. I first prove concavity of the profit function. Using the expression for quantity (8) in (9) and re-arranging, the seller's price can be expressed as

$$p = \left[\frac{\left(\frac{\theta}{\theta-1}\right)^\theta}{\rho A^{\theta-1} \Lambda} (\tilde{a}' - (1 - \delta)a) \right]^{-1/\theta},$$

and therefore, the seller's current profits are

$$\Pi^s(a, w) = \left[\left[\frac{\left(\frac{\theta}{\theta-1}\right)^{-\theta} \rho A^{\theta-1} \Lambda}{(\tilde{a}' - (1 - \delta)a)} \right]^{1/\theta} - \frac{w}{a^\gamma} \right] \frac{1}{\rho} (\tilde{a}' - (1 - \delta)a). \quad (41)$$

Denote the Hessian of this profit equation with respect to the two variables a and $\tilde{a}'$ by $H(a, \tilde{a}')$. The elements of the Hessian matrix are

$$\begin{aligned} H_{11} = & -\frac{\gamma}{\rho} \frac{w}{a^{1+\gamma}} \left\{ (1 + \gamma) \left[\frac{\tilde{a}'}{a} - (1 - \delta) \right] + \left(\frac{1 + \theta}{\theta} \right) (1 - \delta) \right\} \\ & - \frac{1}{\rho} \left(\frac{\theta - 1}{\theta} \right) (1 - \delta) \frac{w}{a^{1+\gamma}} \gamma - \frac{(\theta - 1)(1 - \delta)^2}{\rho \theta^2 [\tilde{a}' - (1 - \delta)a]} p, \end{aligned}$$

and

$$H_{12} = H_{21} = \frac{1}{\rho} \frac{w}{a^{1+\gamma}} + \frac{(\theta-1)(1-\delta)}{\rho \theta^2 [\tilde{a}' - (1-\delta)a]} p,$$

and

$$H_{22} = -\frac{(\theta-1)}{\rho \theta^2 [\tilde{a}' - (1-\delta)a]}.$$

Since $\tilde{a}' \geq (1-\delta)a$, $H_{11} < 0$ and $H_{22} < 0$, and profits are concave in each of the two arguments separately. The determinant D of the Hessian is

$$D = \frac{\gamma}{\rho^2} \frac{w}{a^{2+\gamma}} \left[\left(\frac{\theta-1}{\theta^2} \right) (1+\gamma)p - \gamma \frac{w}{a^\gamma} \right].$$

It follows that the profit function is strictly concave if and only if

$$p > \frac{\gamma \theta}{1+\gamma} \frac{\theta}{\theta-1} \frac{w}{a^\gamma}.$$

Finally, the constraint correspondence $X(a) = [(1-\delta)a, a^\mu]$ is a convex set.

D.3 Slope of the Policy Function

Using (8) and (9) in equation (13) and re-arranging, the first-order condition of the problem becomes

$$FOC = \left(\frac{\theta-1}{\theta} \right) \left[\frac{\rho \left(\frac{\theta}{\theta-1} \right)^{-\theta} A^{\theta-1} \Lambda}{(\tilde{a}' - (1-\delta)a)} \right]^{1/\theta} - \frac{w}{a^\gamma} + \beta p E J_a(a', w') = 0.$$

From the implicit function theorem,

$$\frac{d\tilde{a}'}{da} = -\frac{\frac{\partial FOC}{\partial a}}{\frac{\partial FOC}{\partial \tilde{a}'}}.$$

The denominator is the second-order condition of the problem. By Appendix D.2, the problem is strictly concave, and therefore the SOC is negative. For the numerator we have

$$\frac{\partial FOC}{\partial a} = \frac{1-\delta}{\theta} \left(\frac{\theta-1}{\theta} \right) \frac{p}{\tilde{a}' - (1-\delta)a} + \gamma \frac{w}{a^{1+\gamma}} > 0.$$

Therefore, $d\tilde{a}'/da > 0$, and hence the policy function is strictly increasing in a .

D.4 Decreasing Price with Relationship Capital

Using (8) and (9) in equation (13) and re-arranging, the price can be written as

$$p = \left[\frac{\rho \left(\frac{\theta}{\theta-1} \right)^{-\theta} A^{\theta-1} \Lambda}{(\tilde{a}' - (1-\delta)a)} \right]^{1/\theta}.$$

Taking the derivative with respect to a yields

$$\frac{dp}{da} = -\frac{1}{\theta} \frac{p}{(\tilde{a}' - (1-\delta)a)} \left(\frac{d\tilde{a}'}{da} - (1-\delta) \right).$$

Hence, $dp/da < 0$ if and only if $d\tilde{a}'/da > 1 - \delta$.

Next, note that if the seller were setting the static optimum price $p = \frac{\theta-1}{\theta} \frac{w}{a^\gamma}$, using (9) and differentiating yields

$$\frac{d(\tilde{a}')^M}{da} = (1-\delta) + \gamma\theta \left(\frac{\theta-1}{\theta} \right)^{2\theta} a^{\gamma\theta-1} w^{-\theta} \rho A^{\theta-1} \Lambda, \quad (42)$$

where $(\tilde{a}')^M$ is the implied policy from setting the static optimum price. The expression is weakly greater than $1 - \delta$ and satisfies $\lim_{a \rightarrow \infty} \frac{d\tilde{a}'}{da} = 1 - \delta$ since $\gamma\theta < 1$.

Consider $a_1 < a_2$. Then, $\frac{d\tilde{a}'}{da}|_{a=a_2} \leq \frac{d\tilde{a}'}{da}|_{a=a_1}$ since $J(a, w)$ is concave in a and therefore increasing capital has a smaller and smaller value, and furthermore, by (42), $\frac{d\tilde{a}'}{da}$ is decreasing under static profit maximization, and hence if the seller were to increase $\frac{d\tilde{a}'}{da}$ as a rises she would also incur greater static losses. Since $\frac{d\tilde{a}'}{da}$ is decreasing and since the seller's price is converging to the static optimum price, and since by equation (42) we have $\frac{d(\tilde{a}')^M}{da} \geq 1 - \delta$ everywhere, it must be the case that $\frac{d\tilde{a}'}{da} \geq 1 - \delta$.

D.5 Proof of Proposition 1

Part a): Using (8) and (9) in equation (13), the first-order condition of the problem becomes

$$FOC = \left(\frac{\theta-1}{\theta} \right) \left[\frac{\rho \left(\frac{\theta}{\theta-1} \right)^{-\theta} A^{\theta-1} \Lambda}{(\tilde{a}' - (1-\delta)a)} \right]^{1/\theta} - \frac{w}{a^\gamma} + \beta \rho E J_a(a', w') = 0.$$

From the implicit function theorem,

$$\frac{d\tilde{a}'}{d\rho} = -\frac{\frac{\partial FOC}{\partial \rho}}{\frac{\partial FOC}{\partial \tilde{a}'}}.$$

The denominator is the second-order condition of the problem. By Appendix D.2, the problem is strictly concave, and therefore the SOC is negative. For the numerator we have

$$\frac{\partial FOC}{\partial \rho} = \left(\frac{\theta-1}{\rho\theta^2} \right) p + \beta E J_a(a', w') > 0.$$

Consequently, $d\tilde{a}'/d\rho > 0$, and thus $dp/d\rho < 0$.

Part b): We have

$$\frac{\partial FOC}{\partial \delta} = -\frac{a}{\theta \rho} \left(\frac{\theta - 1}{\theta} \right) \left[\frac{\rho \left(\frac{\theta}{\theta - 1} \right)^{-\theta} P^\theta Q A^{\theta - 1}}{(\tilde{a}' - (1 - \delta)a)} \right]^{1/\theta} \frac{1}{\tilde{a}' - (1 - \delta)a} < 0.$$

Using the implicit function theorem as before, $d\tilde{a}'/d\delta < 0$, and thus $dp/d\delta > 0$.

Part c): We have

$$\frac{\partial FOC}{\partial \gamma} = \frac{1}{\rho} \frac{w}{a^\gamma} \ln(a).$$

This expression is positive for $a > 1$, and is negative for $a < 1$. Therefore, $dp/d\gamma < 0$ for $a < 1$ and $dp/d\gamma > 0$ for $a > 1$.

D.6 Proof of $J_{aw}(a, w) < 0$ and $d\tilde{a}'/dw < 0$

Recall from the main text that $J_w(a, w) < 0$ for all a , and assume for contradiction that $J_{aw}(a, w) > 0$. Fix the level of capital at a , and consider two levels of costs, w and $w + \varepsilon$, where $\varepsilon > 0$ is assumed to be arbitrarily small. By assumption, $J_a(a, w + \varepsilon) > J_a(a, w)$. I show that this fact implies that for ξ small, $J_w(a + \xi, w) > 0$.

From $J_a(a, w + \varepsilon) > J_a(a, w)$, I can choose a $\delta(\varepsilon)$ small enough so that $J_a(a, w + \varepsilon) > J_a(a, w) + \delta(\varepsilon)$. Define $\delta(\varepsilon) \equiv -\frac{\varepsilon}{\xi} J_w(a, w)$, which can be made arbitrarily small for any ε by choosing ξ appropriately since $J_w(a, w)$ is finite and continuous for $w \geq \underline{w} > 0$ from (11). Re-arranging yields

$$\begin{aligned} \frac{J_a(a, w + \varepsilon) - J_a(a, w)}{\varepsilon} &> -\frac{J_w(a, w)}{\xi} \Leftrightarrow J_{aw}(a, w) > -\frac{J_w(a, w)}{\xi} \\ &\Leftrightarrow J_w(a + \xi, w) - J_w(a, w) > -J_w(a, w) \\ &\Leftrightarrow J_w(a + \xi, w) > 0, \end{aligned}$$

which is a contradiction since it must be the case that $J_w(a, w) < 0$ for all a . Therefore, $J_{aw}(a, w) < 0$.

To show that $d\tilde{a}'/dw < 0$, I follow similar steps as in Section D.5 and apply the Implicit Function Theorem to the first-order condition (FOC) of the pricing problem. I have that

$$\frac{d\tilde{a}'}{dw} = -\frac{\frac{\partial FOC}{\partial w}}{\frac{\partial FOC}{\partial \tilde{a}'}} ,$$

where the denominator is the second-order condition, which is negative. Differentiating the numerator with respect to w yields

$$\frac{\partial FOC}{\partial w} = -\frac{1}{a^\gamma} + \beta \rho E J_{aw}(a', w') \frac{dw'}{dw}.$$

Since $J_{aw}(a, w) < 0$ as just shown, and since w is persistent and hence $dw'/dw > 0$, $\partial FOC/\partial w < 0$. It follows that $d\tilde{a}'/dw < 0$.

D.7 First-Order Condition of Seller's Problem under LC

The FOC of the seller's problem is

$$\begin{aligned} & \left[(1 - \theta)p^{-\theta} + \theta \frac{w}{a'} p^{-\theta-1} \right] - \beta \theta \rho E \left[I' p^{-\theta-1} J_a(a', w') \right] \\ & - \lambda p^{-\theta} - \beta \theta \rho \lambda E \left[I' p^{-\theta-1} W_a(a', w') \right] \\ & + \beta \theta \rho \lambda p^{-\theta-1} E \left[\frac{\partial I'}{\partial a'} \{W(a', w') - U(w')\} \right] \\ & + \beta \theta \rho p^{-\theta-1} E \left[\frac{\partial I'}{\partial a'} \{J(a', w') - V(w')\} \right] = 0. \end{aligned}$$

Since $J(a', w') = V(w')$ when the seller decides to break the relationship, the last term is zero. Re-arranging yields (18).

E Variable Mark-Up Model

I describe an alternative setup with variable mark-ups, following [Atkeson and Burstein \(2008\)](#). Individual firms, which may be located in the U.S. or abroad, produce goods which are aggregated into sectors in the U.S. Only a relatively small number of firms operates in each sector. The sectors are then aggregated into final U.S. output. Consumers seek to maximize their consumption of U.S. final output Q_t subject to the budget constraint $P_t Q_t \leq 1$, where P_t is the price index of final consumption.

On the production side, final output is defined as an aggregator over sectors i according to

$$Q_t = \left(\int_0^1 q_t(i)^{(\theta-1)/\theta} di \right)^{\theta/(\theta-1)},$$

where θ is the elasticity of substitution across sectors. Demand for each sector i is then

$$q_t(i) = \left(\frac{p_t^f(i)}{P_t} \right)^{-\theta} Q_t, \quad (43)$$

where $p_t^f(i)$ is the input price of sector i , and the price index of final consumption is $P_t = \left[\int_0^1 (p_t^f(i))^{1-\theta} di \right]^{1/(1-\theta)}$.

Within each sector, there are a finite number K_1 of domestic sellers and an additional K_2 foreign sellers. The domestic firms are indexed by $k = 1, \dots, K_1$ and the foreign firms are indexed by $k = K_1 + 1, \dots, K_1 + K_2$. I abstract from trade costs, and hence all foreign firms participate in the market. Output by each firm is given by

$m(i, k)$. Output in sector i is an aggregate over the goods produced by each firm k in the sector according to

$$q_t(i) = \left[\sum_{k=1}^{K_1+K_2} (m_t(i, k))^{(\eta-1)/\eta} \right]^{\eta/(\eta-1)}, \quad (44)$$

where η is the elasticity of substitution across goods. Demand in each sector is then

$$m_t(i, k) = \left(\frac{p_t(i, k)}{p_t^f(i)} \right)^{-\eta} q_t(i), \quad (45)$$

where $p_t(i, k)$ is the price charged by seller k in sector i , and the price index is $p_t^f(i) = \left[\sum_{k=1}^{K_1+K_2} (p_t(i, k))^{1-\eta} \right]^{1/(1-\eta)}$. The elasticities satisfy $\theta < \infty$ and $\eta > \theta > 1$, and hence goods are more easily substitutable within a sector than across sectors.

Sellers employ a similar production technology as in the main text. Each seller has a production function of the form

$$m = a^\gamma l, \quad (46)$$

where I assume now, contrary to the main text, that a is a seller-specific, rather than relationship-specific, productivity component. Sellers' productivity evolves stochastically over time according to an exogenous process, $a_{t+1} = (1 + \varepsilon)a_t$, where $\varepsilon \sim (\mu, \sigma^2)$ are independent shocks across sellers. Labor input l is subject to marginal input cost w , which differs across domestic and foreign firms but is identical across sectors and for all firms of a given origin. Foreign firms' input cost evolves stochastically over time, reflecting exchange rate fluctuations, while domestic sellers' input costs are constant. The exchange rate shocks are independent of productivity shocks. I assume that sellers have to pay a fixed cost $F > 0$ each period to produce.

The sellers engage in Cournot quantity competition in each period within their sector. Since the productivity process is purely exogenous, each firms' decision in each period is static. Each firm chooses its quantity $m_t(i, k)$ sold, taking as given the quantities sold by the other firms, the final consumption price P_t , and the final quantity Q_t . However, firms do internalize the effect of their quantity choice on sectoral prices $p_t^f(i)$ and sectoral quantities $q_t(i)$, as in [Atkeson and Burstein \(2008\)](#). The profit maximization problem of seller k in sector i is then

$$\Pi^s(a_t(i, k), w_t(k)) = \max_{p_t(i, k), m_t(i, k)} [p_t(i, k) - w_t(k)/a_t(i, k)^\gamma] m_t(i, k) - F, \quad (47)$$

subject to (45), (44), P_t , and Q_t , where sector quantities are given by (44) and the firm takes all other firms' quantities as given. Given the possibility to shut down, sellers do not operate when their profits net of fixed costs $\Pi^s(a_t, w_t) < 0$. I assume that in that case the seller exits and is replaced by a new firm.

As shown in [Atkeson and Burstein \(2008\)](#), the solution to this problem is

$$p(i, k) = \frac{\varepsilon(s(i, k))}{\varepsilon(s(i, k)) - 1} \frac{w(k)}{a(i, k)^\gamma}, \quad (48)$$

where

$$\varepsilon(s(i, k)) = \left[\frac{1}{\eta}(1 - s) + \frac{1}{\theta}s \right]^{-1} \quad (49)$$

is the elasticity of substitution perceived by the seller. As sellers' market share grows, the across sector elasticity becomes increasingly more important than the within-sector elasticity, leading higher market share sellers to charge higher mark-ups since $\eta > \theta$. The market share is given by

$$s(i, k) = p(i, k)m(i, k) / \left(\sum_{k=1}^K p(i, k)m(i, k) \right) = \left(\frac{p(i, k)^{1-\eta}}{\sum_{k=1}^K p(i, k)^{1-\eta}} \right). \quad (50)$$

Firms that receive good shocks to productivity lower their price and thereby gain market share, which leads them to charge higher mark-ups. Log-linearizing equation (48) and using the expression for market shares (50) gives

$$\hat{p}(i, k) = \frac{1}{1 + (\eta - 1)\Gamma(s(i, k))} [\hat{w} - \gamma\hat{a}(i, k) + (\eta - 1)\Gamma(s(i, k))\hat{p}(i)], \quad (51)$$

where $\Gamma(s(i, k))$ is the elasticity of the mark-up with respect to the market share, and hats denote deviations from steady state. This is the equation discussed in the main text. Since $\Gamma'(s(i, k)) > 0$ and $\hat{w} > \hat{p}(i)$, firms with a larger market share put a larger emphasis on changes in the sectoral price index, and respond less to cost shocks. Therefore, pass-through decreases with productivity, and similarly with relationship age since on average older sellers have higher productivity.

F Nash Bargaining Setup

Assume there is a unit mass of buyers indexed by b , and a continuum of sellers indexed by s . I make the same assumptions about production functions, relationship capital, and costs as before. Define by u_b the fraction of unmatched buyers and let u_s be the mass of unmatched sellers. Buyers and sellers come together through a constant return to scale matching function $M(u_b(w), u_s(w)) < \min(u_b(w), u_s(w))$, which I assume to be CES according to

$$M(u_b, u_s) = (u_b^{-\iota} + u_s^{-\iota})^{-\frac{1}{\iota}}. \quad (52)$$

The probability that an unmatched buyer meets a seller is then

$$\pi_b(\vartheta) = M(1, \vartheta) = (1 + \vartheta^\iota)^{-\frac{1}{\iota}}, \quad (53)$$

where $\vartheta = u_b/u_s$ is market tightness. Similarly, the probability that an unmatched seller finds a buyer is

$$\pi_s(\vartheta) = \vartheta(1 + \vartheta^\iota)^{-\frac{1}{\iota}} = \vartheta\pi_b(\vartheta). \quad (54)$$

I solve the bargaining problem in steady state. The firms use Nash bargaining to choose quantities q and a monetary transfer from the buyer to the seller $T = pq$. Let the buyer's bargaining weight be ϕ . Unmatched buyers randomly meet sellers, and hence their outside option U is independent of the costs of any specific seller and depends only on the distribution $H(w)$ of unmatched seller's costs. Let $W(a, w)$ be the value of a matched buyer given state (a, w) . Similarly, let $V(w)$ and $J(a, w)$ be the value of an unmatched seller with cost level w and a seller in a relationship, respectively.

Unmatched buyers pay a per-period cost c to search for matches. The value of an unmatched buyer in state w is then given by:

$$U = -c + \beta [\pi_b(\vartheta)EW(a', w') + (1 - \pi_b(\vartheta))U], \quad (55)$$

where the expectation is taken with respect to the initial distribution of relationship capital $G(a)$ and with respect to the steady state distribution of unmatched sellers' costs $H(w)$. I impose free entry of buyers so that $U = 0$, which implies that

$$EW(a', w') = \frac{c}{\beta \pi_b(\vartheta)}. \quad (56)$$

An unmatched seller has value function

$$V(w) = \beta [\pi_s(\vartheta)EJ(a', w') + (1 - \pi_s(\vartheta))EV(w')]. \quad (57)$$

Once the buyer and the seller are in a relationship, the buyer's value function becomes

$$W(a, w) = (Aq)^{\frac{\theta-1}{\theta}} \Lambda^{\frac{1}{\theta}} - T + \beta E [\max \{W(a', w'), U\}], \quad (58)$$

and the seller's value function is

$$J(a, w) = T - \frac{w}{a^\gamma} q + \beta E [\max \{J(a', w'), V(w')\}], \quad (59)$$

where the continuation values depend on the evolution of costs and relationship capital and the first term in equation (58) are the revenues of a buyer purchasing quantity q from the seller.

Given weight ϕ on the buyer, the optimal payment satisfies

$$T = \operatorname{argmax} (W(a, w) - U)^\phi (J(a, w) - V(w))^{1-\phi}. \quad (60)$$

Taking the first-order condition with respect to $T(q)$ and re-arranging gives:

$$\phi (J(a, w) - V(w)) = (1 - \phi) (W(a, w) - U). \quad (61)$$

From equations (55)-(57), I have that

$$\begin{aligned}
0 &= (1 - \phi) [W(a, w) - U] - \phi [J(a, w) - V(w)] \\
&= (1 - \phi) (Aq)^{\frac{\theta-1}{\theta}} \Lambda^{\frac{1}{\theta}} - (1 - \phi) T + (1 - \phi) \beta E [\max \{W(a', w'), U\}] \\
&\quad + (1 - \phi) c - (1 - \phi) \beta E [\pi_b(\vartheta) W(a', w') + (1 - \pi_b(\vartheta)) U] \\
&\quad - \phi T + \phi \frac{w}{a^\gamma} q - \phi \beta E [\max \{J(a', w'), V(w')\}] \\
&\quad + \phi \beta E [\pi_s(\vartheta) J(a', w') + (1 - \pi_s(\vartheta)) V(w')].
\end{aligned}$$

I can use the fact that condition (61) has to hold at each point in time to simplify and obtain:

$$T = (1 - \phi) \left[(Aq)^{\frac{\theta-1}{\theta}} \Lambda^{\frac{1}{\theta}} + c \right] + \phi \frac{w}{a^\gamma} q + (1 - \phi) \beta \pi_b(\vartheta) (\vartheta - 1) E [W(a', w') - U], \quad (62)$$

where again the expectation is with respect to $G(a)$ and $H(a)$. Using the free entry condition (56) and rearranging yields

$$p = \frac{T}{q} = (1 - \phi) \left[A^{\frac{\theta-1}{\theta}} \Lambda^{\frac{1}{\theta}} q^{-\frac{1}{\theta}} + \frac{\vartheta c}{q} \right] + \phi \frac{w}{a^\gamma}. \quad (63)$$

Next, adding up (58) and (59), and deducting (57), I obtain a total match surplus over the outside value of

$$S(a, w) = (Aq)^{\frac{\theta-1}{\theta}} \Lambda^{\frac{1}{\theta}} - \frac{w}{a^\gamma} q + \beta E [\max \{S(a', w'), 0\}] - \beta \pi_b(\vartheta) \vartheta \frac{1 - \phi}{\phi} E [W(a', w') - U]. \quad (64)$$

Using the free entry condition (56) yields

$$S(a, w) = (Aq)^{\frac{\theta-1}{\theta}} \Lambda^{\frac{1}{\theta}} - \frac{w}{a^\gamma} q + \beta E [\max \{S(a', w'), 0\}] - \frac{1 - \phi}{\phi} c \vartheta. \quad (65)$$

It follows that the surplus $S(a, w)$ is increasing in the current level of capital a , since a higher level of capital raises the current level of profits and increases future capital even without reoptimizing q . By a similar argument, the surplus is declining in w . Therefore, there must exist a threshold level of capital $\underline{a}^{NB}(w)$, which is declining in w , such that $S(a, w) < 0$ whenever $a < \underline{a}^{NB}(w)$, and hence the relationship is optimally terminated at that point. Note that termination is efficient.

The firms choose q to maximize their joint surplus, since that also maximizes their own profits. Taking the first-order condition of (65) with respect to q , I obtain

$$q = \left(\frac{\theta - 1}{\theta} \right)^\theta A^{\theta-1} \Lambda \left[\frac{w}{a^\gamma} - \beta \rho E [I' S_a(a', w')] \right]^{-\theta},$$

where $I' = I(a', w')$ is an indicator that is equal to one if the relationship is continued in state (a', w') , and $E \left[\frac{dI(a', w')}{dq} (S(a', w') - 0) \right] = 0$ since for those states that no longer lead to termination after a marginal change in q it must be the case that the surplus is zero. Note that, similar to the main text, the firms trade a quantity that is larger than under static profit maximization in order to accumulate relationship capital.

Plugging this expression into the pricing equation (63) yields the pricing equation

$$p = (1 - \phi) \left(\frac{\theta}{\theta - 1} \right) \left[\frac{w}{a^\gamma} - \beta \rho E [I' S_a(a', w')] \right] + \phi \frac{w}{a^\gamma} \quad (66)$$

$$+ (1 - \phi) \frac{\vartheta c}{A^{\theta-1} \Lambda} \left(\frac{\theta}{\theta - 1} \right)^\theta \left[\frac{w}{a^\gamma} - \beta \rho E [I' S_a(a', w')] \right]^\theta.$$

Pass-through is given by

$$\frac{d \ln(p)}{d \ln(w)} = \frac{(1 - \phi) \left(\frac{\theta}{\theta - 1} \right) \left[\frac{w}{a^\gamma} - \beta \rho \Psi(a', w') \right] + \phi \frac{w}{a^\gamma}}{p} \quad (67)$$

$$+ \frac{(1 - \phi) \frac{\vartheta c}{A^{\theta-1} \Lambda} \left(\frac{\theta}{\theta - 1} \right)^\theta \theta \left[\frac{w}{a^\gamma} - \beta \rho \Psi(a', w') \right] \left[\frac{w}{a^\gamma} - \beta \rho E [I' S_a(a', w')] \right]^{\theta-1}}{p},$$

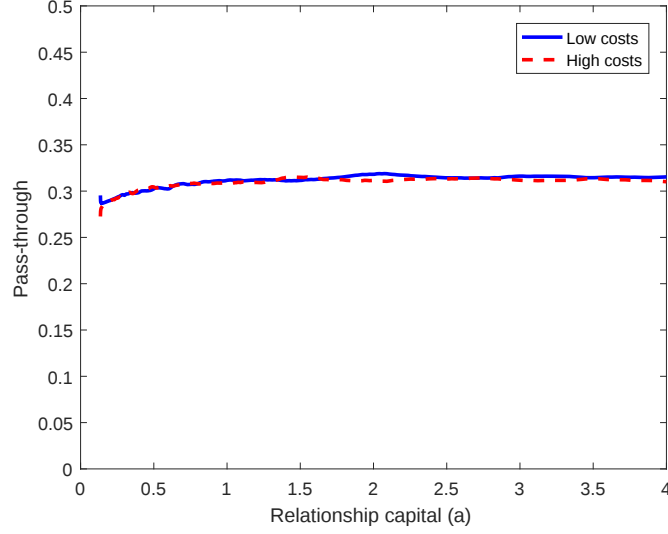
where $\Psi(a', w') \equiv \frac{dE[I' S_a(a', w')]}{dw'} \frac{dw'}{dw} w$.

Consider first the case of $E [I' S_a(a', w')]$ and its derivative being approximately zero. Then, pass through is

$$\frac{d \ln(p)}{d \ln(w)} \approx \frac{(1 - \phi) \left(\frac{\theta}{\theta - 1} \right) \frac{w}{a^\gamma} + \phi \frac{w}{a^\gamma} + (1 - \phi) \frac{\vartheta c}{A^{\theta-1} \Lambda} \left(\frac{\theta}{\theta - 1} \right)^\theta \theta \left(\frac{w}{a^\gamma} \right)^\theta}{(1 - \phi) \left(\frac{\theta}{\theta - 1} \right) \frac{w}{a^\gamma} + \phi \frac{w}{a^\gamma} + (1 - \phi) \frac{\vartheta c}{A^{\theta-1} \Lambda} \left(\frac{\theta}{\theta - 1} \right)^\theta \left(\frac{w}{a^\gamma} \right)^\theta} > 1,$$

since $\theta > 1$. Moreover, pass-through is declining with a in that case. Figure 10 presents a quantitative evaluation of pass-through in the fully specified model, where the parameters are chosen as in the main text and the matching probabilities are selected to match the exogenous matching probabilities from the main model. While the endogenous capital accumulation produces a small increase in pass-through at small levels of capital, pass-through is virtually flat.

Figure 10: Pass-Through under Nash Bargaining



G Setup with Endogenous Matching Market

Assume that the same assumptions as in Section 4.1 hold, but matching probabilities are now endogeneously determined. Let there be a unit mass of buyer firms, each indexed by b . Buyers search for sellers in search markets which differ by their cost level w . Each period, each buyer decides in which search market to look for sellers. Define by $u_b(w)$ the fraction of unmatched buyers searching in the market with cost w , and let $u_s(w)$ be the mass of unmatched sellers with cost state w . In each market, buyers and sellers come together through a constant return to scale matching function $M(u_b(w), u_s(w)) < \min(u_b(w), u_s(w))$. Define $\vartheta(w) = u_b(w)/u_s(w)$ as market tightness of search market w . Then, $\pi_b(\vartheta(w)) = M(1, 1/\vartheta(w))$ is the probability that an unmatched buyer firm finds a seller in market w , and $\pi_b : \mathbb{R}_+ \rightarrow [0, 1]$ is a strictly decreasing function. Similarly, $\pi_s(\vartheta(w)) = M(\vartheta(w), 1)$ is the probability for an unmatched seller in market w to find a buyer, with $\pi_s : \mathbb{R}_+ \rightarrow [0, 1]$ being strictly increasing.

An unmatched seller with cost level w needs to pay a fixed marketing cost of c per period to find a new buyer. A new match is found with probability $\pi_s(\vartheta(w))$ which depends on the current state, and the relationship starts in the next period with cost level w' determined by the evolution of the seller's costs (25). New relationship capital is drawn from the initial distribution $G(a)$. The value of an unmatched seller with state w is then given by

$$V(w) = -c + \beta[\pi_s(\vartheta(w))EJ(a, w') + (1 - \pi_s(\vartheta(w)))EV(w')]. \quad (68)$$

I assume free entry of sellers into any search market w . Therefore, $V(w) = 0$ for all w . Re-arranging equation (68) then yields

$$\pi_s(\vartheta(w)) = \frac{c}{\beta EJ(a', w'|w)}. \quad (69)$$

This equation implies a positive relationship between the current level of costs w and market tightness $\vartheta(w)$ if w is persistent. Matches in high cost markets are less profitable for the seller, leading to lower seller entry and raising the probability that each seller can find a match.

The value function for a matched seller is the same as before and is given by

$$J(a, w) = \max_p \left(p - \frac{w}{a^\gamma} \right) q(p) + \beta E \{ \max [J(a', w'), 0] \}, \quad (70)$$

where $q(p)$ is defined by equation (8) in the main text.

On the buyer side, the value of an unmatched buyer searching in market w is

$$U(w) = \Pi_u^b + \beta [\pi_b(\vartheta(w))EW(a, w') + (1 - \pi_b(\vartheta(w)))U(w)], \quad (71)$$

where Π_u^b are the profits of a buyer from internal production, as defined in Section 4.1. Since buyers can freely choose in which market to search, in equilibrium the value of search in any market must be the same, $U(w) \equiv U$ for all w . The value of a matched buyer is then as in equation (16),

$$W(a, w) = (p^f - p/A)y(p^f) + \beta E [I'W(a', w') + (1 - I')U], \quad (72)$$

where the demand function is given by (5), and $I \equiv I(a, w)$ is an indicator that is equal to one if the relationship continues in state (a, w) . Endogenous separation occurs in states in which the buyer's outside option U is binding in such a way that the seller prefers leaving the relationship.

A steady state equilibrium here consists of a set of value functions $J(a, w)$, $W(a, w)$, $V(w)$, and $U(w)$, prices $p(a, w)$ and $p^f(a, w)$, break-up policies $I(a, w)$, a distribution of relationships across states $\Gamma(a, w)$, and masses of unmatched buyers $u_b(w)$ and sellers $u_s(w)$ in each search market w such that: buyers choose prices $p^f(a, w)$ to maximize profits, taking as given the intermediate goods price, sellers choose prices $p(a, w)$ and separation policies $I \equiv I(a, w)$ to maximize their value function subject to the buyer's participation constraint, taking as given (a, w) , the goods market clears, and in each labor search market the market tightness $\vartheta(w) = u_b(w)/u_s(w)$ is consistent with free entry (69) and $\int u_b(z)dz = 1$.

Compared to the baseline, this setup provides two additional parameters that need to be estimated: the marketing cost c , and a parameter determining the shape of the matching function M . These parameters can be included in the estimation procedure and set to target the empirical matching probabilities π_b and π_s . Since for the overall performance of the model only these probabilities are relevant, in the main text I set these probabilities directly.

H Analysis of Plausibly Exogenous Relationship Break-Ups

In this section, I study whether plausibly exogenous relationship break-ups adversely affect the U.S. importer. Specifically, I analyze whether importers reduce the quantity purchased and experience lower employment growth following a plausibly exogenous break-up of the relationship with one of their suppliers. I also provide some statistics on the time needed to replace a lost supplier, which are used in the estimation of the model.

In my main analysis of break-ups, I study the importer's quantity purchased before and after a break-up, since the LFTTD data do not contain information on profits or sales. I assume that quantities are correlated with these variables. Since I do not have additional data on the exporters, I make the identifying assumption that a break-up is plausibly exogenous from the importer's perspective if the exporter involved had at least three active relationships at the time of the break-up, loses all of these simultaneously, and is never again seen in the dataset.³³ My definition seeks to capture for example a bankruptcy or significant strategy change of the exporter, which require the importer to suddenly replace an established relationship. The fact that the exporter is still in three active relationships suggests that the break-up is sudden. I impose two additional conditions to ensure that separations are not caused by the importer. First, I use only importers that survive in the LBD for at least for two more calendar years after the break-up takes place. Second, I compute the share of the exporter's U.S. sales accounted for by each importer during the year before the break-up, and consider break-ups as exogenous only if the importer accounts for less than 50% of the exporter's U.S. sales in that year. I impose these conditions to eliminate cases where problems originate at the importer but spill over to the exporter due to the importer's importance. To rule out that the declines in quantity are driven by industry-wide forces, I consider break-ups only for products whose total U.S. imports are increasing in the year of the break-up.³⁴ Hence, quantity declines after a break-up would run counter the industry-wide trend.

I run a regression of the total quantity imported of product h by importer m in year t on a dummy for whether the importer experienced a relationship break-up impacting that product. To track the time path of quantities around the time of a break-up, I run separate regressions with dummies for whether a break-up happens in the following calendar year, in the current year, in the previous year, two years ago, and three years ago. These dummies are denoted $d_{mh,i}^b$, with $i \in \{t+1, t, t-1, t-2, t-3\}$. Since importers often have many marginal suppliers, I consider only relationships that are important from the perspective of the importer, defined as cases where the relationship supplied at least 50% of importer m 's purchases of product h over the past year.³⁵ Thus, I run:

$$\ln(q_{mht}) = \beta_0 + d_{mh,i}^b + \gamma_{mh} + \xi_t + \varepsilon_{mht}, \quad (73)$$

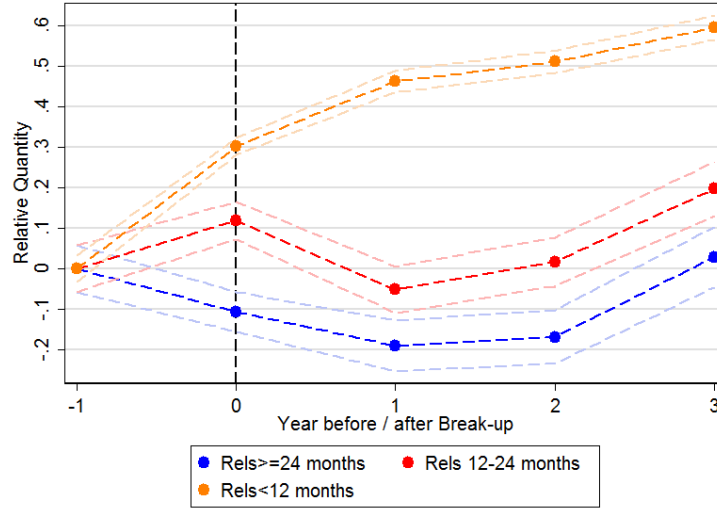
where γ_{mh} are importer-product fixed effects and ξ_t are year fixed effects. If relationships are valuable, the quan-

³³“Simultaneously” means that the maximum gap time has not yet elapsed for these relationships. Break-ups in 2011 are not counted due to right-censoring.

³⁴I require the broad HS6 industry to be increasing to capture wider industry trends. The results are similar if HS10 industries are used.

³⁵Note that this regression uses the entire dataset, from 1995. All restrictions discussed so far only affect whether the break-up dummy is set equal to 1.

Figure 11: Quantity purchased around break-up



tity ordered should decline sharply in the year of a break-up, and then recover gradually as the lost relationship is replaced. I drop break-ups where the importer has not recovered the pre-break-up level of purchases by the third year after the separation to eliminate cases where the reduction in quantity is permanent.

Figure ?? traces out the quantity patterns of these regressions for broken up relationships that have lasted at least 24 months, 12-24 months, and less than 12 months, respectively.³⁶ I normalize the coefficient in the year before the break-up to zero. The figure shows that losing an important long-term relationship is significantly more costly for importers than losing a relatively new relationship. For relationships that have lasted at least 24 months, the quantity imported in the calendar year after the break-up is about 19 percentage points below the quantity imported in the year before the break-up, and recovers only gradually. The drop is significantly smaller for relationships of age 12-24 months. Columns 1-5 of Table ?? present the coefficients of the regression for relationships that have lasted at least 24 months before the break-up. These coefficients can be interpreted as deviations from the average quantity traded in the relationship.

To examine how replacing a lost relationship affects the importer's quantity purchased, I re-run regression (73) for relationships lasting at least 24 months, and interact the break-up indicator with a dummy $d_{mh,t-1}^{new}$. This dummy is equal to one if a new relationship is formed in the same country for the same product in the year after the break-up. I focus on the same country only to avoid picking up new relationships that trade a different variety or a different quality level of the original relationship's product. I then run

$$\ln(q_{mht}) = \beta_0 + d_{mh,t-1}^b + d_{mh,t-1}^b \cdot d_{mh,t-1}^{new} + \gamma_{mh} + \xi_t + \varepsilon_{mht}. \quad (74)$$

Column 6 of Table ?? shows that creating a new relationship in the year after the break-up reduces the drop in quantities slightly, if at all. This suggests that a long-term relationship is valuable and cannot be immediately

³⁶I am currently in the process of disclosing the coefficient for year -2 as well.

Table 11: Break-up regressions, using quantity purchased, relationships 24 months or older

	Dependent variable: $\ln(q_{mht})$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$t + 1$	t	$t - 1$	$t - 2$	$t - 3$	$t - 1$	$t - 2$
$d_{mh,i}^b$	.1166***	.0105	−.0736**	−.0517	.1451***	−.0812**	−.0750*
	(.0293)	(.0250)	(.0321)	(.0336)	(.0379)	(.0400)	(.0440)
$d_{mh,i}^b \cdot d_{mh,i}^{new}$						.0215	.0559
						(.0669)	(.0682)
Fixed effects	mh,t	mh,t	mh,t	mh,t	mh,t	mh,t	mh,t
Observations	9,542,000	9,542,000	9,542,000	9,542,000	9,542,000	9,542,000	9,542,000

replaced with a new one. Column 7 redoes the regression with an interaction term measuring whether a new relationship has been formed in the two years since the break-up.

To estimate the real losses of relationship destruction, I use the LBD to examine the employment growth of firms affected by exogenous break-up. I calculate the growth as the log change in employment across all the firm's plants from one year to the next. Since firms are likely to also have many domestic relationships, the effect is expected to be quite small. Columns 1 in Table ?? shows that for relationships that have lasted at least 24 months, employment growth is 1.5% below average in the year after a break-up. The remaining two columns show that the employment effects are smaller and statistically insignificant for shorter relationships.

As a robustness check, I re-run regressions 73 and 74 without imposing any restrictions on break-ups other than that the exporter must have had at least three customers and lose all of them, and that the exporter account for at least half of the importer's purchases. The results for relationships that have lasted at least 24 months are presented in Table 12, for both quantities (columns 1-7) and employment growth (column 8). The results are strengthened compared to the baseline case.

Table 12: Break-up regressions, using quantity purchased, relationships 24 months or older (robustness specification)

	Dependent variable: $\ln(q_{mht})$							$\Delta \ln(e_{mht})$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$t + 1$	t	$t - 1$	$t - 2$	$t - 3$	$t - 1$	$t - 2$	$t - 1$
$d_{mh,i}^b$	.1846***	.0405***	−.1290***	−.0838***	.0975***	−.1572***	−.0967***	−.0177***
	(.0141)	(.0123)	(.0159)	(.0175)	(.0203)	(.0195)	(.0229)	(.0043)
$d_{mh,i}^b \cdot d_{mh,i}^{new}$						.0827**	.0308	
						(.0334)	(.0354)	
FE	mh,t	mh,t	mh,t	mh,t	mh,t	mh,t	mh,t	mh,t
Obs	9,542,000	9,542,000	9,542,000	9,542,000	9,542,000	9,542,000	9,542,000	9,542,000

Table ?? provides additional statistics for break-ups of relationships that have lasted at least 24 months. After an exogenous break-up, it takes U.S. importers on average 17 months to find a new supplier of the same

Table 13: Break-up regressions, using employment growth

$\Delta \ln(e_{mht})$	≥ 24	$12 - 24$	< 12
	(1)	(2)	(3)
$d_{mh,t-1}^b$	-.0149* (.0086)	-.0126 (.0078)	-.0020 (.0036)
Fixed effects	mh,t	mh,t	mh,t
Observations	9,542,000	9,542,000	9,542,000

Table 14: Statistics of exogenous break-ups, for relationships lasting at least 24 months

	≥ 24 months
Avg. months until new supplier found	17.4
Avg months until new supplier for rel ≥ 24 months found	19.5
Avg. number of suppliers tried before rel ≥ 24 months	0.9
Excess gap time between transactions	10.7

good. Finding a new supplier with whom the relationship will last more than 24 months takes even longer, on average 20 months, and on average importers unsuccessfully try out 0.9 suppliers before forming that long-term relationship. The fourth row shows that the time needed to find a new supplier for a good exceeds the average time gap time of that good by on average 11 months. Thus, locating a supplier to replace a lost relationship takes a significant amount of time.

I Additional Figures and Tables

I.1 Additional Figures

Figure I.12: Trade distribution by industry

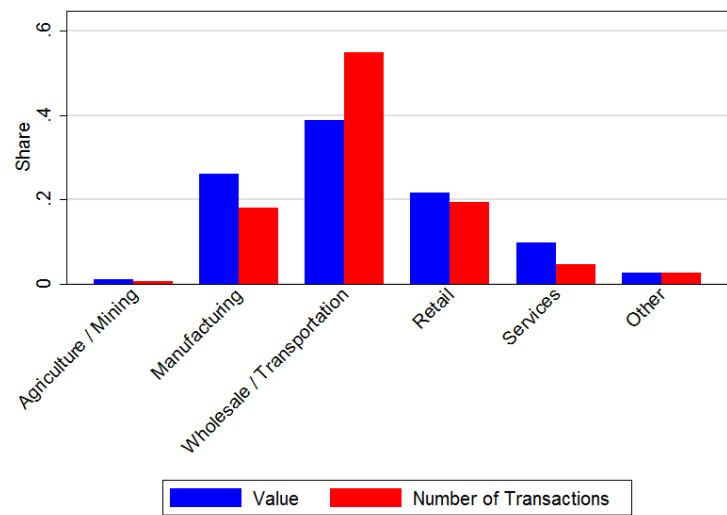


Figure I.13: Relationship life cycle

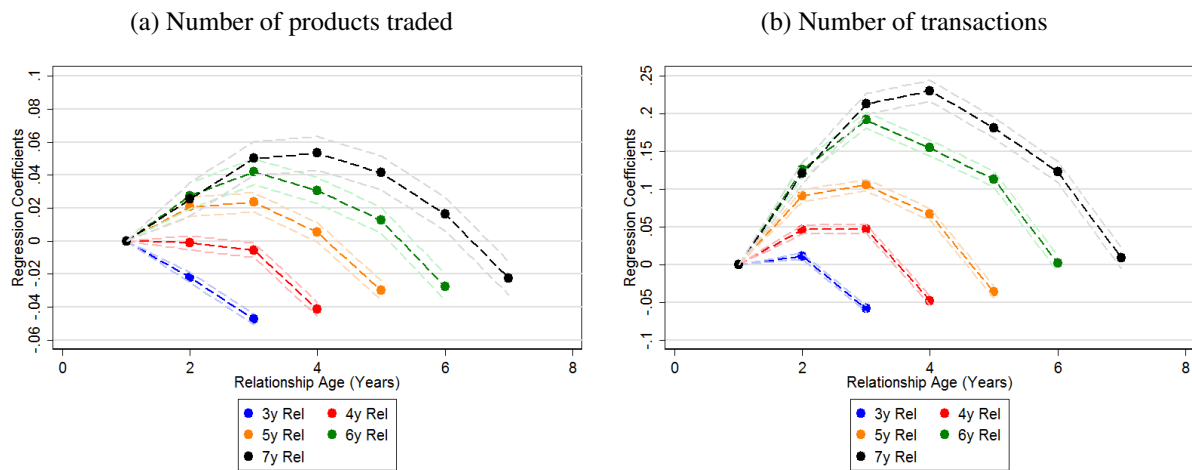


Figure I.14: Total value traded

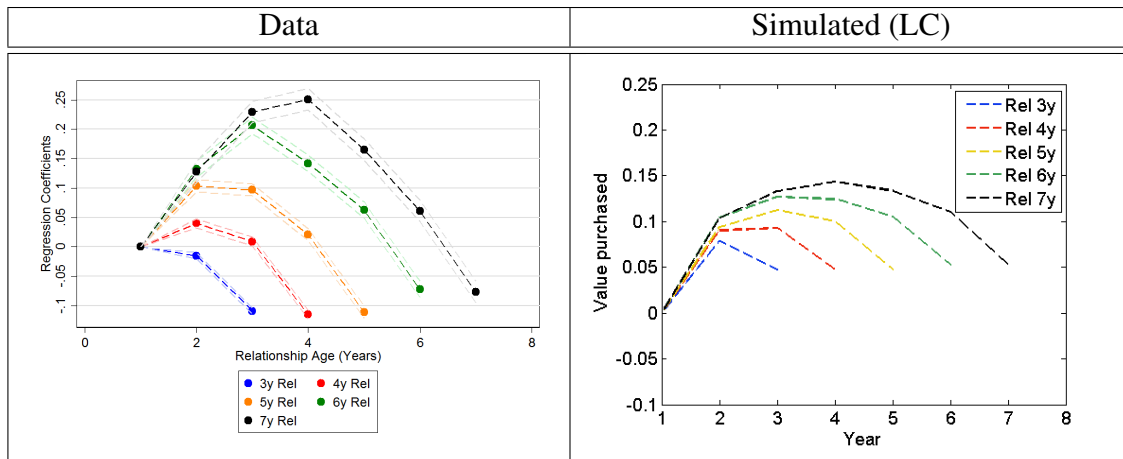


Figure I.15: Hazard rate of breaking up a relationship (quarterly)

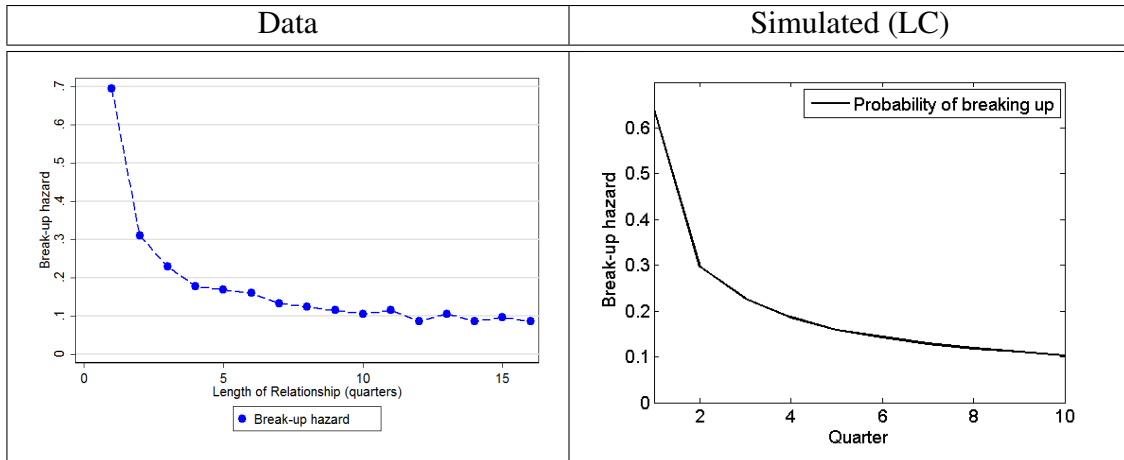
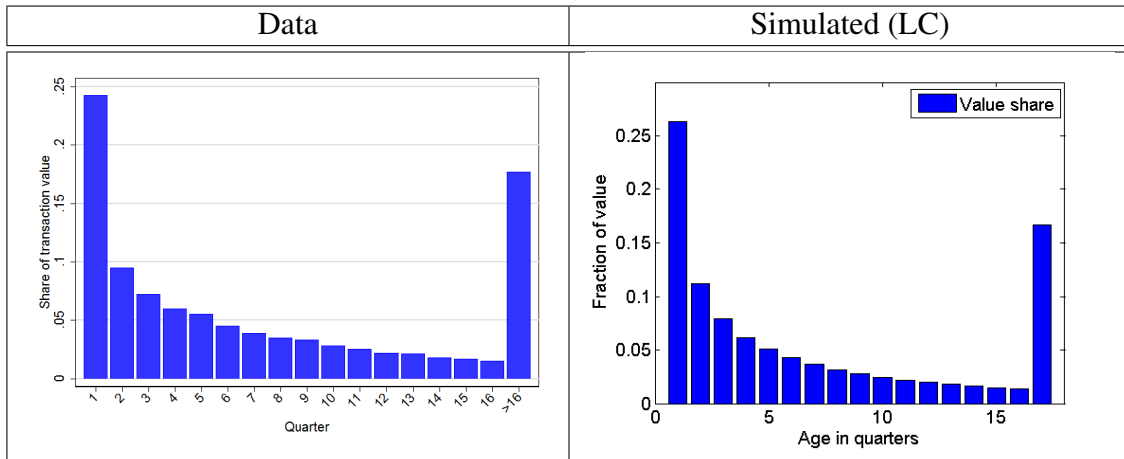


Figure I.16: Average share of trade by length (in quarters)



I.2 Additional Tables

Table I.15: Domestic relationships

Study	Sample	Type of relationship	Average length (years)
Ganesan (1994)	5 department store chains, 52 matched vendors	Random	2.9 (retailer) / 4.2 (vendor)
Doney and Cannon (1997)	209 manufacturing firms from SIC 33-37	1st or 2nd choice in recent purchasing decision	11
Artz (1999)	393 manufacturers from SIC 35-38	Major supplier, at least 3 years	8.8
Cannon and Perreault (1999)	426 firms, mainly manufacturing and distributors	Main supplier of last purchasing decision	11
Kotabe, Martin, and Domoto (2003)	97 automotive component suppliers	Major buyer	26.3
Ulaga (2003)	9 manufacturers from SIC 34-38	Close relationship for an important component	2-25
Claycomb and Frankwick (2005)	174 manufacturers in SIC 30 and 34-38	Key supplier, mature relationship	7.5
Jap and Anderson (2007)	1,540 customers of an agricultural chemical manufacturer	Random	17
Krause, Handfield, Tylor (2007)	373 automotive and electronics manufacturers, 75 matched suppliers	Firms have recently worked to improve performance	12.4

Table I.16: Pass-through robustness I

$\Delta \ln(p_{mch,t})$			Countries		Products		
	No breaks	Selection	High	Low	High	Medium	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta \ln(e_{cht})$	.1200*** (.0365)	.1638*** (.0051)	.3812*** (.0591)	.0592*** (.0155)	.1403*** (.0522)	.1316*** (.0499)	.1922*** (.0636)
$\Delta \ln(e_{cht}) \cdot Months$	.0011*** (.0003)	.0012*** (.0001)	.0008[±] (.0005)	.0011*** (.0003)	.0017*** (.0006)	.0015*** (.0003)	.0013*** (.0003)
λ		.0071*** (.0011)					
FE	<i>mch,t</i>	<i>mch,t</i>	<i>mch,t</i>	<i>mch,t</i>	<i>mch,t</i>	<i>mch,t</i>	<i>mch,t</i>
Obs	8,256,000	13,967,000	5,151,000	11,751,000	4,402,000	9,126,000	3,373,000

Table I.17: Pass-through robustness II

$\Delta \ln(p_{mcxht})$	Fixed length (in months)			Aggregation	
	$\geq 24, < 36$	$\geq 36, < 48$	$\geq 48, < 60$	Annually	Monthly
	(1)	(2)	(3)	(4)	(5)
$\Delta \ln(e_{cht})$	.1106** (.0519)	.1860*** (.0610)	.1457*** (.0501)	.1471*** (.0552)	.1547*** (.0551)
$\Delta \ln(e_{cht}) \cdot Months$	.0049** (.0022)	.0001 (.0012)	.0025*** (.0006)	.0173*** (.0032)	.0016*** (.0002)
FE	mxh,t	mxh,t	mxh,t	mxh,t	mxh,t
Obs	3,431,000	2,711,000	1,982,000	5,129,000	30,691,000

Table I.18: Im-Pasaran-Shin test for unit roots

	e_{mxht}	p_{mxht}
	(1)	(2)
$\bar{Z}$	266.3661	-403.2720
p -value	1	0
Panels	65,100	65,100
Observations	1,676,000	1,676,000

Table I.19: Firm size of exporters and importers

	Employees (Mean)	Shipment value (Mean, \$ '000)	Year	Source
U.S.	319	5,224.4	2000	Bernard, Jensen, and Schott (2009)
France	70		2006	Di Giovanni, Levchenko, and Mejean (2014)
Belgium		6,250.3	2000	World Bank Exporter Dynamics Database
Cambodia		2,061.7	2000	World Bank Exporter Dynamics Database
Cameroon		1,087.3	2000	World Bank Exporter Dynamics Database
Costa Rica		2,630.0	2000	World Bank Exporter Dynamics Database
Mexico		4,233.7	2000	World Bank Exporter Dynamics Database
New Zealand		1,245.6	2000	World Bank Exporter Dynamics Database
Norway		1,416.5	2000	World Bank Exporter Dynamics Database
Peru		1,628.8	2000	World Bank Exporter Dynamics Database
Portugal		1,613.8	2000	World Bank Exporter Dynamics Database
Senegal		624.3	2000	World Bank Exporter Dynamics Database
Sweden		2,479.7	2000	World Bank Exporter Dynamics Database
Uganda		1,425.9	2000	World Bank Exporter Dynamics Database

Table I.20: Price regression by industry - overall effect

	Animal	Vegetables	Fats	Food	Minerals	Chemicals	Plastics	Leather	Wood
d_6	-0.0016** (0.0007)	-0.0035*** (0.0007)	-0.0007 (0.0039)	-0.0040** (0.0008)	-0.0028 (0.0028)	-0.0032* (0.0017)	-0.0063*** (0.0018)	-0.0025** (0.0011)	-0.0008 (0.0013)
d_{11}	-0.0012 (0.0008)	-0.0053*** (0.0008)	0.0013 (0.0051)	-0.0035*** (0.0010)	0.0018 (0.0034)	-0.0038* (0.0022)	-0.0061*** (0.0022)	-0.0010 (0.0015)	-0.0041** (0.0017)
d_{16}	-0.0011 (0.0009)	-0.0073*** (0.0009)	-0.0015 (0.0061)	-0.0033*** (0.0011)	0.0040 (0.0039)	-0.0058** (0.0026)	-0.0063** (0.0026)	-0.0007 (0.0017)	-0.0057*** (0.0020)
d_{21}	-0.0015* (0.0008)	-0.0122*** (0.0008)	-0.0085 (0.0062)	-0.0067*** (0.0011)	0.0012 (0.0034)	-0.0088*** (0.0025)	-0.0084*** (0.0024)	-0.0019 (0.0016)	-0.0063*** (0.0019)
d_{41}	-0.0029*** (0.0010)	-0.0095*** (0.0010)	-0.0047 (0.0083)	-0.0073*** (0.0014)	0.0081* (0.0043)	-0.0121*** (0.0034)	-0.0048 (0.0031)	-0.0040* (0.0021)	-0.0123*** (0.0024)
Instruments	No	No	No	No	No	No	No	No	No
Fixed effects	mxh	mxh	mxh	mxh	mxh	mxh	mxh	mxh	mxh
Observations	1,706,000	2,761,000	87,000	2,688,000	238,000	1,518,000	2,561,000	2,798,000	2,574,000
	Textiles	Footwear	Ceramics	Jewelry	Metal prods	Machinery	Transport	Optics	
d_6	0.0008*** (0.0003)	0.0002 (0.0006)	-0.0046*** (0.0013)	-0.0051 (0.0038)	-0.0066*** (0.0008)	-0.0107*** (0.0011)	-0.0073*** (0.0017)	-0.0029* (0.0015)	
d_{11}	0.0007* (0.0004)	-0.0011 (0.0007)	-0.0069*** (0.0017)	-0.0145*** (0.0048)	-0.0090*** (0.0010)	-0.0136*** (0.0014)	-0.0086*** (0.0020)	-0.0028 (0.0019)	
d_{16}	0.0004 (0.0005)	-0.0011 (0.0009)	-0.0065*** (0.0020)	-0.0180*** (0.0055)	-0.0123*** (0.0012)	-0.0182*** (0.0016)	-0.0095*** (0.0023)	-0.0098*** (0.0022)	
d_{21}	-0.0010** (0.0004)	-0.0035*** (0.0008)	-0.0086*** (0.0019)	-0.0171*** (0.0052)	-0.0146*** (0.0011)	-0.0239*** (0.0015)	-0.0078*** (0.0020)	-0.0094*** (0.0021)	
d_{41}	-0.0024*** (0.0006)	-0.0089*** (0.0010)	-0.0098*** (0.0026)	-0.0202*** (0.0067)	-0.0170*** (0.0014)	-0.0307*** (0.0019)	-0.0096*** (0.0024)	-0.0136*** (0.0027)	
Instruments	No	No	No	No	No	No	No	No	
Fixed effects	mxh	mxh	mxh	mxh	mxh	mxh	mxh	mxh	
Observations	20,890,000	3,526,000	2,612,000	543,000	5,553,000	8,680,000	2,347,000	2,387,000	