Firm-to-Firm Relationships and the Pass-Through of Shocks

Theory and Evidence

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Abstract

Economists have long suspected that firm-to-firm relationships might lower the responsiveness of prices to shocks due to the use of fixed-price contracts. Using transaction-level U.S. import data, I show that the pass-through of exchange rate shocks in fact rises as a relationship ages. Based on novel stylized facts about a relationship's life cycle, I develop a model of relationship dynamics in which a buyer-seller pair accumulates relationship capital to lower production costs under limited commitment. The structurally estimated model generates countercyclical mark-ups and countercyclical pass-through of shocks through variation in the economy's rate of relationship creation, which falls in recessions. (JEL E30, E32, F14, L14) (Keywords: Prices, Exchange Rates, Supply Chain, Trade Relationships)

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1 Introduction

This paper examines how relationships between firms affect the pass-through of shocks, 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, lowering the responsiveness of prices to shocks due to the use of fixed-price contracts (e.g., Barro (1977), Carlton (1986)). Such contracts might explain why pass-through of exchange rate shocks into prices is incomplete, an important puzzle in international economics.[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. I rationalize this finding via a theory in which relationships accumulate relationship capital to lower production costs, and structurally estimate the model using new stylized facts about prices and the value traded over a relationship's life cycle. My findings suggest that aggregate mark-ups and the responsiveness of prices to shocks co-vary negatively with an economy's relationship creation rate, which falls in recessions.

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, there is little work investigating the aggregate effects of relationships, since transaction-level data mapping the linkages between domestic buyers and sellers are hard to obtain.[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 between 1992 and 2011. 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 two thirds higher when the relationship is four years older. In a new relationship, price movements on average reflect 12% of the exchange rate change since the last transaction, compared to 20% in a four-year relationship. Pass-through also rises with various measures of relationship intensity. For example, each additional transaction raises pass-through by on average 0.4

[1] See e.g., Gopinath et al. (2010), Burstein and Gopinath (2014).

[2] For 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 et al. (2003) find that suppliers in the U.S. automotive industry have on average been transacting with major buyers for 26 years.

[3] Surveys suggest that long-term relationships have become more common over the last three decades. See e.g. Han et al. (1993), Helper and Sako (1995), Liker and Choi (2004).

[4] Recent work by, e.g., Duprez and Magerman (2018), Bernard et al. (2019), and Tintelnot et al. (2019) uses annual VAT data to study domestic linkages in Belgium. These data do not show individual transactions, however.

percentage points. Pass-through also increases with how much the relationship trades relative to its first year. These results are robust to a wide range of specifications, and hold conditional on firm size and country.

I document several additional facts on the dynamics of relationships, which will discipline a model. I find that on average, an old relationship trades more, sets lower prices relative to the market average, and is less likely to separate compared to when the relationship was young. Individual relationships' trade also follows a life cycle. New relationships trade small values, and increase trade as the relationship ages and survives. 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 a new relationship.

I interpret these findings through a model in which a buyer and a seller firm interact repeatedly and build up *relationship capital* to lower marginal production costs. Relationship capital represents learning about the partner or the build-up of customized equipment, as suggested in the management literature.[5] Capital accumulates endogenously in proportion to the quantity traded, for example because a larger trade volume allows the seller to become better at producing to the seller's specifications. Relationship capital is also subject to idiosyncratic shocks, for example reflecting staff turnover. When capital is low, marginal costs are high and the firms trade little. To increase profits, the seller sets a lower price than under static profit maximization to sell more, which allows her to build up capital and to increase future sales, as in learning-by-doing models (e.g., Dasgupta and Stiglitz (1988)) or in models with *customer* capital (e.g., Gourio and Rudanko (2014)) or demand accumulation (Foster et al. (2016)). Relative to these models, a novel feature of my setup is that buyer and seller trade under limited commitment. When capital becomes sufficiently low due to bad idiosyncratic shocks, the partners separate to search for a different partner, while good shocks reinforce capital accumulation. The stochastic process of capital generates a stochastic life cycle of trade.

Limited commitment leads to a positive correlation between relationship capital and pass-through. The seller's production costs are subject to aggregate shocks, which I will interpret as arising from exchange rate movements. When a shock raises costs, the buyer's value of the relationship with the seller falls relative to her outside option of separating to search for an alternative supplier in another country. If the buyer's participation constraint binds as a result, the seller incentivizes the buyer to continue the relationship by lowering her mark-up, passing through the cost shock incompletely, to raise the buyer's surplus. On the other hand, if the buyer's constraint does not bind, pass-through is complete and the mark-up is not reduced. Since high-capital relationships are more valuable to both partners due to their lower costs, such relationships' outside options are less likely to bind. Consequently, high-capital relationships have higher pass-through and higher mark-ups.

[5] Rauch and Watson (2003) find that buyers train suppliers to meet their specifications. Anderson and Weitz (1992) and Dyer (1996) find that relationships allow partners to build up customized assets, and Doney and Cannon (1997) show that relationships allow partners to build trust over time.

My model provides a tight link between relationship capital and age via selection. By virtue of having survived for longer, the average old relationship must have received relatively good idiosyncratic shocks, which have increased its capital away from the threshold level at which the partners would separate. It therefore has relatively high capital, and thus low marginal costs. As a result, the average old relationship exhibits higher pass-through, trades more, and sets lower prices than the average young relationship, as in the data. The relationship capital setup therefore provides a mechanism that jointly generates all observed facts. It is also consistent with the fact that pass-through not only rises with age but also with relationship intensity.

I estimate the model structurally with a continuum of relationships using simulated method of moments. When calibrated to the life cycle, the model quantitatively matches the untargeted empirical correlation between pass-through and relationship age.[6] I then use the model to interpret a novel fact. In the data, the creation rate of new relationships is procyclical while the relationship destruction rate is acyclical. At the same time, as previously documented by Berger and Vavra (2019), exchange rate pass-through rises in recessions. My model provides a novel micro foundation for this observation. In a downturn, the share of old relationships in the economy rises due to the lack of relationship creation. Since older relationships have a higher average responsiveness of prices to shocks and set higher mark-ups, exchange rate pass-through and mark-ups increase.[7] This pattern can be further amplified if the bargaining power of buyers rises in recessions, for example because sellers cannot find alternate customers. In that case, if the dollar simultaneously appreciates against foreign currencies as in Q2/01 or Q4/08, then all sellers are forced to simultaneously pass through this cost reduction to buyers to prevent them from leaving, and pass-through spikes, as observed empirically.

Literature. My paper makes several contributions. First, my paper shows that an economy's average relationship length may affect *macroeconomic* outcomes of interest. Prior work studying relationships with two-sided international trade data has mostly analyzed relationships' micro-level properties, and has not studied price setting in relationships. For example, Eaton et al. (2015) provide evidence on the matching patterns of Colombian exporters with U.S. importers, and Macchiavello and Morjaria (2015) show that longer relationships can relax limited commitment constraints through learning about the seller's reliability. Monarch and Schmidt-Eisenlohr (2018) study the value traded and age of relationships over time and across countries. In contrast to this work, I document novel facts on relationship price setting to argue that relationship age is a relevant state variable for aggregate pass-through and mark-ups. While price setting has been static in most previous work, I develop a dynamic theory of relationships in which prices endogenously affect the relationship's evolution.

[6] I assume that imported inputs priced in dollars insulate part of the seller's costs in dollars from exchange rate fluctuations to target the right *average* level of pass-through, in line with evidence by Amiti et al. (2014) that large exporters are also large importers.

[7] See Rotemberg and Woodford (1999) for evidence on countercyclical mark-ups.

Second, I point out an additional source of heterogeneity in exchange rate pass-through across firms. Prior work has documented local costs (Goldberg and Verboven (2001)), imported inputs (Amiti et al. (2014)), or imperfect competition (Atkeson and Burstein (2008)) as sources of incomplete pass-through. Berman et al. (2012) document that high performance, larger firms pass through less into import prices, and Neiman (2010) shows that pass-through is higher in intra-firm relationships. I show that, even conditional on firm size and country, pass-through rises as a relationship's length and intensity increase. In my framework, pass-through is low in young relationships because the buyer's limited commitment constraint is close to binding, and hence the seller has to absorb exchange rate fluctuations to incentivize the buyer to stay. More generally, my results suggest that heterogeneity in average relationship length across countries, as documented by Monarch and Schmidt-Eisenlohr (2018), could help explain cross-country differences in exchange rate pass-through.

Third, I develop a theory of dynamic mark-ups in relationships. Setting lower mark-ups at the beginning of an association allows a firm to increase relationship capital more quickly, for example due to a learning-by-doing mechanism as in Dasgupta and Stiglitz (1988) or Besanko et al. (2014). While the learning-by-doing literature finds increasing markups, it has not investigated how learning affects the pass-through of shocks. My mechanism also relates to the literature on price setting under customer base concerns (Phelps and Winter (1970)). For example, in Gourio and Rudanko (2014) customers are a form of capital, which can be increased more quickly when firms offer larger introductory discounts. Kleshchelski and Vincent (2009) and Paciello et al. (2019) show that firms set lower mark-ups than under static profit maximization and pass through shocks incompletely when customer retention concerns play a role, and Foster et al. (2016) develop a model in which firms set lower prices to build up demand stock. In contrast to this literature, I use transaction-level data to follow firm-to-firm relationships over time. I document life cycle properties that are not present in consumer markets and argue that aggregate pass-through and mark-ups can vary with average relationship length.

Finally, the paper is related to the literature on firm-to-firm networks in international trade (e.g., Chaney (2014), Lim (2018), Tintelnot et al. (2019)), and in particular to recent work studying heterogeneity in firms' markups (Kikkawa et al. (2019)). My work is complementary to this literature by examining one layer of the supply chain in more detail with transaction-level data, which is usually not available in the network literature. I show that pass-through rises with relationship age for a variety of network configurations observed in my data. My finding of a larger price response to shocks when firms have been in a longer relationship is of relevance for the transmission of shocks throughout a network more generally.

This paper proceeds as follows. In Section 2, I present the empirical analysis. I first introduce the data, define a relationship, and then present reduced-form evidence on pass-through and document stylized facts on relationship dynamics. Section 3 presents the model and characterizes its equilibrium. In Section 4, I estimate the model and examine aggregate implications. Section 5 concludes.

2 Firm-to-Firm Relationships: Stylized Facts

In this section, I present several novel facts. First, I show that the pass-through of exchange rate shocks into U.S. import prices increases with the length of a U.S. importer's relationship with its foreign supplier and with various measures of a relationship's intensity. Second, I study the dynamics of a relationship to understand the potential mechanism behind this result. I show that (i) relationships follow a life cycle and (ii) on average, older relationships trade more, set lower prices, and are less likely to separate.

2.1 Data

Due to the lack of transaction-level data of customer-supplier interactions 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. 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 goods[8] made by U.S. firms during the period 1992-2011. These data record for each import transaction an identifier of the U.S. importer as well as a foreign exporter ID. This information on both transaction partners makes the study of relationships possible. Monarch (2018) and Kamal and Monarch (2018) suggest that the foreign firm identifiers are reliable over time and in the cross-section.

In addition to the firm identifiers, the LFTTD dataset also comprises the 10-digit Harmonized System (HS10) code of the product traded[9], 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 the *Longitudinal Business Database (LBD)*, which provides annual information about a firm's employees and industry.

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 (2018) and Monarch and Schmidt-Eisenlohr (2018). To account for outliers, for all analyses involving prices I trim the dataset in each quarter by removing transactions whose prices lie below the 1st or above the

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

[9]Examples 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".

[10]Based 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".

99th percentile of the price distribution for the associated product-country pair, and drop price changes larger than four log points within the same importer-exporter-HS10 triplet. Appendix A.1 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. Whenever another transaction of the importer-exporter pair occurs in any good, the relationship length is increased by the number of months passed.[11] To determine the termination date of a relationship, I first compute the time gaps between subsequent transactions for all importer-exporter-product (HS10) triplets in the data. I then take the distribution of these time gaps for each HS10 product across the entire dataset and determine the 95th percentile for each of these distributions. I refer to this product-level statistic as the product's *maximum gap time*. It provides an idea of the time horizon during which a product is typically re-traded within a relationship. I assume that a relationship has 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. 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 has two advantages relative to identifying a relationship's end as the last time a pair is observed in the data. First, it addresses the fact that the data are right-censored in 2011 and allows me to determine more clearly whether relationships that have last traded near the end of the sample period are likely terminated. Second, there exist a number of importer-exporter pairs which exhibit zero trade in most years of the association. My definition focuses on relationships that trade regularly. Table I.1 in Appendix I provides summary statistics on matching and relationship length, and shows that there do not exist significant differences in average relationship length between industries.[13]

Figure 1 presents the distribution of value traded by relationship length based on my length definition.[14] The blue bars in the figure show the distribution of value traded in an average quarter by current relationship length. 53% of the value traded in arms' length transactions is accounted for by

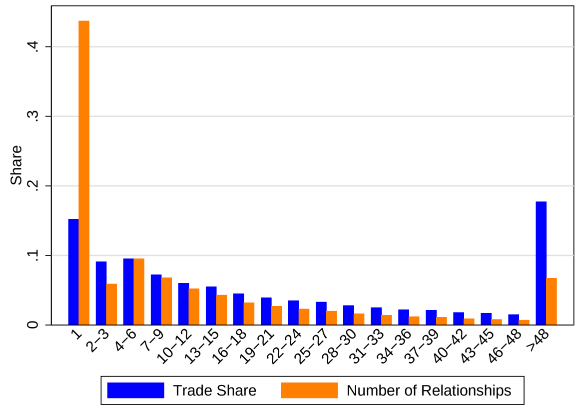
[11] An alternative would be to define age based on the number of transactions. I examine this variable below.

[12] I show below that my results are robust to a "naive" definition of relationship length, where I define a relationship as ending at the last ever observed transaction of the importer-exporter pair in the data.

[13] Figure H.1 in Appendix H shows the overall distribution of trade by importer industry.

[14] I compute the trade value by relationship length in each quarter, and average across quarters. To account for relationship lengths up to 48 months, I drop the first five years for this analysis, up to and including 1996.

Figure 1: Distribution of Relationships by Length (in Months)



Source: U.S. Census Bureau

relationships that have been together for more than 12 months, and 18% is due to pairs that have been together for more than four years. However, most matches are actually quite short-lived. The orange bars in Figure 1 display the equally-weighted distribution of buyer-seller associations by length, and show that close to 44% of all pairs observed in an average quarter are less than one month old. However, such new matches account for only 15% of the value traded.

In Appendix A.2, I use Bloomberg data on supply chain linkages to construct a similar relationship length distribution for *domestic* relationships and for several large U.S. firms individually. Table I.2 in Appendix I presents the average length of domestic buyer-seller associations from management surveys. These data show that long-term relationships are prevalent for domestic transactions as well.

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

I now examine the connection between relationship length and the pass-through of shocks. Barro (1977) and Carlton (1986) suggest that relationship prices could be less responsive to shocks due to the use of contracts which specify fixed prices for a period of time. Since long-term relationships are presumably more likely to use either implicit or explicit contracts, they might exhibit lower pass-through of shocks. To study this claim, I use exchange rate shocks as an easily observable source of exogenous variation in the exporter's costs, as in, e.g., Berger and Vavra (2019), and examine the share of exchange rate movements that is passed through into U.S. dollar import prices as a function of relationship length. I first analyze a baseline specification with a minimal set of controls reflecting the theory I develop in Section 3. I then discuss factors that could confound my results and show that my findings are robust to appropriate controls and alternative definitions of relationship length.

Baseline

Let m index an importer, x the exporter, c the exporter's country, h the HS10 product, and t the quarter. A relationship, which may trade one or several products, is indexed by mx. I apply a more stringent filter from now on and focus only on relationships which are market-based throughout their life, dropping all relationships which are ever related at any point, and aggregate the data to the quarterly level to smooth out noise in the unit values.[15] My baseline specification is

$$\Delta \ln(p_{mxht}) = \beta_1 \Delta \ln(e_{mxht}) + \beta_2 Length_{mxt} + \beta_3 Length_{mxt} \cdot \Delta \ln(e_{mxht}) + \beta_4 X_{mxht} + \gamma_{mxh} + \omega_t + \varepsilon_{mxht}, \quad (1)$$

where $\Delta \ln(p_{mxht})$ is the log nominal price change of product h in relationship mx between quarter t and the relationship's last transaction of the product, $\Delta \ln(e_{mxht})$ is the cumulative change in the exchange rate between the U.S. and exporter x's country since the relationship's last transaction of product h, $Length_{mxt}$ is the number of months the overall relationship has lasted, across all of its products, at the first transaction of quarter t, and X_{mxht} is a set of controls. I obtain exchange rates from the OECD's Monetary and Financial Statistics database, measured in U.S. dollar per foreign currency unit, and supplement these data with rates from Datastream for Eurozone countries.[16] I measure relationship length across all products to allow for spillovers, but will alternatively analyze a product-specific measure of relationship length below. The relationship-product fixed effects γ_{mxh} control for the effect of fixed heterogeneity in product or relationship characteristics (which includes heterogeneity in exporter countries) on average pass-through. My regressions therefore assess pass-through within the same relationship-product triplet over time. Finally, ω_t are time fixed effects. Standard errors are clustered at the country-level. While the specification is based on standard pass-through regressions (e.g., Campa and Goldberg (2005)), the novelty is that I take into account the length of the importer-exporter pair's relationship.

I include two controls to bring the empirical analysis closer to the model I develop below. First, while in practice relationships trade at irregular intervals dependent on for example demand fluctuations, in my model I will abstract from the endogenous choice of order times and assume that relationships trade in every quarter. If pass-through is correlated with the frequency of trade, for example because prices are more likely to be reset after longer lag times, then pass-through could vary with relationship age due to changes in the order frequency.[17] I control for this channel by adding the number

[15] This implies that all relationships that switch related party 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.

[16] Euro 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 Table I.3 in Appendix I.

[17] See Gopinath and Itskhoki (2010); Gopinath et al. (2010) for a discussion of a mechanism connecting frequency of price adjustment and pass-through.

of months passed since the relationship's last transaction of product h, Time Gap_{mxht}, both on its own and interacted with the exchange rate change. Second, my theory will focus on the dynamic evolution of a relationship and abstract from other sources of heterogeneity in importer or exporter size, for example due to differences in productivity. Larger firms have higher transaction volumes, which may affect pass-through for example because larger sellers price more to market (Berman et al. (2012)). To separate the effect of a relationship's evolution from the effect of average relationship size, I control for a relationship's average size, measured by its log average quarterly trade value, $\ln(\text{Avg Size}_{mx})$. I will examine alternative ways to control for relationship size below. Note that I only need to add the interaction of size with the exchange rate since the level effect is captured by γ_{mxh}.

Table 1 presents the results for the key coefficients. In column (1), I run a standard pass-through regression without the relationship terms. Average pass-through is about 0.2. This magnitude is comparable to the aggregate quarterly exchange rate pass-through for all U.S. imports documented by Gopinath et al. (2010). Column (2) adds all terms from the baseline regression except average size. This specification allows me to show the level of pass-through in a new relationship unconditional on size, which is 0.12. The third column shows the full specification. I find that for each additional month a relationship has lasted, the responsiveness of prices to exchange rate shocks rises by 0.0016. Thus, pass-through in a relationship that is four years old is about 7.7 percentage points higher than when the relationship was new, a substantial increase. The coefficients on the controls X_{mxht} highlight that pass-through is higher when more time has passed since the last transaction, and that on average larger relationships have lower pass-through into prices in the importer's currency: a one log point increase in the average quarterly value traded lowers pass-through by 4 percentage points.

Figure 2 visualizes my findings by running the baseline regression (1) with annual dummies instead of the continuous variable Length_{mxt}. Older relationships, which presumably are the most likely to rely on contracts, exhibit a higher responsiveness of prices to shocks, 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 than trade between arms' length partners (Neiman (2010)), since related partners could be thought of as having a very close relationship.

The remaining columns document that pass-through is also correlated with various alternative measures of relationship length and intensity. In column (4), I replace the number of months with the number of transactions since the beginning of the relationship, $Trans_{mxt}$, as an alternative measure of relationship length. In column (5), I construct a measure for how much the relationship has grown relative to the first year by calculating the difference in the log value traded between the current year of the relationship and the relationship's first year, $\Delta\ln(YValue_{mxt})$. This variable focuses on relationship growth since year one as opposed to fixed differences in size, which are picked up by Avg Size_{mx}. In column (6), I compute the cumulative value traded by the relationship up to the current year minus Avg Size_{mx} as an alternative measure of relationship growth. Finally, in column (7), I

Table 1: Pass-Through Regressions

	Length			Intensity			
				Trans	Chg value	Cum value	Prod months
$\Delta \ln(p)$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta \ln(e)$	$.2045^{***}$	$.1204^{**}$	$.5681^{***}$	$.5797^{***}$	$.5812^{***}$	$.5289^{***}$	$.5593^{***}$
	(.0513)	(.0474)	(.1629)	(.1643)	(.1654)	(.1655)	(.1621)
Length $\cdot \Delta \ln(e)$		$.0013^{***}$	$.0016^{***}$				
		(.0002)	(.0002)				
Time Gap $\cdot \Delta \ln(e)$		$.0083^{***}$	$.0063^{***}$	$.0072^{***}$	$.0079^{***}$	$.0075^{***}$	$.0065^{***}$
		(.0023)	(.0021)	(.0021)	(.0020)	(.0021)	(.0021)
Avg Size $\cdot \Delta \ln(e)$			$-.0390^{***}$	$-.0399^{***}$	$-.0369^{***}$	$-.0395^{***}$	$-.0381^{***}$
			(.0120)	(.0120)	(.0121)	(.0120)	(.0122)
Intensity $\cdot \Delta \ln(e)$				$.0043^{***}$	$.0141^{***}$	$.0400^{***}$	$.0019^{***}$
				(.0005)	(.0045)	(.0066)	(.0003)
Time FE	Y	Y	Y	Y	Y	Y	Y
Rel-product FE (γ)	N	Y	Y	Y	Y	Y	Y
Observations	13,850,000	13,850,000	13,850,000	13,850,000	13,850,000	13,850,000	13,850,000

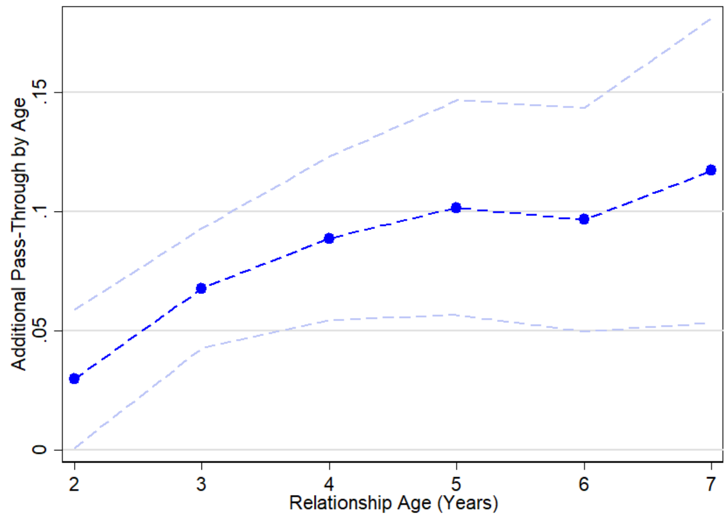
Note: Number of observations has been rounded to four significant digits as per U.S. Census Bureau Disclosure Guidelines. Standard errors are clustered at the country-level. Coefficients for the terms in levels are omitted. Length is the time passed since the first transaction of the importer-exporter relationship in months. Time Gap is the time passed in months since the relationship last traded product h. Avg Size is the average value traded by the relationship per quarter. Intensity is one of the four alternative relationship intensity measures described in the text.

replace overall relationship length with its product-specific analogue, the time passed since the first transaction of product h in the relationship, $PLength_{mxht}$. Pass-through increases significantly with all four measures. Thus, conditional on average relationship size, pass-through increases dynamically both as the relationship ages and as it trades more. I show in Section 2.4 that the two are related, with older relationships on average trading more, and will build my theory to reflect this fact. The consistently negative coefficient on Avg Size$_{mx}$ could be consistent with a mechanism as in Atkeson and Burstein (2008), where larger sellers price more to market and therefore have lower pass-through into import prices. I next show that these conclusions are robust to a battery of robustness checks.

Robustness

I begin by analyzing the sensitivity of my results more thoroughly with respect to my first main control, the frequency of trade, to ensure that differences in the trading frequency of old versus new relationships do not drive my results. First, I re-run the baseline regression for only those relationship-product triplets that transact in every quarter of their existence. By construction, in this sample the effect of relationship length on pass-through is not affected by differences in the frequency of trade. I still find increasing pass-through with relationship age (column (1) of Table 2). Tables I.4-I.7 in

Figure 2: Additional Pass-Through Relative to Year One



Appendix I replicate this table separately for each of the four alternative measures of relationship intensity discussed above, and show that my findings hold for each of these alternative measures. In column (2) of Table 2 (and the analogues in the appendix), I explicitly model firms' choice to trade in a given quarter as a function of covariates, and estimate a selection model using the selection correction for panel data proposed in Wooldridge (1995). This approach, described in Appendix B, takes into account that firms' choice to trade may itself be endogenous to the exchange rate. It yields similar results. Table I.8 in Appendix I splits the sample into relationship-product triplets with a frequency of trade below and above the median and shows that pass through increases for both subsamples.

A related concern is that the difference in pass-through between new and old relationships could disappear over longer time horizons. To assess this possibility, I aggregate the dataset to the annual level and then re-run regression (1) with annual changes in the average price and exchange rate, where $Length_{mxt}$ is now measured in years (Column (3) of Table 2 and the analogues in the appendix). Second, I run the baseline regression with lags

$$\Delta \ln(p_{mxht}) = \sum_{k=1}^{K} \alpha_k \Delta \ln(e_{mxh,t(k),t(k-1)}) + \beta Length_{mxt} + \sum_{k=1}^{K} \theta_k \Delta \ln(e_{mxh,t(k),t(k-1)}) \cdot Length_{mxt} + \xi X_{mxht} + \gamma_{mxh} + \omega_t + \varepsilon_{mxht}, \quad (2)$$

where $\Delta \ln(e_{mxh,t(k),t(k-1)})$ is the exchange rate change between the quarter of transaction k and transaction $k-1$, and X_{mxht} is the same set of controls as before, except that I now include the time passed since the last transaction for each of the lags k, Time $\text{Gap}_{mxh,t(k),t(k-1)}$ and their interactions with the corresponding exchange rate change. The results are similar to before (Table I.9 in Appendix I).

Table 2: Pass-Through Robustness - Relationship Length in Months ($Length_{mxt}$)

$\Delta\ln(p)$	Every qtr	Selection	Annual	Size	Trans Val	GDP/Law	Full FE	Pos	Neg	Tot Length	Exp FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\Delta\ln(e)$	.4437***	.5518***	.5301***	.8572***	.3733***	.2505**	.1591	.5550**	.3006**	.5663***	.5700***
	(.1468)	(.1639)	(.1474)	(.1953)	(.1114)	(.0927)	(.3569)	(.2059)	(.1352)	(.1624)	(.1650)
Length $\cdot\Delta\ln(e)$	.0014***	.0013***	.0187***	.0019***	.0012***	.0009**	.0006***	.0009**	.0010**	.0010***	.0015***
	(.0003)	(.0002)	(.0028)	(.0004)	(.0004)	(.0002)	(.0002)	(.0004)	(.0004)	(.0004)	(.0002)
Time Gap $\cdot\Delta\ln(e)$		.0083***	.0273*	.0068***	.0063***	.0066***	.0043***	.0069	.0034	.0063***	.0047**
		(.0027)	(.0141)	(.0021)	(.0020)	(.0021)	(.0016)	(.0087)	(.0028)	(.0021)	(.0019)
Avg Size $\cdot\Delta\ln(e)$	−.0276**	−.0386***	−.0320***			−.0201**	−.0078**	−.0341**	−.0206*	−.0401***	−.0385***
	(.0108)	(.0119)	(.0100)			(.0080)	(.0033)	(.0165)	(.0100)	(.0121)	(.0123)
Imp Size $\cdot\Delta\ln(e)$				−.0136***							
				(.0029)							
Exp Size $\cdot\Delta\ln(e)$				−.0321***							
				(.0095)							
Trans Val $\cdot\Delta\ln(e)$					−.0235***						
					(.0076)						
Length $\cdot\Delta\ln(e)\cdot d^{GDP}_{\text{med}}$						.0002					
						(.0006)					
Length $\cdot\Delta\ln(e)\cdot d^{GDP}_{\text{high}}$						−.0001					
						(.0007)					
λ		−.0016									
		(.0037)									
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Rel-product FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	–
GDP/Law FE $\cdot\Delta\ln(e)$	–	–	–	–	–	Y	–	–	–	–	–
Country FE $\cdot\Delta\ln(e)$	–	–	–	–	–	–	Y	–	–	–	–
Total Length $\cdot\Delta\ln(e)$	–	–	–	–	–	–	–	–	–	Y	–
Exp-product FE	–	–	–	–	–	–	–	–	–	–	Y
Observations	6,113,000	26,560,000	2,717,000	13,850,000	13,850,000	13,850,000	13,850,000	7,422,000	5,196,000	13,850,000	15,290,000

Note: Number of observations has been rounded to four significant digits as per U.S. Census Bureau Disclosure Guidelines. Standard errors are clustered at the country-level. Level coefficients are omitted for brevity. λ denotes the selection term in a Heckman model. Column (1) runs on the sample of only relationship-product triplets that transact in every quarter. Column (2) is estimated via the selection model described in in Appendix B. Column (3) re-runs the regression on data aggregated to the annual level. Column (4) controls for importer and exporter size separately. Column (5) controls for the actual value transacted of the product in the quarter. Column (6) includes two dummies d^{GDP}_{med} and d^{GDP}_{high}, respectively, capturing whether a country's average GDP per capita over the sample period was in the second or third tercile, respectively, and two average Rule of Law dummies from Kaufmann et al. (2010). Column (7) has a fixed effect for each individual country interacted with the exchange rate change. Columns (8) and (9) re-run the regression on the sample of positive (including zero) and negative exchange rate changes, respectively. Column (10) includes a control for how long the relationship is going to last in total. Column (11) contains exporter-product fixed effects.

I next examine the sensitivity of my findings with respect to my second main control, relationship size, to ensure that heterogeneity in firm size does not drive my findings. In Column (4) of Table 2, I include controls for the importer's and the exporter's size separately, rather than the average relationship size, where firm size is computed as the total real value of trade conducted by the firm with all partners throughout the entire dataset. I find that average pass-through is lower both when the importer or the exporter is larger, but it increases with relationship age and intensity. Second, in column (5), I run the baseline regression controlling for the relationship's actual value traded of product h in the given quarter, Trans Val_{mxht}, rather than average size Avg Size_{mx}, and find similar results. Third, I split the sample into relationships with average size above and below the median of Avg Size_{mx}, respectively, and re-run the regression for both samples. Alternatively, I split the sample into relationships trading only one product throughout their life and multi-product relationships. The results in Table I.8 in Appendix I show that pass-through increases with relationship length in all specifications, but most strongly for large, single-product relationships.

In the third set of robustness checks, I study the impact of exporter country heterogeneity. Monarch and Schmidt-Eisenlohr (2018) find that the average relationship is longer in countries with a higher GDP per capita or better rule of law, which could spuriously generate my findings if for example a country's exchange rate process is correlated with its level of economic development. In Column (6) of Table 2, I therefore add to my baseline specification two dummies for whether a country's average GDP per capita over the sample period is in the middle tercile or in the top tercile of countries, respectively, and two dummies for the country's average rule of law from Kaufmann et al. (2010), all interacted with exchange rate changes. I further add triple interactions of the exchange rate change, the length of the relationship, and GDP per capita to analyze whether higher GDP affects the pass-through-age gradient. The increase in pass-through with relationship age is robust to these controls, and does not systematically depend on GDP per capita. Column (7) interacts a fixed effect for each individual country with the exchange rate. In this most stringent specification, I continue to find rising pass-through with relationship age and intensity, although the coefficients become smaller and noisier. Finally, to explore the cross-country heterogeneity more fully, I run the baseline regression separately for countries with on average low, medium, and high GDP per capita throughout the period, for different geographical regions and major U.S. trading partners, and for OECD and non-OECD members, respectively. The results in Table I.10 in Appendix I indicate that pass-through increases with relationship length for every country group and major trading partner (although the effect is insignificant for Mexico), and most strongly for high-GDP OECD members. Table I.11 in analyzes the effect of the currency of invoice. While around 90% of U.S. imports are priced in U.S. dollars, Gopinath et al. (2010) show that the responsiveness of import prices is significantly higher when pricing occurs in the foreign currency. Since the currency of invoice is not observed in the LFTTD, I construct groups of countries and products based on their likelihood of foreign currency use from

Gopinath et al. (2010). I find that pass-through increases to a similar extent with age for all groups.

As a fourth robustness check, I run the baseline regression only for positive and negative exchange rate shocks, respectively, to see if either of them is driving the results (Columns (8) and (9) of Table 2). The positive coefficients in both regressions indicate that prices change in the direction of the shock. The rise in pass-through with relationship age is similar for both types of shocks.

Fifth, I investigate whether the overall duration of the relationship affects my results. If relationships that last longer in total are different from the outset from those that last only a short period, then this difference in relationship "types" could lead to the positive correlation between relationship length and pass-through. To analyze this possibility, I additionally control for how long a relationship is going to last in total, $TotLength_{mx}$, interacted with the exchange rate change (Column (10) in Table 2). While controlling for total relationship length lowers the effect slightly, there is still a significant dynamic effect. Table I.13 in Appendix I presents the results for subsets of relationships based on their total length. In my theory below, I will allow pass-through to differ both because some relationships start out better than others and due to the dynamic evolution of the relationship.

Sixth, the pass-through of shocks could be affected by a firm's network of suppliers or customers. Kikkawa et al. (2019) find that firms that account for a larger share of a customer's inputs set higher markups, and Tintelnot et al. (2019) show that a firm's unit cost change in response to a foreign cost shock depends on the economy's network structure. If the length of relationships is correlated with the number of a firm's connections, my findings could be due to firms with long relationships having a systematically different network configuration. While I do not observe firms' full network, I analyze the sensitivity of my results to this channel by running the baseline regression separately for buyers that have only one foreign supplier and for buyers that have several foreign suppliers, respectively, and similarly for suppliers that have one or several U.S. customers (Table I.12 in Appendix I). I find that the pass-through increases with relationship age within each of these configurations, and even for pairs that have no other partners in the dataset.

Seventh, I replace γ_{mxh} with exporter-HS10 fixed effects to analyze variation in pass-through across relationships of a given exporter, rather than over time within a given relationship (Column (11) in Table 2). I find a positive relationship age effect on pass-through, implying that a given exporter passes through more to those customers with whom it has been in a longer relationship. In Appendix I, Table I.14 examines the exchange rate and price processes for unit roots via the testing procedure by Im et al. (2003) to study whether the exchange rate and prices could be cointegrated. The test strongly rejects the null that all panels contain a unit root for exchange rates ($p < .0001$), and hence cointegration does not appear to be present. Finally, Table I.15 in Appendix I presents my key regressions where I do not use the procedure described in Section 2.2, but instead define relationship length simply as the number of months passed since the first ever transaction of the importer-exporter pair in the data, regardless of the time gaps between transactions. The results are similar.

2.4 Further Properties of Relationships

My findings suggest that pass-through increases with relationship age and various measures of relationship intensity, which is not explained by, e.g., differences in countries or firm size. To determine the potential mechanism behind this result, I next document a number of additional stylized facts about the *evolution* of relationships. I find that (i) the value traded in relationships follows a hump-shaped life cycle; (ii) the average old relationship trades more, sets lower prices, and is less likely to separate than a new relationship. Relationship age and intensity thus appear to be related. I will use these findings to discipline a model of relationships, and use the previously documented pass-through dynamics to validate the model.

Dynamics of value traded

I first study the link between relationship age and value traded. For each relationship, I compute the total value traded across all products within month 1-12 of the relationship, months 13-24, etc., up to the relationship's end. Since many relationships do not trade in every year, I apply a smoothing procedure to fill in intermittent years with zero trade. Otherwise, since by definition each relationship trades a positive quantity in year one, I would overstate the importance of the first year year relative to the second year. I therefore assume that the value purchased is equally distributed across intermittent years with zero trade.[18] I distribute the last trade of the relationship linearly over a time period corresponding to the average time gap between transactions for that relationship. I then first run a simple cross-sectional regression of annual trade on dummies for relationship age τ

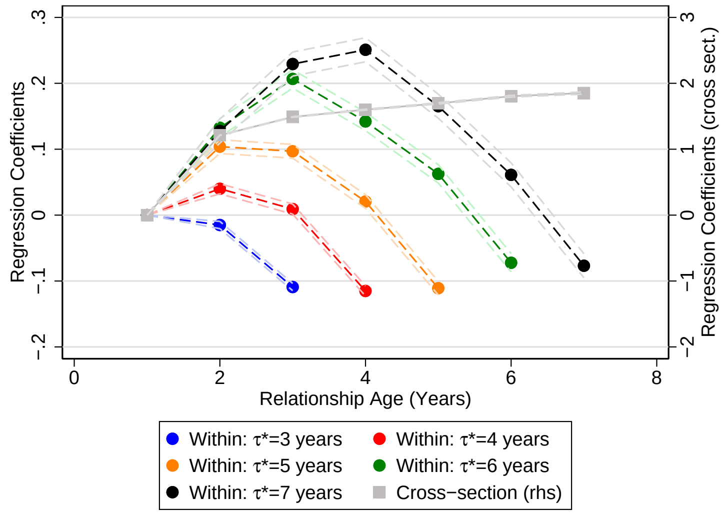
$$\ln(y_{mx\tau}) = \sum_{i\geq 2} \beta_i d_{mx,i} + \varepsilon_{mx\tau}, \tag{3}$$

where $y_{mx\tau}$ is the total trade value of relationship mx in relationship year τ and $d_{mx,i}$ are dummies for the relationship's age in years. The gray squares in Figure 3 plot the coefficients and 95% confidence bands from this regression, with year one normalized to zero. The cross-sectional regression shows a clear positive correlation between relationship age and trade, consistent with a framework in which older relationships on average trade more. Figures H.2a-H.2b in Appendix H show that the number of products traded and the frequency of trade follow a similar pattern, consistent with the average relationship's intensity increasing with age.

Since the set of relationships used to estimate trade in year τ contains only those that last for $\tau^* \geq \tau$ years, the cross-sectional specification is subject to composition effects. In particular, trade rises sharply from year one to year two because many new relationships trade only once. To address this concern, I sort relationships into groups based on how many complete years a relationship lasts in

[18] This is consistent with a linear inventory policy with repurchase once the inventory level hits zero.

Figure 3: The Life Cycle of Value Traded



total, $\tau^* = \{3,4,5,6,7\}$. I then examine relationship dynamics within sets of relationships of equal total duration by running regression (3) within each of these groups separately, where I add relationship fixed effects γ_{mx} to control for relationship heterogeneity.[19] The circles in Figure 3 plot the β_i coefficients from these regressions, again with year one normalized to zero. The figure shows a clear life cycle. For all relationships lasting at least four years in total, the value traded follows a hump-shaped pattern, with the value traded increasing over the first few years and then stabilizing and declining gradually until the relationship's end. The effect is quantitatively important: for example, for relationships lasting six years in total, 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. Since based on the cross-sectional regression older relationships trade more, the average old relationship appears to be far from the end of its life cycle.

The life cycle pattern 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. My findings are consistent with Fitzgerald et al. (2019), who show that exporters gradually increase their sales into a new destination country. My results highlight that the pattern also holds for individual relationships.

The empirical relationship life cycle corroborates evidence from a large, mostly survey-based management literature. Previous work by Dwyer et al. (1987) and Ring and van de Ven (1994) suggests

[19]Thus, the $\tau^* = 3$ group consists of relationships lasting $36-47$ months, the $\tau^* = 4$ group consists of relationships lasting $48-59$ months, etc. This setup and the use of "relationship time" ensure that each relationship in a group trades throughout the entire time horizon considered and avoids partial year concerns (Bernard et al. (2017)).

that relationships go through several stages, beginning with an *exploration stage*, in which buyers search for partners and run trials by placing small purchase orders with possible suppliers (see also Egan and Mody (1992)).[20] In the *build-up and maturity stage*, the benefits of being in the relationship gradually increase as products become more customized and production more efficient. Informal agreements increasingly replace formal contracts, and the partners work together to solve their problems jointly. In the *decline stage*, the relationship unravels, for example because of changing product requirements, increased transaction costs, or a breach of trust.

Dynamics of prices

I next examine the path of prices over the duration of a relationship. I analyze relationship-product triplets because overall relationships may trade several products with different prices. For each transaction i in quarter t, I compute the *relative* log price $\ln(\tilde{p}_{mxhi})$ 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, and regress the relative price on the overall relationship's length in months at transaction i, Length_{mxi}.[21] I include two additional controls: first, I include dummies measuring how often the relationship has transacted product h, where d_6, d_{11}, d_{16}, d_{21}, and d_{41} are dummies for whether the triplet has conducted 6-10, 11-15, 16-20, 21-40, or 41-60 transactions, respectively (transactions beyond 60 are dropped since few relationships trade that often). This control will ensure that the regression is closer to my theory, where trade occurs once every quarter, while in the data some relationships may transact significantly more frequently than others. Second, I control for whether the relationship has previously broken up and is now continuing, $Cont_{mxi}$. This variable picks up whether price setting is different in continued relationships compared to ones that are genuinely new. I run:

$$\ln(\tilde{p}_{mxhi}) = \alpha \cdot Length_{mxi} + \sum_j \rho_j d_j + \beta \cdot Cont_{mxi} + \gamma_{mxh} + \varepsilon_{mxhi}, \tag{4}$$

where γ_{mxh} are fixed effects for the triplet.[22]

Column 1 in Table 3 shows that the relative price obtained in a relationship declines slightly, by about .03% per relationship month. Additionally, repeated transactions of the same product lead to lower prices, up to about -1.3% by transaction 41-60. Since the average relationship trades about once per month, the total price reduction after four years is about 2.7%. While this effect is small, the fact that prices are not increasing with relationship age will be useful to discipline my model below.

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

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

[22] Country dummies are a linear combination of γ_{mxh}. Since prices are de-meaned, time dummies are not needed.

Table 3: Price Setting by Relationship Length

	$\ln(\tilde{p}_{mxh})$	$\ln(\tilde{q}_{mxh})$	$\ln(\tilde{p}_{mxh})$	$\ln(\tilde{p}_{mxh})$
	(1)	(2)	(3)	(4)
Length	$-.0003^{***}$	$-.0002^{***}$	$-.0007^{***}$	$-.0006^{***}$
	(.0000)	(.0000)	(.0000)	(.0000)
d_6	$-.0036^{***}$	$.0131^{***}$	$-.0006^{***}$	$-.0018^{***}$
	(.0002)	(.0005)	(.0002)	(.0002)
d_{11}	$-.0050^{***}$	$.0243^{***}$	.0003	$-.0019^{***}$
	(.0003)	(.0006)	(.0003)	(.0003)
d_{16}	$-.0069^{***}$	$.0332^{***}$	.0002	$-.0027^{***}$
	(.0004)	(.0007)	(.0003)	(.0004)
d_{21}	$-.0096^{***}$	$.0434^{***}$	$-.0006^{**}$	$-.0043^{***}$
	(.0003)	(.0006)	(.0003)	(.0004)
d_{41}	$-.0131^{***}$	$.0554^{***}$	$-.0019^{***}$	$-.0066^{***}$
	(.0004)	(.0008)	(.0004)	(.0005)
Cont	$-.0193^{***}$	$.0035^{***}$	$-.0314^{***}$	$-.0264^{***}$
	(.0003)	(.0006)	(.0003)	(.0004)
$\ln(q)$			$-.2160^{***}$	$-.1272^{***}$
			(.0000)	(.0000)
Instruments	–	–	–	Y
Relationship FE	Y	Y	Y	Y
Observations	67,868,000	67,868,000	67,868,000	67,868,000

Note: Number of observations has been rounded to the nearest 1000 as per U.S. Census Bureau Disclosure Guidelines. *Length* is the number of months the relationship has lasted. d_i are dummies for the number of transactions the relationship has conducted. *Cont* is a dummy for whether the relationship has previously separated. q is the quantity traded.

Management surveys have previously found evidence for price declines in longer relationships, both resulting from a *direct effect* due to (possibly required) productivity improvements and learning curve effects (Lyons et al. (1990), Kalwani and Narayandas (1995)), and an *indirect effect* due to quantity discounts as order volumes rise (Cannon and Homburg (2001), Claycomb and Frankwick (2005)). I therefore next examine to what extent the price declines are due to quantity discounts versus the direct effect. To analyze the role of quantity, I re-run regression (4), using the log deviation of quantity ordered from the market average for the product as dependent variable (column 2 in Table 3). The quantity ordered increases with the number of transactions, which may increase the price discount the buyer receives. To investigate this possibility, I need to specify 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. 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 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.[23] 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 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 Table I.16 in Appendix I. I regress log quantity on $ProdDown_{1t}$ to $ProdDown_{18t}$ and GDP_{1t} to 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 (4) 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, holding quantity fixed, relative price falls by about 0.06% per relationship month, and additionally by 0.7% by transaction 41-60. In Appendix I, Table I.17 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. 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.

Separations

I finally analyze the hazard rate of breaking up a relationship. 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. Since a relationship ends only when the maximum gap time has elapsed for all its products, it does not need to trade at t to be ongoing. Define ω_{mxt} as the relationship's value traded during the past twelve months. The weighted hazard rate at t is defined as a weighted average over all relationships having that length at t:

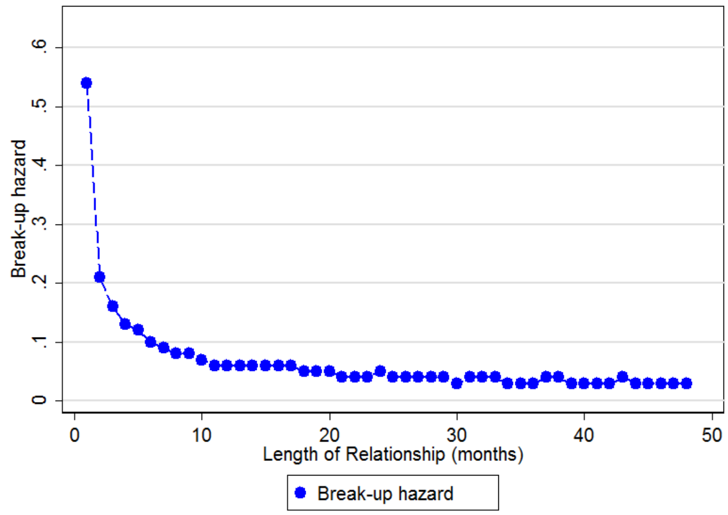
$$\{\bar{I}_{mxt}|\tau_{mxt} = \tau\} = \frac{\sum_{mx} \omega_{mxt} I\{\tau_{mxt} = \tau\}}{\sum_{mx} \omega_{mxt}}. \quad (5)$$

Figure 4 shows the simple average over the hazard rates at all t. It declines very rapidly: from 55% in the first month to 6% in month 12.[24] This result is consistent with findings by Eaton et al. (2015) and

[23] I use the most detailed input-output matrix containing 417 industries.

[24] 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.

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



Monarch (2018) who report a high rate of attrition in the first year for relationships with Colombian and Chinese suppliers, respectively. The finding that relationships are likely to break up early aligns well with the presence of an "exploration phase" of the relationship life cycle, and mirrors the negative association between job tenure and separation in worker-firm relationships (e.g., Mincer and Jovanovic (1979)).

3 Model

I now develop a theory of relationship dynamics. The model rationalizes my empirical findings: (i) pass-through increases with relationship age and intensity, (ii) on average, older relationships trade more, set lower prices, and separate less often, and (iii) relationships follow a life cycle. I will use the model below to analyze how cyclical variation in relationship creation affects aggregate pass-through.

To capture the empirical facts, I assume that a relationship builds up *relationship capital*, which lowers the pair's marginal production costs. Relationship capital parsimoniously captures a number of relationship build-up mechanisms suggested by survey evidence, such as learning of the supplier or the customization and development of specialized machines. Consistent with a rich literature on supplier selection and the high separation rate in my data, I also assume that the buyer can leave the relationship to trade with a better supplier, while the seller must be paid at least her reservation value to participate. I show that as relationship capital increases, the seller charges lower prices and trade increases. Moreover, when capital is low, the seller transfers surplus to the buyer by reducing her markups and by not passing through cost shocks fully to incentivize the buyer to stay in the relationship. As relationship capital rises, the buyer's outside option to trade with a different seller becomes less valuable relative to staying, and pass-through and mark-ups rise. Stochastic shocks to relationship capital generate a life cycle, and lead to termination when capital is sufficiently low.

While the model has relationship capital at its core, empirically I observe relationship age. As I will show in Section 4, however, a relationship's age is tightly correlated with the level of relationship capital due to selection. By virtue of having survived for longer, older relationships on average have more capital. The relationship capital setup therefore provides a mechanism that jointly generates all observed facts.

Section 3.1 first analyzes the model under full commitment (no separations). Section 3.2 then introduces separations. I discuss the key model assumptions in greater detail in Section 3.3. Throughout this section, I present relationship dynamics as a function of relationship capital. In Section 4, I will then show how my results carry over to relationship age via a selection mechanism.

3.1 Full Commitment

Setup

Let time t be discrete. There are N countries, indexed by $i \in \{0, ..., N\}$. A buyer firm located in country 0 (called "domestic", this will be the U.S. in the quantitative exercise below) produces output via the linear production function $y_t = Aq_t$, where q_t is an input purchased from a foreign seller in country $i > 0$ at price p_t, expressed in domestic currency. The buyer faces the CES final demand function $y_t = \Lambda(p_t^f)^{-\theta}$ at home, where p_t^f is the price charged by the buyer for her final output in domestic currency, $\theta > 1$ is the elasticity of final demand, and Λ is a demand shifter. Profit maximization implies that the buyer sets $p_t^f = \frac{\theta}{\theta-1}\frac{p_t}{A}$.

The seller uses an input or an input bundle $x_{i,t}$ to produce q_t for the buyer, and produces subject to the marginal cost function $c(a_t, \omega_i)$. The seller's marginal costs thus depend on two components. First, they depend on a productivity shifter a_t. I assume $\partial c/\partial a < 0$ and $\partial^2 c/\partial a^2 > 0$, i.e., costs decrease at a declining rate with a_t. An increase in a_t can reflect any process that reduces costs or that raises the amount of quality produced per unit of input. Second, marginal costs are increasing in the cost of the seller's input, ω_i, denoted in country i's currency, $\partial c/\partial \omega_i > 0$.

Previous work on relationships has suggested that long-term relationships allow the seller to learn about the buyer's requirements and to become gradually more able to fulfill them (e.g., Rauch and Watson (2003)). In particular, learning enables the seller to customize outputs to the requirements of the buyer (Bernard et al. (2018)) or to collaborate more efficiently (Defever et al. (2016)). To capture these mechanisms in a reduced-form way, I assume that the productivity shifter a_t is specific to the relationship and will refer to it as *relationship capital*. I assume that relationship capital evolves according to

$$a_{t+1} = (1-\delta)a_t + \rho q_t(p_t) + \varepsilon_{t+1}, \tag{6}$$

where δ is the depreciation rate, ρ is a proportionality constant, and $\varepsilon_{t+1} \sim N(0, \sigma_\varepsilon^2)$ is an additive random shock, and show in Appendix C.1 that this process can by micro founded as a generalization of a learning-by-doing mechanism à la Dasgupta and Stiglitz (1988). Through the lens of a learning-by-doing framework, a would be interpreted as learning stock which accumulates in proportion to the quantity traded, the depreciation term captures the gradual obsolescence of knowledge, for example as final customer tastes change, and the random shocks reflect disturbances in adapting the product to the buyer's specifications. As the relationship trades more, the seller becomes gradually more able to fulfill the buyer's requirements or customizes her output. An appealing feature of my process is that it is analogous to commonly used processes of *customer* capital accumulation (e.g., Paciello et al. (2019)).[25] In my framework, the inflow of customers would be re-interpreted as build-up of a given relationship.

My modeling choice of relationship capital is also motivated by the empirical facts presented above: first, the hump-shaped relationship life cycle indicates that the value of a relationship is not simply an increasing function of time. Instead, there must be a mechanism that allows relationships to grow for an arbitrary time period, and to decline after reaching a peak until the relationship terminates. Second, the fact that prices decrease (or at least do not increase) with relationship age motivates the introduction of a shifter of productivity, rather than of demand. Building on the learning-by-doing literature discussed above, I therefore introduce relationship capital as a stochastic productivity term. As capital increases, production costs decline, and thus, if markups are unchanged, prices fall, leading to an increase in trade. I discuss my assumptions further in Section 3.3 below.

The production cost ω_i in country i's currency can be converted into country 0's currency via $w_{i0,t} = e_{i0,t}\omega_i$, where $e_{i0,t}$ is the exchange rate between exporter country i and country 0 expressed in buyer country currency per foreign currency unit. This exchange rate follows a persistent, stochastic process on $[\underline{e}, \infty)$, $\underline{e} > 0$. The per-period profits of the seller, denoted in country 0's currency, are then $\Pi^s(a_t, w_{i0,t}) = (p_t - c(a_t, w_{i0,t}))q(p_t)$, where $c(a_t, w_{i0,t}) = c(a_t, e_{i0,t}\omega_i)$, and

$$q(p_t) = \left(\frac{\theta}{\theta-1}\right)^{-\theta} p_t^{-\theta} A^{\theta-1} \Lambda \tag{7}$$

from the buyer's final goods price together with the final goods demand function. The equation for profits shows that exchange rate fluctuations act as a cost shock for the seller: her inputs are priced in

[25] Appendix C.2 shows how the customer capital framework is connected to my model.

foreign currency, but she sets her output price in country 0's currency.[26] The seller's marginal costs are affected by two stochastic variables: the relationship-specific a_t, and the exchange rate $e_{i0,t}$, which affects $w_{i0,t}$.

At the beginning of each period, the state $(a_t, w_{i0,t})$ is revealed to both agents. The seller then determines the price that maximizes her relationship value, and the buyer chooses a final goods price p^f. Given the buyer's price, consumer demand is realized, the buyer orders the necessary quantities from the seller, and the period ends. In Appendix D.1, I prove that a recursive representation of the problem and an optimal policy exist provided that the marginal cost function is sufficiently convex in relationship capital.[27] I therefore omit time subscripts going forward and write the seller's problem in recursive form,

$$J(a, w_{i0}) = \max_p \, (p - c(a, w_{i0}))\, q(p) + \beta E J(a', w'_{i0}), \tag{8}$$

where primes indicate the next period.

Characterization

I now solve for the optimal price p and show that it is decreasing with relationship capital while the mark-up is increasing. In Appendix D.2 I show that under my assumption of sufficient convexity of the cost function the value function is concave and the optimal policy is unique. Taking the first-order condition of problem (8), using (7) and (6), I obtain an implicit expression for the optimal price charged by the seller

$$p = \frac{\theta}{\theta - 1} \left[c(a, w_{i0}) - \beta \rho E J_a(a', w'_{i0}) \right], \tag{9}$$

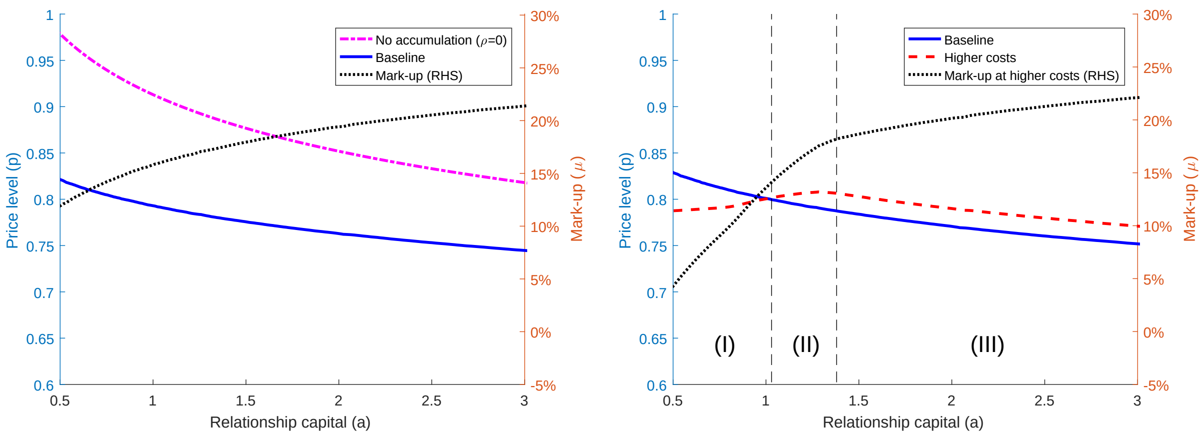
where $EJ_a(a', w'_{i0})$ is the derivative of the expected value function with respect to relationship capital. This equation highlights that the seller sets a lower price than under static profit maximization, trading off reduced profits today with the benefits of higher relationship capital in the future. This result mirrors models with demand stock accumulation or customer capital (e.g, Foster et al. (2016), Paciello et al. (2019)). Instead of setting lower prices to attract customers, in my setup the seller chooses a path of prices to affect the dynamics of a specific relationship. I prove in Appendix D.3 that the seller's implied capital choice for the next period $\tilde{a}' \equiv (1-\delta)a + \rho q(p)$ is strictly increasing in a. Since $J(a, w_{i0})$ is concave in a, the price therefore becomes closer to the monopoly price as capital increases and the incentive to accumulate more capital diminishes.

[26] In line with this assumption, around 90% of U.S. imports are priced in U.S. dollars (Gopinath et al. (2010)).

[27] Intuitively, there are two forces at play: on the one hand, since marginal costs $c(a_t, w_{i0,t})$ are convex in a, they decline less and less as capital rises. On the other hand, lowering costs raises the quantity sold at an increasing rate due to the convexity of $q(p_t)$ in p_t. Appendix D.1 shows that if marginal costs satisfy $c''(a_t, w_t) > (1+\theta)\frac{\left[c'(a_t, w_t)\right]^2}{c(a_t, w_t)}$, where primes indicate the derivative with respect to a, then the former force is stronger than the latter. Then, profits are concave in capital and the seller's choice of next period's expected level of capital is bounded.

Figure 5: Price and Mark-up as a Function of Capital

(a) Full Commitment (b) With Separation



The solid line in Figure 5a depicts a typical pricing schedule as a function of relationship capital. For comparison, the dashed-dotted line presents the case when $\rho = 0$ and hence when the price is just the standard, fixed mark-up over marginal costs. As shown in Appendix D.4, the seller's optimal price is strictly decreasing in a. It approaches the static optimum from below as a becomes large. Appendix D.5 shows that i) $dp/d\rho < 0$ and ii) $dp/d\delta > 0$.

Since the price approaches the static optimum from below, the seller's mark-up $\mu = p/c(a, w_{i0})$, rises with capital. The dotted line in Figure 5a plots on the right axis a typical mark-up schedule. While the seller's price falls as capital rises, she increases her share of the joint profits by raising her mark-up towards $\theta/(\theta-1)$, since the marginal cost reductions due to additional capital decline in a. Interpreted through the lens of a learning-by-doing framework, additional learning provides smaller and smaller benefits, which causes the seller to set a price that is closer to the static optimum.

Compared to previous work such as Fudenberg and Villas-Boas (2007) or Gourio and Rudanko (2014), which has documented low introductory prices and increasing mark-ups, my model offers another rationale for initially low mark-ups: they allow the seller to build up relationship capital, for example due to learning. Consistent with this view, Doney and Cannon (1997) document that firms' choice of new suppliers is significantly influenced by a competitive price, but that prices become less important as the relationship builds up experience and trust. Jap (1999) shows that long-term relationships increase profits for both the buyer and the seller, consistent with higher mark-ups and falling costs.

3.2 Limited Commitment

Relationship linkages do not last indefinitely. As documented in Section 2.4, more than half of all relationships terminate after one transaction, and even a two-year relationship still has a separation rate of 5% per month. A substantial literature has argued that buyers frequently leave relationships to search for better suppliers. For example, Rauch and Watson (2003) provide evidence that buyers abandon a relationship if they find a better match, and Defever et al. (2016) develop a model in which firms engage in costly search for better suppliers. Monarch (2018) documents that buyers are more likely to separate when their supplier charges a high price, and Bernard et al. (2018) show for Colombian importers that two thirds of firms both drop an old and add a new supplier in the same year.

Given this evidence, I now assume that the buyer can choose to terminate the relationship to transact with an alternate seller from any country at any time. These alternative sellers offer country-specific input costs in the buyer's currency of $\{w_{10},...,w_{N0}\}$, yielding an outside option value of $\tilde{U}(w_{10},...,w_{N0})$, which does not depend on the current relationship's capital since that is fully specific.[28] Similarly, the seller in country i has the option to separate if the relationship does not at least provide her reservation value, which may depend on the seller country's exchange rates with respect to other countries. I denote the seller's outside option by $\tilde{V}_i(w_{i0},...,w_{iN})$, with $w_{ij} = e_{ij}\omega_i$. To simplify notation, I define the vector of decision-relevant costs for a relationship between countries 0 and i by $\mathbf{w}_{i0} \equiv [w_{10},...,w_{N0},w_{i1},...,w_{iN}]$, and let the value functions take this vector as input, e.g., $U(\mathbf{w}_{i0}) \equiv \tilde{U}(w_{10},...,w_{N0})$. I do not impose any assumptions on the currency in which prices are set between countries i and $j \neq 0$, or on how U or V are determined. For example, upon separating the buyer could start trading with the best alternative seller, in which case her outside option would be $U(\mathbf{w}_{i0}) \equiv \max_{i'} E\{W_{i'}(a,\mathbf{w}_{i'0})\}$, where $W_i(a,\mathbf{w}_{i0})$ is the buyer's value of a relationship with a supplier from country i with capital a, given decision-relevant cost vector $\mathbf{w}_{i0}$. I will estimate the value of specific outside options in Section 4 below.

After the state $(a,\mathbf{w}_{i0})$ is revealed to both agents, the seller determines whether to terminate the relationship. If she decides to offer a price to the buyer, the buyer decides to accept. If she accepts, trade occurs as before. The buyer's value from a relationship with a seller from country i that is continued in the current period is

$$W(a,\mathbf{w}_{i0}) = \Pi^b(a,w_{i0}) + \beta E\left[I'W(a',\mathbf{w}'_{i0}) + (1-I')U(\mathbf{w}'_{i0})\right], \tag{10}$$

where $\Pi^b(a,w_{i0}) \equiv (p^f - p/A)y(p^f)$ are the buyer's per period profits given seller price $p(a,\mathbf{w}_{i0})$, primes indicate the next period, and $I' \equiv I(a',\mathbf{w}'_{i0})$ is an indicator that is equal to one if the relationship

[28] In a more general version of the model, the outside option could also depend on the distribution of costs across suppliers *within* a given country. Specifically, each supplier could itself source inputs from abroad (some of which from country 0), and thus be exposed differently to a change in the exchange rate with respect to country 0 due to different sourcing strategies.

is continued in state $(a', \mathbf{w}'_{i0})$, which depends on the outside options. The seller's value function in each period is now a modified version of (8)

$$J(a, \mathbf{w}_{i0}) = \max_p (p - c(a, w_{i0}))\, q(p) + \beta E \left\{ \max \left[J(a', \mathbf{w}'_{i0}), V(\mathbf{w}'_{i0}) \right] \right\}. \tag{11}$$

The seller's problem is to maximize (11), subject to the final demand function, the final goods price, and $W(a, \mathbf{w}_{i0}) \geq U(\mathbf{w}_{i0})$. Since $J(a, \mathbf{w}_{i0})$ is a maximized value, the seller must always be better off terminating the relationship if her reservation value becomes binding, and hence $I' = 0$ if and only if $J(a, \mathbf{w}_{i0}) < V(\mathbf{w}_{i0})$.[29] Holding constant the input costs of other countries, the seller's value is decreasing in w_{i0} and increasing in a, and hence the seller's constraint will become binding if capital falls below a lower bound, $a < \underline{a}(\mathbf{w}_{i0})$. This bound is increasing in w_{i0} given the other elements of $\mathbf{w}_{i0}$. The buyer's participation constraint is also more likely to bind when relationship capital is low, since the seller's price falls with a. Thus, $\partial W(a, \mathbf{w}_{i0}) / \partial a > 0$.

In Appendix D.6, I show that the first-order condition of the problem is

$$p = \frac{\theta}{\theta - 1 + \lambda} \left\{ c(a, w_{i0}) - \beta \rho E \left\{ I' \left[J_a(a', \mathbf{w}'_{i0}) + \lambda W_a(a', \mathbf{w}'_{i0}) \right] + \lambda \frac{\partial I'}{\partial a'} \left[W(a', \mathbf{w}'_{i0}) - U(\mathbf{w}'_{i0}) \right] \right\} \right\}, \tag{12}$$

where λ is the Lagrange multiplier on the buyer's participation constraint. When the buyer's outside option binds ($\lambda > 0$), the seller lowers the price by more than in the full commitment case to provide additional surplus to the buyer to incentivize her to stay in the relationship, via three terms. First, there is a direct reduction in the mark-up. Second, the $\lambda W_a(a', \mathbf{w}'_{i0})$ term shows that the price is lower when the slope of the buyer's value function $W_a(a', \mathbf{w}'_{i0})$ is higher, since in that case small increases in a allow the seller to leave the buyer's constrained region quickly. Finally, the $\lambda \frac{\partial I'}{\partial a'}$ term 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 buyer is likely to be unconstrained in the next period. Thus, if the buyer threatens to leave the relationship ($\lambda > 0$), the seller's price may be significantly below the unconstrained price.

Figure 5b above presents an example of a pricing schedule for two levels of w_{i0} conditional on the other values in $\mathbf{w}_{i0}$. In this example, at the baseline level of costs (solid line) the buyer is unconstrained for all values of a in the figure and prices fall with relationship capital. By contrast, at a higher level of w_{i0} (red dashed line) the buyer's outside option becomes binding at low levels of capital, depicted by regions (I) and (II). In this region, the seller's pricing schedule is increasing in a. Analytically, this result can be seen from re-arranging the buyer's binding participation constraint $W(a, \mathbf{w}_{i0}) = U(\mathbf{w}_{i0})$

[29] Note that if $J(a, \mathbf{w}_{i0}) < V(\mathbf{w}_{i0})$ and $W(a, \mathbf{w}_{i0}) > U(\mathbf{w}_{i0})$, the buyer would like to make a side payment to the seller to incentivize her to maintain the relationship. However, since the seller cannot commit to maintain the relationship once the side payment has been received, such as side payment is not made in equilibrium.

to get

$$p = \left[\frac{1}{U(\mathbf{w}_{i0}) - \beta E\left[I'W(a', \mathbf{w}'_{i0}) + (1-I')U(\mathbf{w}'_{i0})\right]} \left(\frac{1}{\theta - 1}\right) \left(\frac{\theta}{\theta-1}\right)^{-\theta} A^{\theta-1}\Lambda \right]^{1/(\theta-1)}, \qquad (13)$$

since $W(a', \mathbf{w}'_{i0})$ is increasing in a'. Intuitively, a higher level of relationship capital increases the relationship's value for the buyer. In the constrained region, the seller extracts this additional value by raising her mark-up to keep the buyer exactly indifferent between leaving and staying, up to the point where the price corresponds to the unconstrained optimum ($\lambda = 0$). Beyond this point, the seller again sets the price to the unconstrained optimum.

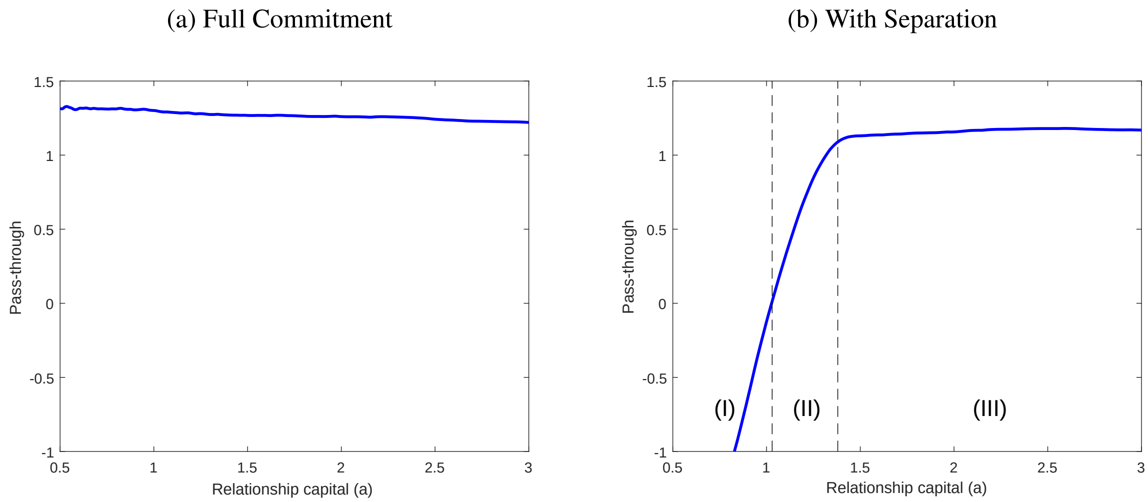
Higher costs w_{i0} reduce the buyer's value of the relationship, for example because they make separation more likely. If an increase in w_{i0} lowers the relationship's value more than the outside option, $\frac{\partial W(a, \mathbf{w}_{i0})}{\partial w_{i0}} < \frac{\partial U(\mathbf{w}_{i0})}{\partial w_{i0}} \leq 0$, then the seller has to cut her mark-up to provide additional value to the buyer. In the figure, in region (II) the seller can still set a higher price under high costs than under low costs to provide enough value to the buyer to prevent a relationship break-up. In region (I), in contrast, the seller has to set a lower price under high costs than under low costs to keep the buyer indifferent between leaving and staying. The seller terminates the relationship if her own outside option becomes binding. The dotted line on the right axis shows the seller's mark-up for the high cost case, which is depressed in the constrained region as the buyer appropriates more of the surplus.

I next investigate the pass-through of an exchange rate shock increasing the costs w_{i0}. To provide intuition, I first analyze the pass-through in the full commitment scenario. Figure 6a shows that with full commitment, pass-through is above one. Intuitively, an increase in w_{i0} raises the price both by increasing marginal costs and through its impact on the expected marginal value of additional capital, $EJ_a(a', w'_{i0})$. I show in Appendix D.7 that rising costs (weakly) reduce the expected marginal value of additional capital at all a'. As a result, the seller raises the price further than the cost change since future relationship capital has become less valuable, pushing pass-through above one. Pass-through is nearly constant, and in fact marginally declines with capital since capital accumulation is most affected by costs at low capital levels.

Figure 6b shows the analogous figure once firms are able to separate. Pass-through is now negative in region (I), since the price falls with costs in that region, as can be seen by comparing the two pricing policies in Figure 5b. The presence of negative pass-through at low-capital relationships is a key feature of my model. I will verify empirically in Section 4.4 that negative pass-through is more likely when relationship capital is plausibly low. In region (II), pass-through is positive but less than under full commitment since the buyer is still constrained. Pass-through in region (III) is complete since the buyer is unconstrained in that region.

In Section 4, I will link relationship capital and age. I will show that new relationships start with on

Figure 6: Pass-Through as a Function of Capital



average low relationship capital close to the separation bound (regions (I) or (II) in Figure 6b). Those relationships that survive and age on average received good idiosyncratic shocks. Consequently, due to selection, old relationships are on average high-capital relationships (region (III) in Figure 6b). This mechanism will generate increasing pass-through with relationship age.

3.3 Discussion of Model Assumptions

The model has three key assumptions: i) relationships accumulate relationship capital, ii) prices are set by sellers, and iii) one-to-one relationships.

The relationship capital setup builds on previous work documenting that relationships feature learning-by-doing and customization as they develop (e.g., Rauch and Watson (2003)). It captures, in a reduced form, some of the key ingredients of long-term buyer-supplier matches such as customization (e.g., Bernard et al. (2018)), the search for better suppliers and supplier switching, and efficiency gains over time (e.g., Defever et al. (2016)). As discussed, the setup is also motivated by two stylized facts in my data. First, the value traded in a relationship follows a hump shape. This pattern cannot be explained by a mechanism where the relationship improves perpetually, such as learning about the supplier's quality as in Monarch and Schmidt-Eisenlohr (2018). Instead, it matches qualitative survey evidence of a relationship life cycle (Dwyer et al. (1987)), which demands a mechanism that allows relationships to decline after some time. Second, prices are decreasing (or at least not rising) with relationship age. This finding rules out a simple mechanism in which relationship improvements operate via the demand side, since such a mechanism would counterfactually raise the relationship's price over time (see Appendix E.1). Instead, it is in line with survey evidence that production costs in relationships fall, for example due to productivity improvements (Kalwani and Narayandas (1995)). My relationship capital model fits these requirements and is well supported by the survey evidence.[30] Since the empirical analysis has shown that pass-through rises with relationship age even when controlling for firm size or supplier country, I do not add these sources of heterogeneity to my model and focus on a mechanism that can explain rising pass-through in an average relationship.

The second key assumption of my model is that sellers set prices. This assumption is less restrictive than it appears because limited commitment of the buyer implies that the model can accommodate different degrees of pricing power of the seller. If the buyer's outside option is sufficiently valuable, for example, then the seller may have to set prices equal to marginal costs, as under perfect competition. A possible interpretation of the model is therefore that the seller offers a list price and then negotiates with the buyer, with the final price based on the two parties' outside options.[31] The key requirement of my theory is that the seller adjusts her markup in response to a binding participation constraint of the buyer. By lowering her markup when the buyer's outside option binds, the seller reduces her pass-through of the shock. This mechanism is similar to risk sharing models (e.g., Kocherlakota (1996)), where one party transfers surplus when the other party's outside option binds. As I show in Appendix E.3, this requirement rules out a standard Nash bargaining model. In such a model the price is set to always split the relationship's surplus in fixed proportion, and pass-through is therefore constant. The markups are not adjusted because the relationship terminates once the outside options become binding, since in that case the surplus is zero.

Third, my theory focuses on one-to-one relationships, while recent work by Duprez and Magerman (2018) and Kikkawa et al. (2019) stresses the relevance of a firm's network for its price setting. As shown by Table I.12 in Appendix I, pass-through indeed differs based on the number of a seller's customers and on the buyer's number of suppliers. Importantly, however, the baseline finding of increasing pass-through with relationship age is robust to the firm's network configuration in my trade data, and holds even for firms that have no other connections. While I do not model firms' choice to trade with several network partners, my theory models a firm's network structure implicitly via its outside option. For example, a buyer with a larger number of alternate suppliers could be assumed to have a better outside option. My theory predicts that pass-through would be lower for such buyers, since they are more likely to be in the constrained region. The results in Table I.12 are largely consistent with that interpretation. Comparing buyers with one supplier relative to buyers with several suppliers, I find that pass-through in one-to-one relationships is higher than in other relationships (column 5 and column 6), and that pass-through is higher when a buyer has only one supplier than when

[30] My stylized facts also do not support a framework in which older relationships are associated with higher market shares, rather than more relationship capital, and price setting is as in Atkeson and Burstein (2008). This alternative model is discussed in Appendix E.2. In that framework, sellers with high market shares price *more* to market in exporter currency, and therefore adjust their U.S. dollar price by *less* than new sellers in response to an exchange rate shock. Hence, pass-through counterfactually declines with relationship age.

[31] Such a mechanism is used for example in the car manufacturing industry. See Ben-Shahar and White (2006).

it has several, unless the relationship is very old (columns 1 and column 2). While firms' domestic networks may still affect the pass-through increase, these findings at least give some confidence in my mechanism.

4 Quantitative Analysis

I now structurally estimate the model with a continuum of relationships, and show that the relationship capital model can quantitatively match the increase in pass-through with relationship age. I then verify several implications of the model in the data. Finally, I use the model to study relationships' aggregate implications. I document that the rate of relationship creation is procyclical in the data, and use the model to show how the resulting variation in the economy's relationship age distribution and in firms' outside options lead to cyclical variation in pass-through and mark-ups.

4.1 Parametrization

I take country 0 to be the U.S., and let a time period correspond to a quarter. There is a unit mass of U.S. buyer firms indexed by b with the production technology described before, each selling a differentiated good to a representative household. The household aggregates goods according to

$$Y = \left(\int_0^1 y(b)^{(\theta-1)/\theta} db \right)^{\theta/(\theta-1)}, \tag{14}$$

where $y(b)$ is the quantity sold by importer b. The demand equation then holds with $\Lambda = P^\theta Y$, where $P = \left(\int p^f(b)^{1-\theta} db \right)^{1/(1-\theta)}$ is the index over final goods prices. I fix total income exogenously, $PY = 1$. Finally, I parametrize the cost function as $c(a, w_{i0}) = w_{i0}/a^\gamma$, where I require $\gamma < 1/\theta$.[32] I will estimate γ below.

There exists a mass S of foreign sellers in each country $i = 1, ..., N$. Foreign sellers combine two primary inputs l and z according to $x_i = l_i^\alpha z^{1-\alpha}$. To match the incomplete average pass-through in the data, I assume that l_i is a local input, such as labor, and that z is an input priced in U.S. dollars. Such an input could be a commodity or an input imported from the U.S..[33] Under this assumption, the seller's costs in U.S. currency are $w_{i0} = (w_{i0}^l)^\alpha (\omega_0^z)^{1-\alpha}$, where $w_{i0}^l = e_{i0}\omega_i^l$ is the dollar cost of the local input and ω_0^z is the dollar cost of the imported input. Since then $\Delta \ln(w_{i0}) = \alpha \Delta \ln(e_{i0})$, exchange rate pass-through into the buyer's import price is approximately α in the unconstrained region. This

[32] This condition is the analogue of the more general convexity condition on marginal costs with respect to relationship capital which ensures existence of a solution.

[33] Amiti et al. (2014) show that large exporters also tend to be large importers.

assumption provides a simple way to generate the observed average level of pass-through, which is not a central object in my theory. I will examine the variation of pass-through around this average.

Foreign sellers search randomly in a frictional market for buyers across both the U.S. and countries $j = 1,...,N$. The non-U.S. countries will be relevant for the sellers' outside option but do not play any further role. Each country contains a mass one of potential buyers. Denote by u_{bj} the mass of unmatched buyers in country j, with $u_b = \sum_{j=0}^{N} u_{bj}$. Similarly, denote by u_{si} the mass of unmatched sellers in country i, with $u_s = \sum_{i=1}^{N} u_{si}$. Buyers and sellers meet through a CES matching function $M(u_b, u_s) = (u_b^{-\iota} + u_s^{-\iota})^{-(1/\iota)}$, with $\vartheta = u_b/u_s$ defining market tightness. Then, $\pi_b(\vartheta) = (1+\vartheta^{\iota})^{-(1/\iota)}$ is the probability that an unmatched buyer finds a seller, and $\pi_s(\vartheta) = \vartheta(1+\vartheta^{\iota})^{-(1/\iota)}$ is the probability that an unmatched seller finds a buyer. Once a match occurs with a seller, initial relationship capital is drawn from a lognormal distribution $G(a)$ with parameters (μ_a, σ_a). I assume that in the first period the seller cannot search for an alternate partner due to the time needed to set up the production, and hence her outside option in that period is zero. This model feature will generate the high initial separation rate (Figure 4). Unmatched buyers need to purchase the input from domestic relationships at marginal cost χ, yielding a profit of $\Pi_u^b = (1/(\theta-1))(\theta/(\theta-1))^{-\theta}(\chi/A)^{1-\theta}P^{\theta}Y$. As I will show below, χ is significantly higher than the marginal costs in a trade relationship. The resulting profit loss reflects the costs of searching for a new supplier, setting up a production line domestically, etc.

To parametrize the outside options as parsimoniously as possible, I assume that the exchange rate process for each country pair follows

$$\ln(e'_{ij}) = \varphi \ln(e_{ij}) + \xi_{ij} \tag{15}$$

with $\varphi < 1$ and $\xi_{ij} \sim N(0, \sigma_\xi^2)$ independent across countries and time, and that $w_{ij} = (w_{ij}^l)^{\alpha}(\omega_j^z)^{1-\alpha}$ for any i-j pair. Under these assumptions, as $N \to \infty$ the central limit theorem applies, and unmatched buyers and sellers randomly meet their counterparts sampled from a stationary exchange rate distribution. Therefore, the outside options for a relationship between a U.S. buyer and a foreign seller are simply $U(\mathbf{w}_{i0}) \equiv U$ and $V_i(\mathbf{w}_{i0}) \equiv V$, respectively, where

$$U = \Pi_u^b + \beta[\pi_b(\vartheta)EW(a,w) + (1-\pi_b(\vartheta))U], \tag{16}$$

and

$$V = \beta[\pi_s(\vartheta)EJ(a,w) + (1-\pi_s(\vartheta))V], \tag{17}$$

where the expectations are taken both with respect to relationship capital and the stationary distribution of exchange rates across countries.

The assumption of independent exchange rates removes the need to keep track of a vector of aggregate state variables (the world exchange rates), which simplifies the computation considerably. Given this assumption, I only focus on the pass-through dynamics in an average trade relationship, and do not investigate cross-country patterns of trade. Importantly, since in my model relationships with sufficient capital are unaffected by the outside options and always have pass-through of approximately α, introducing more general outside options would only affect the gradient of pass-through with respect to relationship capital (or age, as shown below). Generalizing the outside options would affect this gradient in two main ways. First, if a foreign country's exchange rate with the U.S. were positively (negatively) correlated with the exchange rate of other countries, it would increase (lower) pass-through at low relationship capital levels. For example, when exchange rates are positively correlated, an unfavorable exchange rate shock not only lowers a U.S. buyer's current relationship's value but also the buyer's outside option, since it becomes more difficult to switch to a country with a more favorable shock. This would raise pass-through at low capital levels. Second, if some foreign countries were more important than others, it would increase the relative importance of these countries' exchange rates for the outside options. For example, a buyer trading with a large country might find it difficult to switch to another supplier country, leading to higher pass-through at low capital levels. In my estimation, I will not target the gradient of pass-through with respect to age, and instead use it to validate the model. I show that my simplified model approximately matches the empirically observed slope of pass-through with relationship age, and thus appears to be a reasonable approximation for the average relationship.

I solve the value functions and policies for one representative buyer country. A steady state equilibrium consists of a set of value functions $J(a,w)$, $W(a,w)$, V, 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 tightness ϑ such that sellers maximize (11) subject to $W(a,w) \geq U$, buyers set prices $p^f(a,w)$ to maximize their profits, the buyer country's final goods market clears at $P = \left(\int p^f(b)^{1-\theta} db\right)^{1/(1-\theta)}$, and $\Gamma(a,w) = \bar{\Gamma}(a,w)$, $u_b = \bar{u}_b$, and $u_s = \bar{u}_s$ are constant.

4.2 Estimation and Identification

Exogenously Set Parameters

I set several parameters exogenously. First, I set the quarterly discount factor to $\beta = 0.992$, and choose an elasticity of substitution of $\theta = 4$ as in Nakamura and Steinsson (2008). I discretize the exchange rate process (15) using the methodology by Tauchen (1986) on a five-state Markov chain, and normalize the mean of costs $E[w_{ij}]$ to one. I determine σ_ξ by calculating in the data the average quarterly standard deviation of exchange rate innovations, across all currencies used, which yields $\sigma_\xi = .068$, and set $\varphi = 0.99$ to match the persistence of exchange rates. Finally, since I focus only on the relative prices and quantities traded over a relationship's life cycle, I normalize productivity to

$A = 1$, and set the mean parameter of new relationship capital $\mu_a = 0$. I therefore abstract from ex-ante heterogeneity in the buyers, which I controlled for in the data.

Since I observe the matching behavior of firms, I set the probabilities π_b and π_s directly from the data, and use their values to back out the deep matching parameters.[34] I set π_b using the time U.S. importers spend to find a new supplier following a plausibly exogenous relationship break-up. Appendix F presents a strategy for identifying exogenous supplier deaths in the data, using cases where a supplier suddenly stops trading with at least three independent customers and disappears forever. Following such a break-up, an importer takes on average 10.7 months longer than usual until the next shipment arrives. Interpreting this time gap as the time needed to find a new supplier, I set the quarterly matching probability to $\pi_b = 0.28$. For the seller's matching probability π_s, I do not observe whether sellers that appear unmatched have in fact started a relationship with a non-U.S. firm. As an estimate of how frequently foreign firms meet new customers, I use the time it takes an average foreign firm to start relationships with two subsequent customers in the U.S., which is about 14 months. Thus, I set $\pi_s = 0.22$. The probabilities imply $\vartheta = 0.78$ and $\iota = 0.5$. These deep parameters will be used in the counterfactuals below.

Targeted Parameters

Seven parameters remain to be estimated: α, δ, σ_ε, γ, σ_a, ρ, and χ. While all are jointly estimated, each is identified from a different set of moments.

I set α to match the level of pass-through of an average three-year relationship implied by the baseline regression (1) with annual dummies. I run the same regression in the simulated data, omitting the control for the time gap since in the model firms trade in every quarter. As discussed above, a higher α implies higher average pass-through. I do not explicitly target the pass-through gradient with relationship age, which will be a key moment to determine the model's success.

I choose σ_ε to generate the break-up hazard of relationships in their first and second quarter (Figure 4), and set δ to match the value shares of relationships that are in their first quarter or older than four years, respectively (Figure 1). A higher value of σ_ε makes large shocks more likely, which raises the break-up hazard of new relationships. A higher δ pulls relationships towards lower a and therefore reduces survival, lowering the share of old relationships. The break-up hazard of new relationships is the key moment identifying the two parameters separately. A higher σ_ε raises the likelihood of large positive shocks, which tightens the separation bound $\underline{a}(\mathbf{w}_{ij})$ and increases separations of young relationships. On the other hand, a higher δ makes relationships less valuable and therefore shifts the separation bound to the left. Consequently, the break-up hazard of very new relationships remains relatively unaffected, since it takes time for capital to drift down to the new separation bound.

[34] Alternatively, I could estimate ι and S to generate the right matching probabilities, which are also two parameters.

I set γ to match the steepness of the life cycle profile of value traded (Figure 3) between year three and year five for relationships that last five years, and target the peak value of trade in year three to match σ_a. A higher γ decreases the returns to relationship capital, which reduces the difference between a relationship at its peak and at termination. A higher σ_a increases the average capital in new relationships that survive after the first transaction. Due to diminishing returns, relationships with more initial capital add less further capital, and therefore trade in year three is on average more similar to initial trade. The two parameters are separately identified because σ_a has little effect on trade at relationship termination. To improve identification of σ_a, I also target the average price in year two as an additional moment. A high σ_a causes surviving relationships in the first year to already have relatively low prices, and so prices fall by less in year two.

I set ρ to match the autocorrelation of a relationship's annual quantity traded and the break-up hazard in quarter eight relative to quarter two. A higher ρ makes the quantity traded more persistent, which increases autocorrelation. A higher ρ also reduces the relative importance of shocks and makes older relationships less likely to break, which steepens the separation hazard.

Finally, a higher marginal cost parameter χ makes the buyer's constraint less binding, which increases the dispersion of new relationship prices (compare the blue line to the red line in Figure 5b). I set this parameter in the simulation by regressing the price of relationships in their first quarter on their cost draw w_{ij}, and compute the standard deviation of the resulting residuals to obtain the price dispersion net of exchange rate effects. To compute the analogue in the data, I regress the unit value of new relationships on exporter-quarter fixed effects to remove variation in the exchange rate, and on importer-product-source country fixed effects to control for importer and product heterogeneity. To be as close as possible to the model, I include only importers with one supplier for a given product in the regression, and run the regression only for homogeneous products based on Rauch (1999). I trim the residual distribution below the 10th and above the 90th percentile to remove outliers.

Figure H.3 in Appendix H presents scatter plots from 6,000 simulations for all parameters against their main identifying moments, and shows that all correlations are as described. I estimate the model via simulated method of moments, following the MCMC procedure by Chernozhukov and Hong (2003). For each proposed set of parameter values, I guess an aggregate U.S. price level P and solve for the value functions and policies. Given these, I simulate a panel of buyer firms and obtain their distribution of intermediate prices p and final goods prices p^f. These prices imply a new aggregate price level P. I iterate until convergence, given demand $PY = 1$. The estimated parameter values $\hat{\Psi}$ solve

$$J = \min_{\hat{\Psi}} E\left[\left(\frac{G(\hat{\Psi})-G(\Psi)}{G(\Psi)}\right)' \left(\frac{G(\hat{\Psi})-G(\Psi)}{G(\Psi)}\right) \right],$$

where Ψ is the true parameter vector and $G(\Psi)$ and $G(\hat{\Psi})$ are the data moments and the model moments, respectively.

Table 4: Parameters and Moments

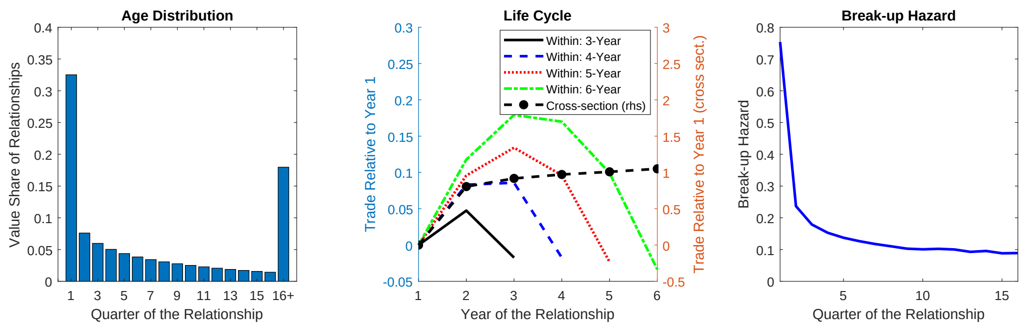
Parameter			Moment		
	Value	s.e.		Model	Data
α	.349	(.091)	Pass-through in year 3	.225	.188
σ_ε	.332	(.022)	Break-up hazard Q1	.753	.695
			Break-up hazard Q2	.237	.311
δ	.051	(.013)	Value share of rels in Q1	.325	.243
			Value share of rels in >Q16	.180	.177
γ	.227	(.020)	Value traded in Year 5 - Value traded in Year 3 (for 5y rel)	−.157	−.208
σ_a	.427	(.048)	Value traded in Year 3 relative to Year 1 (for 5y rel)	.134	.097
			Price in Year 2 / Price in Year 1	−.010	−.012
ρ	.036	(.012)	Autocorrelation of quantity	−.359	−.300
			Break-up hazard Q8/Q2	.466	.400
χ	3.202	(.657)	Std initial price (residual)	.030	.052
			J (objective)	.688	

4.3 Results

Table 4 presents the estimated parameter values from the converged Markov chains, and compares the moments identifying these parameters to the data. The estimated value of α indicates that unconstrained relationships have a pass-through of 0.35. Shocks to capital play a large role in driving the model: a one standard deviation positive shock would raise relationship capital by 33.2% relative to the average capital of new relationships, which is one. With such large shocks, a high fraction of young relationships receive sufficiently bad shocks to terminate, generating the high initial separation hazard. However, the estimate for γ suggests that there are substantial decreasing returns, and hence the differences in relationship capital translate into smaller differences in value traded. Holding exchange rates fixed, a one standard deviation increase in initial relationship capital from the mean translates into an average increase in value traded per quarter of only 3%. The large decreasing returns are needed to generate the relatively muted life cycle of values. In contrast to the shocks, the depreciation rate of relationship capital δ is low, at about 5% per quarter. This feature generates the right share of old relationships, since many relationships that survive the first quarters last for a long time. My estimated marginal cost of domestic relationships χ is about three times as high as the marginal cost of an average new relationship, capturing the additional search and setup costs with a suboptimal domestic supplier. These costs imply that a buyer who is not in a trade relationship has approximately zero profits. Consistent with this finding, Appendix F shows that importers that lose an important supplier experience significant reductions in employment growth and sales.

To visualize the model's performance, Figure 7 shows the model-generated cross-sectional share of trade by relationship age (left), the life cycle of value traded as in Figure 3 (middle), and the hazard

Figure 7: Model-Generated Moments Targeted in Estimation



rate of break-ups (right). Overall, the model fits well. It generates an exponentially declining length distribution of relationships, a life cycle of value traded, and a sharply decreasing separation hazard.

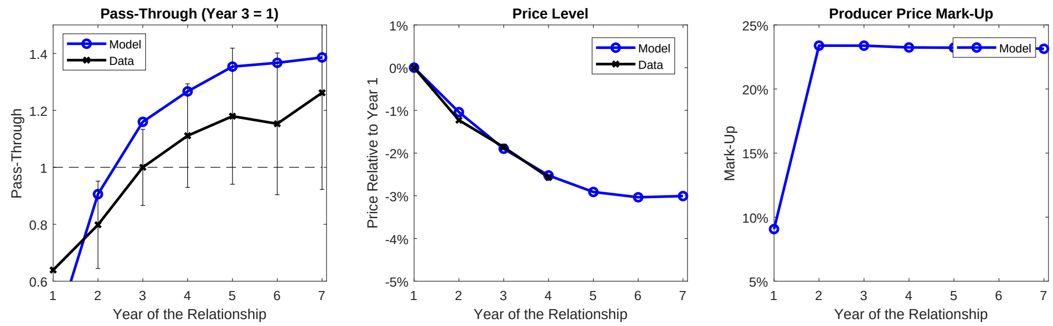
Figure 8 presents the non-targeted moments generated by the model. The left panel depicts the coefficients from regression (1) with annual dummies, together with their 95% confidence bands, where I normalize the average pass-through in year three to one to focus on the increase in pass-through relative to the mean. I compare the empirical estimates to the analogues from the simulation. The simulated coefficients lie within the 95% confidence interval of the data for nearly all relationship ages, although the slope of pass-through is steeper than in the data. Matching the untargeted increase in pass-through well is a success of the model. The middle panel compares the model-generated slope of the price level by relationship age to the corresponding data moment, computed from column (1) of Table 3 at the mid-point of each year, where I assume that relationships trade about once per month based on Table I.1 in Appendix I.[35] While the price level in year two was targeted in the estimation, I find that the model matches the price decline for all other ages very well. The right panel of Figure 8 presents the average producer price mark-up by relationship age. Mark-ups rise from on average 9% for relationships in their first year to 24% for older relationships.

The model generates these patterns through selection. New relationships on average start with little capital, which results in a high initial separation hazard. Relationships that age and survive on average received good shocks and build up capital, while terminating relationships lose capital until they reach the termination bound. This produces a stochastic life cycle. Figure H.4 in Appendix H illustrates the selection mechanism more thoroughly by plotting distributions of relationship capital for different relationship ages, together with pass-through and mark-ups. It shows that the capital distribution of older relationships stochastically dominates that of younger ones. Since by virtue of having survived for longer old relationships on average have more capital, trade increases with age in the cross-section (dashed line in the life cycle figure), and older relationships have higher pass-through.

As in the data, in my model pass-through rises with the intensity of trade as measured by the

[35] e.g., for year 2, the relationship has traded about 18 times by month 18, leading to a price effect of $-.0069 + 18 \cdot (-.0003) = -.0123$.

Figure 8: Model-Generated Moments not Targeted in Estimation



value traded, which is correlated with relationship capital. Note that my model does not feature any explicit time dependence of pass-through: conditional on the same level of relationship capital, pass-through in relationships of different age is the same. One implication of the model is that pass-through declines again towards the end of the relationship, when relationship capital falls towards the termination bound. I verify this implication next.

4.4 Model Validation

I verify four model implications in the trade data to build additional confidence in the model. I then use the model to study the aggregate implications of relationships.

First, an important implication of my model is that it generates negative pass-through, which becomes less frequent as a relationship ages and trades more. To test this implication, I define pass-through in quarter t of triplet mxh as $PT_{mxht} = \Delta \ln(p_{mxht})/\Delta \ln(e_{mxht})$, and let the dummy variable ς_{mxht} equal to one if $PT_{mxht} < 0$. On average, negative pass-through arises for about 40% of transactions in the data, and hence occurs frequently. I then run

$$\varsigma_{mxht} = \beta_1 Length_{mxt} + \gamma_{mxh} + \omega_t + \varepsilon_{mxht}, \tag{18}$$

where $Length_{mxt}$ is the length of the relationship in months. Column 1 of Table 5 shows that the likelihood of negative pass-through declines with a pair's relationship age, as predicted. Column 2 drops outliers with $PT_{mxcht} < -0.5$, which could be explained by large idiosyncratic shocks to a that swamp the price response to the observed cost shocks. In Column (3), I define d^{med}_{mxt} to be a dummy that is equal to one if relationship mx trades 25%-50% more in the year associated with quarter t than in year one, and d^{high}_{mxt} a dummy that is one if the relationship trades over 50% more than in the first year. Increases in trade lower the likelihood of negative pass-through, consistent with the theory.

A second model prediction is that average pass-through is negatively correlated with the buyer's outside option value. As discussed above, a better buyer outside option makes it more likely that the

Table 5: Model Implication Tests

Dep. var.	Neg Pass-Through Indicator (ς)			$\Delta\ln(p)$			TotLength	$\Delta\ln(p)$
	(1)	(2)	(3)	(4)	(5)		(6)	(7)
Length	$-.0026^{***}$	$-.0067^{***}$				PT Year 1	$.0056^{***}$	
	(.0005)	(.0003)					(.0004)	
Med. Trade			$-.0013$			First Y $\cdot\,\Delta\ln(e)$		$-.0456^{***}$
			(.0011)					(.0133)
High Trade			$-.0033^{***}$			Last Y $\cdot\,\Delta\ln(e)$		$-.0176$
			(.0011)					(.0106)
N Supp $\cdot\,\Delta\ln(e)$				$-.0109^{***}$	$-.0283^{***}$			
				(.0027)	(.0103)			
Time FE	Y	Y	Y	Y	Y		Y	Y
Rel-product FE	Y	Y	Y	–	–		–	Y
Country, Prod FE	–	–	–	Y	Y		–	–
Imp-prod, Exp FE	–	–	–	–	–		Y	–
Observations	13,850,000	7,908,000	7,908,000	16,780,000	16,780,000		1,877,000	9,349,000

Note: Number of observations has been rounded to the nearest 1000 as per U.S. Census Bureau Disclosure Guidelines. Standard errors are clustered at the country level. Only the coefficients discussed in the main text are shown.

buyer trades under a binding participation constraint, which reduces pass-through. I use the buyer's number of suppliers for a given product category as proxy for the outside option, since buyers with more suppliers should be able to walk away more easily from a given relationship, and run

$$\begin{aligned}\Delta\ln(p_{mxht}) = \beta_1\Delta\ln(e_{mxht}) + \beta_2\ln(NSupp_{mht}) + \beta_3\ln(NSupp_{mht})\cdot\Delta\ln(e_{mxht}) \\ + \beta_4 Length_{mxt} + \beta_5 Length_{mxt}\cdot\Delta\ln(e_{mxht}) + \beta_6 X_{mxht} + \gamma_c + \xi_h + \omega_t + \varepsilon_{mxcht},\end{aligned} \tag{19}$$

where $NSupp_{mht}$ is the number of suppliers used by importer m in the year associated with quarter t, and X_{mxht} are the same time gap and size controls as in the baseline regression. I use country and product fixed effects, γ_c and ξ_h, rather than relationship-specific fixed effects, since I want to compare pass-through across relationships. Column 4 of Table 5 shows that pass-through conditional on relationship length and size is indeed lower when the buyer has more suppliers. In Column 5, I alternatively run the regression using the total number of suppliers selling the product category to *any* U.S. buyer in the given year, since the existence of many potential suppliers should also make the buyer's outside option more binding. Consistent with this view, pass-through is lower when there exist many potential suppliers.

Third, the model implies that relationships with higher pass-through in the first year last longer, since higher initial pass-through is indicative of higher initial relationship capital. To test this implication, I calculate for each relationship the total number of months it exists ($TotLength_{mx}$). In then regress this variable on the log average pass-through in the relationship's first year, $\ln(PT^1_{mxht})$, where pass-through is computed from price changes that occur between subsequent quarters since the capital level could have changed significantly over a longer time horizon,

$$\ln(Totm_{mx}) = \beta_1 \ln(PT^1_{mxcht}) + \xi_{mh} + \gamma_x + \omega_t + \varepsilon_{mxcht}. \tag{20}$$

Since I only have one observation per relationship, I cannot use relationship-product fixed effects, and instead use importer-product fixed effects and exporter fixed effects separately. Column 6 highlights that higher pass-through in the first year implies a longer relationship, consistent with the theory.

The final prediction is that relationships close to separation have a low level of relationship capital. Such relationships should therefore have lower pass-through. To test this implication, I run the pass-through regression (1), where I replace $Length$ with the dummies d^{first} and d^{last} for whether the relationship is in its first year or in its last year, respectively, for all relationships lasting longer than two years. The point estimate in column 7 of Table 5 suggests that pass-through is lower in the last year compared to the omitted intermediate years, although the result is only close to significant at conventional levels (t-stat=1.66).

4.5 Aggregate Implications

To conclude, I argue that relationships have aggregate implications. I first document that relationship creation is procyclical in the data. I then use the model to illustrate how this cyclicality could impact pass-through and mark-ups.

To study the cyclicality of relationship creation, I decompose the change in U.S. real aggregate imports between quarter t and quarter $t-4$ into six margins. Let r index relationships between importer m and exporter x, and $y_{rh,t}$ be the total value transacted of product h by relationship r in quarter t. Furthermore, let R_t be the set of relationships that exist in quarter t, and similarly let $H_{r,t}$ be the set of active products of relationship r in quarter t. The aggregate change in real U.S. imports between quarters $t-4$ and t can be decomposed into

$$\begin{aligned}\sum_{r\in R_t}\sum_{h\in H_{r,t}} y_{rh,t} - \sum_{r\in R_{t-4}}\sum_{h\in H_{r,t-4}} y_{rh,t-4} = & \left[\sum_{r\in R_t, r\notin R_{t-4}}\sum_{h\in H_{r,t}} y_{rh,t} - \sum_{r\notin R_t, r\in R_{t-4}}\sum_{h\in H_{r,t-4}} y_{rh,t-4}\right] \\ & + \left[\sum_{r\in R_t\cap R_{t-4,t}}\sum_{h\in H_{r,t}, h\notin H_{r,t-4}} y_{rh,t} - \sum_{r\in R_t\cap R_{t-4}}\sum_{h\notin H_{r,t}, h\in H_{r,t-4}} y_{rh,t-4}\right] \\ & + \sum_{r\in R_t\cap R_{t-4}}\sum_{h\in H_{r,t}\cap H_{r,t-4}}\left[\left\{y_{rh,t}-y_{rh,t-4}\right\}^+ + \left\{y_{rh,t}-y_{rh,t-4}\right\}^-\right].\end{aligned} \tag{21}$$

The first bracket represents the value traded by new relationships in t minus the value traded by relationships in $t-4$ that no longer exist in t. The second term is the change in trade due to new product additions minus product removal in continuing relationships. The last term is the intensive margin change in trade of existing products in continuing relationships, split into positive and negative value changes. Together, these margins fully account for the change in imports.

Figure 9 implements the decomposition in the LFTTD. Figure 9a shows the value of the three creation terms for each quarter t divided by total U.S. imports in $t-4$. New relationship creation is by far the most important margin. On average, imports by new relationships in t amount to about 58% of total trade in $t-4$. Product additions and the intensive margin contribute with on average 9% and 15%, respectively. Figure 9b shows the analogous three destruction terms in absolute value. If no new trade were added, imports would fall by about 52% over the course of a year because relationships that existed in $t-4$ no longer trade in t. Product removals and the intensive margin contribute similarly as on the creation side.

The key observation from the figures is that relationship creation displays strong cyclicality, falling sharply in recessions.[36] While product additions and the intensive margins also display some cyclical behavior, the drop in net relationship creation explains about 60% of the fall in total U.S. imports in the Great Recession and 55% of the drop in the recession of 2001. To check whether my specific definition of relationships is driving the results, in Appendix G I perform a second decomposition of trade under an alternative, "naive" definition of relationship length, where I do not use the procedure described in Section 2.2. Instead, I compute relationship length simply as the time passed since the first transaction of the importer-exporter pair. While the importance of the intensive margin increases by design, relationship creation still explains about 40% of the fall in U.S. imports in the Great Recession. I also present a third trade decomposition into importer entry and exit and the analogous product and intensive margins, and show that the drop in relationship creation is not due to a lack of importer entry. Instead, most of the drop in creation is due to continuing importers not forming new relationships.

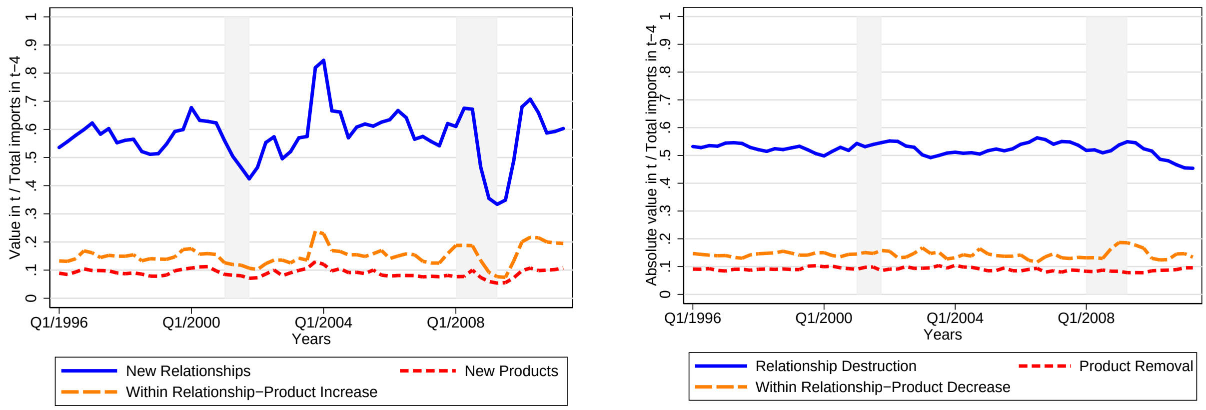
The lack of relationship creation shifts the relationship age distribution towards older relationships in recessions. According to my findings, this shift should generate cyclicality in pass-through. Figure 10a plots the relationship creation rate against the pass-through coefficients estimated by Berger and Vavra (2019), using import price data from the Bureau of Labor Statistics. They observe prices rather than unit values, and compute pass-through conditional on a firm changing price with a number of item and country controls. As expected, the series is strongly negatively correlated with relationship creation over the business cycle. For comparison, Figure H.5 in Appendix H presents the coefficients of a regression of price changes on exchange rate changes interacted with quarter dummies in the LFTTD. These pass-through coefficients are much noisier, but pass-through increases at the onset of a recession, though earlier than in Berger and Vavra (2019).

How much did the lack of relationship creation contribute to the increase in pass-through in the

[36] The HP-filtered relationship creation margin exhibits a correlation with filtered U.S. GDP of 0.75.

Figure 9: Decomposition of the Annual Change in Total Imports

(a) Creation Margins as Share of Total Imports (b) Destruction Margins as Share of Total Imports



Source: U.S. Census Bureau, LFTTD data

Source: U.S. Census Bureau, LFTTD data

Great Recession? I first perform a simple decomposition in the data to provide some intuition. I then highlight that the full model can better account for the observed pass-through dynamics by also taking into account the endogenous change in firms' outside options.

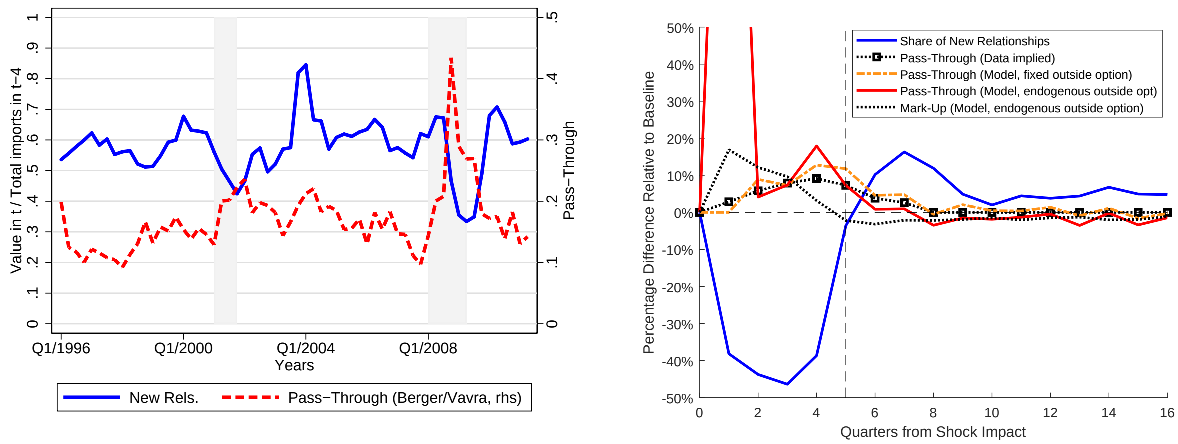
I first perform a simple empirical exercise. I compute steady state pass-through as the weighted mean of the age-specific pass-through from Figure 2, using the value share of each age from Figure 1 as weights. Starting in Q3/2008, I then lower the share of relationships of age one quarter through the Great Recession to match the creation profile given in Figure 9a, and let the relationship age distribution evolve according to the steady state survival probabilities implied by the age distribution.[37] The increase in pass-through due to the drop in relationship creation is depicted by the black squares in Figure 10b. From its steady state level, pass-through rises by 9% during the Great Recession, before gradually falling back to the baseline. The smooth trajectory is somewhat at odds with the sharp spike in pass-through at the beginning of the Great Recession observed empirically.

I next show that the model can better match the observed rise in pass-through. Starting in steady state in period $t = 0$, which represents Q3/2008, I introduce a shock in $t = 1$ which exogenously causes a fraction κ_1 of currently unmatched buyers to become "inactive" and to stop searching for sellers. This shock represents for example a productivity shock, which causes firms to exit from international sourcing. From $t = 2$ onwards, I then reduce this fraction of inactive buyers back to zero to match the empirical change in the trade share of new relationships from the data. I compare this economy to a baseline economy without the shock. In both economies, the exchange rate process follows the law of motion (15) plus a sequence of aggregate shocks such that my model matches the import-weighted

[37] These probabilities are closely related to the hazard rate from Section 2.4, though not completely identical since the hazard rate was computed using 12-month lagged weights.

Figure 10: Cyclical Properties of Relationships

(a) Pass-Through and Relationship Creation in the Data (b) Impact of Shock to the Mass of Active Firms



Source: LFTTD data, Berger and Vavra (2019)

average exchange rate of the U.S. against its major trading partners over the period Q3/2008-Q4/2009. I compare both economies in partial equilibrium at the steady state aggregate price level, since there was no burst of deflation during the Great Recession (Gilchrist et al. (2017)). I assume that from $t = 1$ onwards firms have full information about the evolution of the economy, and solve for the transition path of value functions $\{J_t, W_t, V_t, U_t\}$ that constitute a rational expectations equilibrium.

The dashed orange line in Figure 10b shows average pass-through in the shocked economy relative to the baseline when firms' outside options, break-up, and pricing policies are held fixed. This case is the analogue to the empirical exercise, and isolates the effects of the distributional shift only. Pass-through rises by about 13%, slightly more than in the data due to the steeper pass-through gradient with age in the model. The solid red line shows the pass-through when I allow the value and policy functions to vary. In this case, pass-through spikes sharply in $t = 1$. This outcome arises due to a relative improvement in the buyer's outside option. As some buyers drop out of the search market due to inactivity, the fraction of unmatched available buyers u_b falls, raising market tightness. This higher tightness improves the buyers' relative outside option by raising their matching probability $\pi_b(\vartheta)$, while sellers' matching probability $\pi_s(\vartheta)$ falls. To prevent the buyers from leaving the relationship, sellers in low-capital relationships therefore have to transfer surplus to the buyers by lowering their price. Since the trade-weighted dollar appreciated by 11% against the other currencies in my data in Q4/2008, these sellers experience declining costs, which they pass through to buyers. Unconstrained relationships also pass through the cost decline fully, and therefore prices and costs fall significantly in most relationships and pass-through spikes. I find that my model generates about two thirds of the empirically observed increase in pass-through from the 2007 average (a 170% increase relative to a

250% rise in pass-through).[38] Note that there was a smaller synchronized appreciation of the dollar against most currencies, together with a drop in relationship creation, in the recession in Q2/2001, consistent with a smaller jump in pass-through in that quarter.

The estimated mark-up rises by 16% during the recession due to the shift to older relationships, which set higher mark-ups. Moreover, some sellers are able to pass through the cost reduction less than fully. The countercyclical mark-ups generated by my model are consistent with evidence discussed in Rotemberg and Woodford (1999).

5 Conclusion

In this paper, I show that a relationship's price becomes more responsive to exchange rate shocks both as the relationship ages and trades more intensively. This effect is large: a four-year relationship exhibits exchange rate pass-through that is about two thirds higher than a new relationship. To understand how old relationships differ from new ones, I document a set of stylized facts about the life cycle of a relationship. I rationalize these findings via a model in which a buyer and a seller firm interact repeatedly under limited commitment and build up relationship capital to lower production costs, for example due to learning-by-doing. 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. Variation in average relationship length across countries could also help explain cross-country differences in exchange rate pass-through.

Several questions remain for future research. First, my theory focuses on the evolution of buyer-supplier relationships in isolation, and abstracts from the fact that many firms have multiple suppliers for the same good. Better insights into how firms choose their suppliers and how an importer's relationships across suppliers interact with pass-through would provide a better understanding of price adjustments. Second, while this paper has focused on arms' length trade, related party trade makes up a large share of U.S. imports. Empirical work illuminating the trading patterns and pricing in intra-firm trade could shed light on firms' transfer pricing and decision to integrate. Finally, while I have attempted to provide some information on domestic relationships, direct transaction-level data on domestic trade is scarce. Such data could allow for a better calibration of network models studying how the network of firms amplifies or attenuates shocks.

[38] The remaining increase in the responsiveness of prices to shocks can be generated by a number of mechanisms, discussed in Berger and Vavra (2019), for example ambiguity aversion, learning about shocks, or experimentation.

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Online Appendix - For Online Publication

A Construction of the Datasets

A.1 LFTTD Data

This section describes in detail the preparation of the LFTTD dataset. I use the version of the data spanning 1992-2011. 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.[39] Monarch (2018) and Kamal and Monarch (2018) 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 lower than the total value of trade recorded in official publications. In order to

[39] Specifically, 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.

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.

A.2 Bloomberg Data

The "SPLC" function in Bloomberg displays the customers and suppliers of a given firm that are active at a specific date. These data are obtained from two main sources. First, under U.S. accounting rules, firms are required to report any customer that accounts for at least 10% of revenues. For example, if firm A accounts for more than 10% of firm B's revenues, then firm B will report firm A as its customer in its 10-K filing, and Bloomberg will record firm B as firm A's supplier. Second, Bloomberg analysts use press releases and industry information to discover firms' additional relationships. For example, if a representative from firm A states in an interview with a trade journal that it is a supplier to firms B and C, Bloomberg will record A as supplier to these firms if its analysts discover this interview, even if A's business does not exceed the revenue threshold. This feature distinguishes the data from customer datasets that rely only on regulatory returns, such as the Compustat segment files. The additional suppliers account for the majority of relationships recorded in Bloomberg. For example, in March 2016, Intel had 6 suppliers where it accounted for more than 10% of suppliers' revenues, but Bloomberg records 109 suppliers for the firm.

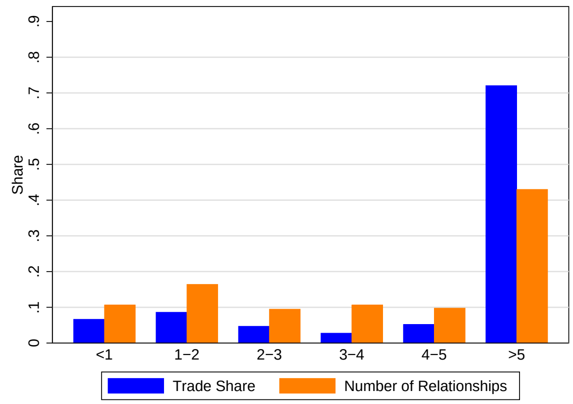
After recording a relationship for the first time, Bloomberg keeps track of it and drops the relationship if it appears to become inactive. Furthermore, Bloomberg re-estimates the annual value traded by each relationship at least once every year. For relationships exceeding 10% of the customer's revenues, the trade value is directly reported in the customer's financial statements. For relationships below this threshold, the threshold value and the buyer's purchase costs ("cost of goods sold" or "selling, general, and administrative expenses") provide bounds on the trade value. Bloomberg then uses further information such as sales by different business units of the supplier firm, sales by geography, and industry estimates to derive an approximate relationship value.

I hand-collect the list of firms' suppliers on March 1 for each year in 2012-2018, for each of the top-200 firms in the S&P500 on March 1, 2018. Supplier data becomes sparser before 2012, raising questions about time-varying selection, and are therefore not used. I keep only suppliers that are located in the U.S. I then compute the length of each of the relationships existing in 2018 as the number of years passed between the first time a supplier is recorded as dealing with a given firm and March 2018. For relationships that are interrupted, I use the first time the supplier is ever recorded a dealing with its customer as the relationship start date. Relationships for which Bloomberg does not record a value are dropped ($< 1\%$ of observations). I then allocate the relationships' value traded as recorded on March 1, 2018 to buckets based on relationship length.

Figure A.1 presents the resulting distributions. Since the data contain only relationships that Bloomberg discovered in public information, they are most likely biased towards larger, longer relationships. Nevertheless, the figure shows two interesting facts. First, almost 90% of relationships in the data last longer than one year. These long-term relationships accounted for an estimated $190bn in annual sales for the top-200 firms in the

S&P500 in 2017. Second, the longest relationships (> 5 years) represent the largest share of total value traded, accounting for 43% of relationships but 72% of value. Thus, while I will focus on trade relationships in the remainder of the paper due to data limitations, long-term relationships appear not to be only an international trade phenomenon. Figure A.2 presents distributions for several individual U.S. firms.

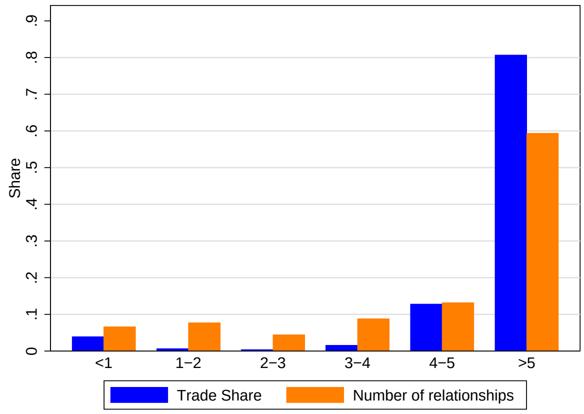
Figure A.1: Domestic U.S. Relationships (in Years)



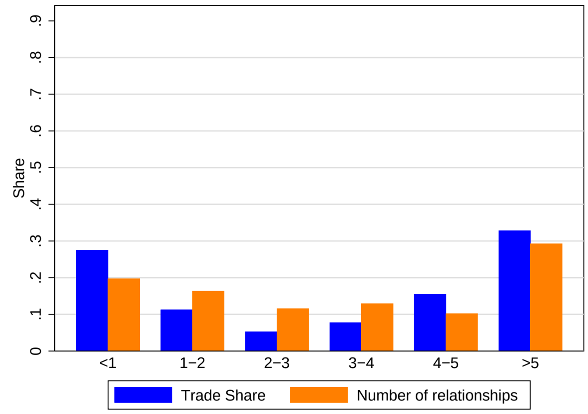
Source: Bloomberg

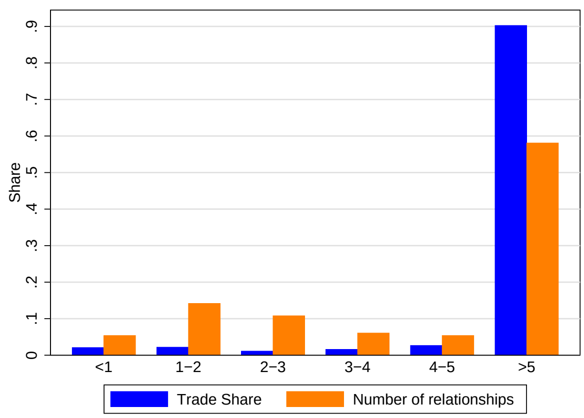
Figure A.2: Domestic Relationships

(a) Apple

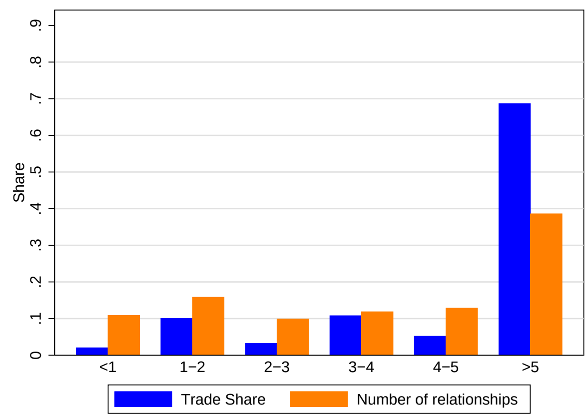


(b) Amazon

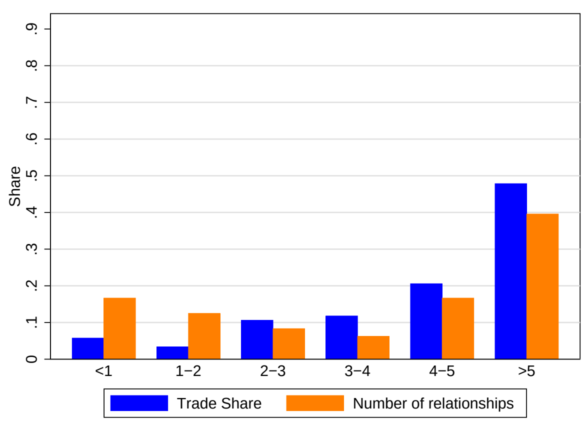




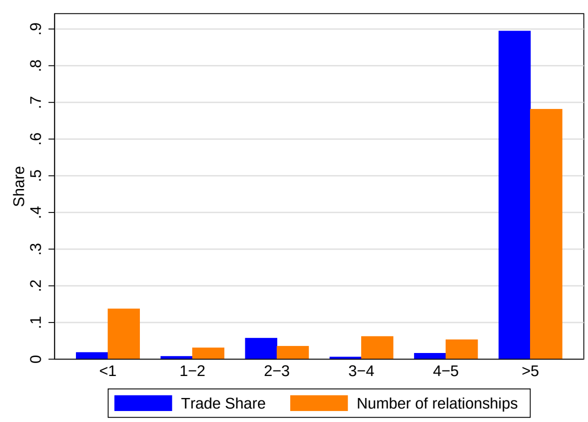
(c) Boeing



(d) General Motors



(e) Johnson & Johnson



(f) Wal-Mart

Source: Bloomberg SPLC function.

B Correcting the Pass-Through Regressions for Selection

I re-write regression specification (1) as

$$\Delta \ln(p_{mxht}) = z^1_{mxht}\beta + \gamma_{mxh} + \omega_t + \tilde{\varepsilon}_{mxht}, \tag{22}$$

where z^1_{mxht} is a 1xK vector of regressors used in the pass-through regression and includes unity, β is a 1xK vector of parameters, γ_{mxh} accounts for relationship-product specific unobserved heterogeneity, ω_t captures unobserved time-varying effects, and $\tilde{\varepsilon}_{mxht}$ is an error term. The selection equation is specified as

$$s_{mxht} = 1\left[z_{mxht}\delta + \xi_{mxh} + \rho_t + \tilde{a}_{mxht} > 0\right], \tag{23}$$

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

If firms choose not to trade for unobservable reasons, then $E[\tilde{\varepsilon}_{mxht}|z^1_{mxht}, \gamma_{mxh}, \omega_t, s_{mxht} = 1] \neq 0$, and the standard fixed effects estimator produces inconsistent estimates. While differencing equation (22) could remove the triplet-fixed effect and eliminate the selection problem, this approach only works if

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

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

$$\omega_t = GDP_t\varphi_1 + e_1 \tag{24}$$

and

$$\rho_t = GDP_t\varphi_2 + e_2. \tag{25}$$

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

$$\Delta \ln(p_{mxht}) = z^1_{mxht}\beta + GDP_t\varphi_1 + \gamma_{mxh} + \varepsilon_{mxht}, \tag{26}$$

with

$$s_{mxht} = 1\left[z_{mxht}\delta + GDP_t\varphi_2 + \xi_{mxh} + a_{mxht} > 0\right]. \tag{27}$$

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 $(z_{mxh1},\ldots,z_{mxhT})$ is linear.

Based on this assumption, the selection equation (27) can be written as

$$s_{mxht} = 1\left[\psi_0 + z_{mxh1}\psi_1 + \ldots + z_{mxhT}\psi_T + GDP_t\varphi_2 + v_{mxht} > 0\right], \tag{28}$$

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_{mxht} is independent of the entire matrix of observables $[\mathbf{z}_{mxh} \quad \mathbf{GDP}]$ and is distributed $v_{mxht} \sim N(0,1)$.

Assumption 3. The conditional expectation of γ_{mxh} given $\mathbf{z}_{mxh}$ and v_{mxht} is linear.

Under this assumption,

$$E[\gamma_{mxh}|\mathbf{z}_{mxh}, v_{mxht}] = \pi_0 + z_{mxh1}\pi_1 + \ldots + z_{mxh1}\pi_T + \phi_t v_{mxht}. \tag{29}$$

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

$$E[\varepsilon_{mxht}|\mathbf{z}_{mxh}, \mathbf{GDP}, v_{mxht}] = E[\varepsilon_{mxht}|v_{mxht}] = \rho v_{mxht}. \tag{30}$$

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

$$\Delta\ln(p_{mxht}) = z^1_{mxht}\beta + \bar{z}_{mxh}\pi + GDP_t\varphi_1 + \mu\lambda\left[z_{mxht}\rho + \bar{z}_{mxh}\eta + GDP_t\varphi_2\right] + \varepsilon_{mxht}, \tag{31}$$

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

$$s_{mxht} = 1[z_{mxht}\rho + \bar{z}_{mxh}\eta + GDP_t\varphi_2 + v_{mxht} > 0]. \tag{32}$$

While it would be desirable to estimate the equation on a fully squared dataset that records a missing observation in every one of the 68 quarters 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 relationship-product triplets 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 quarters before the start of the 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 by only including for each triplet the quarters between the first transaction and four quarters after the last transaction. For each triplet the time averages $\bar{z}_{mxh}$ are only taken over the relevant period.

As in the main text, z_{mxht} contains the cumulative exchange rate change $\Delta \ln(e_{mxht})$ and the length of the relationship in months $Length_{mxht}$, the time gap since the last transaction of product h, Time Gap_{mxht}, the average size of the relationship, Avg Size_{mx}, and the interactions of these variables with the exchange rate change. 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, and the average time gap between transactions across all U.S. importers. A higher value traded at the last transaction should diminish the probability to transact again. The transaction 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 (31). Thus, z^1_{mxht} includes all regressors except the average time gap across all U.S. importers. Under the assumption that ε_{mxht} is normally distributed, I can estimate the system via Maximum Likelihood in the same way as a Heckman selection model.

C Micro Foundations of the Relationship Capital Process

C.1 Learning-by-Doing

I present the setup of the learning-by-doing model by Dasgupta and Stiglitz (1988), and show that it provides a micro foundation for my relationship capital process.

Dasgupta and Stiglitz (1988) postulate that a monopolistic competitor faces downward sloping demand $q(p)$, and seeks to optimally set prices. The firm's marginal costs are c_0 in period zero, and for periods $t>0$ are given by a function of the past quantities sold, $c(\sum_{\tau=0}^{t-1} q(p_\tau))$. Learning-by-doing implies that $c_t'(\sum_{\tau=0}^{t-1} q(p_\tau)) < 0$. Thus, in Dasgupta and Stiglitz (1988) learning is based on production experience, as in my framework. Denote by $a_{t-1} \equiv \sum_{\tau=0}^{t-1} q(p_\tau)$ the total quantity sold up to period $t-1$.

The firm maximizes profits by solving:

$$\max_{\{p_\tau\}_{\tau=0}^{\infty}} p_0 q(p_0) - c_0 q(p_0) + \sum_{t=1}^{\infty} \beta^t \left\{ p_t q(p_t) - c(a_{t-1}) q(p_t) \right\}$$

subject to

$$a_t = a_{t-1} + q(p_t).$$

Under similar conditions as discussed in Section D.1, a recursive representation of the problem exists, and the problem can be re-written as

$$J(a) = \max_p \left[pq(p) - c(a)q(p) + \beta J(a') \right],$$

subject to

$$a' = a + q(p) \tag{33}$$

$$c(0) = c_0. \tag{34}$$

The learning-by-doing setup mirrors the setup introduced in the main text. The process for relationship capital, equation (6), is a generalization of the process presented in equation (33), which allows for (i) depreciation of the knowledge stock at a fixed rate δ, (ii) random shocks ε affecting the learning speed, and (iii) a scale parameter ρ. The depreciation rate δ and the scale parameter ρ are primarily needed for quantitative reasons to match the data. The random shocks ε are important to generate the relationship life cycle. When these features are added to the process (33), the model in Dasgupta and Stiglitz (1988) becomes identical to my baseline model without limited commitment.

C.2 Customer Capital

I show that the relationship capital accumulation process (6) is similar to the accumulation processes of *customer capital*. There is a substantial literature on customer capital accumulation, starting with Phelps and Winter (1970) and Gourio and Rudanko (2014). The closest formulation to my framework is in Paciello et al. (2019).

In Paciello et al. (2019), a firm's sales depend on the mass of customers a that bought from it in the previous period. Each firm has a productivity z that evolves stochastically. Given customer base a, the mass of customers actually buying from the firm in the current period, $\mathscr{M}(a,p,z)$, depends additionally on the firm's price and its productivity. The (slightly simplified) pricing problem of a firm in Paciello et al. (2019) is

$$J(z,a) = \max_p \mathscr{M}(a,p,z)\pi(p,z) + \beta EJ(z',a')$$

subject to

$$a' = (1-\delta)\mathscr{M}(a,p,z)$$

and

$$z' = z + \varepsilon,$$

where $\pi(p,z)$ are the firm's static profits per customer and ε is a random productivity shock. Similar to my framework, there is a unique price p that maximizes the static profits. Furthermore, p also affects the dynamics of the state variable, the customer base. Similar to my framework, firms set the price below the static optimum in order to speed up the accumulation of the customer base.

To derive tractable solutions, Paciello et al. (2019) assume that the growth rate of the customer base does not depend on the initial mass of customers, and that the law of motion of the customer base satisfies $\mathscr{M}(a,p,z) \equiv a\Delta(p,z)$. Customers decide whether to switch to another firm subject to a stochastic search cost, leading to a customer outflow of $\mathscr{G}(p,z)$. At the same time, customers of other firms choose to switch to the given firm, leading to a customer inflow $\mathscr{F}(p,z)$. This setup leads to a law of motion for customer capital of

$$a' = (1-\delta)a + (1-\delta)a\mathscr{F}(p,z) - (1-\delta)a\mathscr{G}(p,z)$$

(see their equation (12)).

This equation is somewhat similar to my framework. The second and third terms are multiplied by $(1-\delta)$ due to their timing assumptions, and scaled by a due to the assumption that $\mathscr{M}(a,p,z) \equiv a\Delta(p,z)$. These assumptions are absent in my framework. Removing these terms, the process becomes

$$a' = (1-\delta)a + \mathscr{F}(p,z) - \mathscr{G}(p,z).$$

In my framework, the first term is identical. The inflow of customers, $\mathscr{F}(p,z)$, is replaced by a build-up of relationship capital $q(p)$. Both functions are decreasing in price. While in the customer capital framework a lower price leads to the attraction of more customers, in my framework a lower price can be interpreted as increasing the attraction, or commitment, of the unique customer. The outflow of customers, $\mathscr{G}(p,z)$, is replaced by the stochastic shocks ε in my model. These can lead to a decline in the state variable, but are not dependent on p as in Paciello et al. (2019).

D Proofs

D.1 Existence of Recursive Representation and an Optimal Policy

The seller's problem in sequence form is

$$J(a_0, w_{i0,0}) = \max_{\{p_t\}_{t=0}^{\infty}} E \sum_{t=0}^{\infty} \beta^t \left[(p_t - c(a_t, w_{i0,t}))\, q(p_t) \right]. \tag{35}$$

Denote by $A \in \mathbb{R}$ the set of values that a can take. Define $\tilde{a}_{t+1} \equiv (1-\delta)a_t + \rho q_t(p_t)$ as the expected level of capital in the next period. Since, given a_t, choosing $\tilde{a}_{t+1}$ is equivalent to choosing p_t, the seller's problem (35) can be transformed into a problem with choice variables $\{\tilde{a}_{t+1}\}_{t=0}^{\infty}$ instead of $\{p_t\}_{t=0}^{\infty}$. 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 $w_{i0,t} = e_{i0,t}\omega_i$ with $e_{i0} \in [\underline{e}, \infty)$, any solution to the sequence problem (35) 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 $H(a_t)$ is non-empty for all $a_t \in A$, compact-valued, and continuous
3. The profit function $\Pi^s(a_t, w_{i0,t}; \tilde{a}_{t+1})$ is continuous in a_t and $\tilde{a}_{t+1}$ and $\lim_{n\to\infty} \sum_{t=0}^{n} \beta^t \Pi^s(a_t, w_{i0,t}; \tilde{a}_{t+1})$ exists and is finite.

To prove these statements, I first show the following two Lemmas. To ease notation, in the following I omit the country indices of $w_{i0,t}$.

Lemma 1. *The seller's profit function $\Pi^s(a_t, w_t; \tilde{a}_{t+1})$ 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 (7) and the definition of $\tilde{a}_{t+1}$ 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

$$\Pi^s(a_t, w_t; \tilde{a}_{t+1}) = \left[\left[\frac{\left(\frac{\theta}{\theta-1}\right)^{-\theta} \rho A^{\theta-1}\Lambda}{(\tilde{a}_{t+1} - (1-\delta)a_t)} \right]^{1/\theta} - c(w_t, a_t) \right] \frac{1}{\rho} (\tilde{a}_{t+1} - (1-\delta)a_t). \tag{36}$$

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 $p_t^* = (\theta/(\theta - 1))c(w_t, a_t)$, which maps into a unique $\tilde{a}_{t+1}^*$. It yields the static optimum of profits of

$$(\Pi^s)^*(a_{t,}, w_t) = \left(\frac{1}{\theta - 1}\right)\left(\frac{\theta}{\theta - 1}\right)^{-2\theta} c(a_t, w_t)^{1-\theta} A^{\theta-1}\Lambda > 0. \tag{37}$$

□

Lemma 2. *Assume that the marginal cost function is sufficiently convex in a_t, i.e., $c''(a_t, w_t) > (1+\theta)\frac{[c'(a_t,w_t)]^2}{c(a_t,w_t)}$ (primes indicate derivatives with respect to a_t). Then, 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. The proof consists of two parts. First, I show that profits are concave in the level of relationship capital, and hence the benefit of additional capital diminishes as more is accumulated. Second, I show that the cost of accumulating additional capital increases with the level of capital. Consequently, there exists a level of relationship capital beyond which the seller would not want to accumulate more.

For the first part, by differentiating equation (37) I find that the static profit function is strictly concave in relationship capital if and only if

$$c''(a_t, w_t) > \theta \frac{[c'(a_t, w_t)]^2}{c(a_t, w_t)}.$$

This condition is implied by the assumption. Hence, the marginal benefits of additional relationship capital decline with a_t.

For the second part, consider the new capital accumulated by setting the optimal static price, $p_t^* = \frac{\theta}{\theta-1}c(a_t, w_t)$. From the capital evolution equation (6), at this price the seller in expectation gets additional capital of

$$\rho q(p_t) = \rho\left(\frac{\theta}{\theta - 1}\right)^{-2\theta} c(a_t, w_t)^{-\theta} A^{\theta-1}\Lambda.$$

This expression is increasing in the current capital stock a_t. It is concave in a_t if and only if

$$c''(a_t, w_t) > (1+\theta)\frac{[c'(a_t, w_t)]^2}{c(a_t, w_t)},$$

which holds by assumption. Therefore, $\rho q(p_t)$ is concave in a_t. Since the net capital accumulation is $\rho q(p_t) - \delta a_t$ and δa_t is linear in a_t, as the capital stock rises incrementally less and less further capital is obtained by setting the optimal price. Then, there must exist an $\hat{a}_t$ satisfying

$$\delta \hat{a}_t = \rho q(p_t^*(\hat{a}_t))$$

such that for $a_t > \hat{a}_t$ the depreciated capital exceeds the accumulated capital at the optimal price in expectation. Consequently, to maintain the level of the capital stock (or to increase it further), the seller has to set a price that is strictly below the static optimum (or equivalently, an $\tilde{a}_{t+1}$ strictly above the profit maximizing level), and this deviation increases further and further as a_t rises. Since the quantity sold rises with a_t, deviations from the optimal price become more and more costly since the suboptimal price affects more and more units. It follows that the implicit loss by not setting the optimal price rises with a_t.

Overall, since the current period implicit loss from increasing the expected value of a_t beyond $\hat{a}_t$ grows with a_t, while the marginal benefit of increasing capital declines with a_t, 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 $w_t \geq \underline{w}$. Therefore, the seller will choose $\tilde{a}_{t+1} < a_t$.

□

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 without stochastic shocks to capital it would never exceed $\bar{a}$ for any process with $a_0 < \bar{a}$. 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 $a^u \gg \bar{a}$ goes to zero for sufficiently large a^u. Formally, I impose an upper bound a^u on the capital process which is sufficiently large to never bind with probability one, and hence $A = [0, a^u]$ is a compact subset of $\mathbb{R}$.

2. The correspondence $H(a_t)$ **is non-empty for all** $a_t \in A$**, compact-valued, and continuous**

Since $p_t \geq 0$ by assumption, it follows that the choice set $H(a_t)$ satisfies $\tilde{a}_{t+1} \in [(1-\delta)a_t, a^u]$ for all t. This set is non-empty, compact, and continuous.

3. $\Pi^s(a_t, w_t; \tilde{a}_{t+1})$ **is continuous in both** a_t **and** $\tilde{a}_{t+1}$ **and** $\lim_{n\to\infty} \sum_{t=0}^{n} \beta^t \Pi^s(a_t, w_t; \tilde{a}_{t+1})$ **exists and is finite**

From the expression in (36), $\Pi^s(a_t, w_t)$ is continuous for all $\tilde{a}_{t+1} > (1-\delta)a_t$. Furthermore, from equation (37), since a^u is finite we have $(\Pi^s)^*(a^u, w) < \infty$ (given $\underline{w} > 0$). Therefore, the maximum possible profits the seller can obtain in any given state are finite. Hence, $\lim_{n\to\infty} \sum_{t=0}^{n} \beta^t \Pi^s(a_t, w_t; \tilde{a}_{t+1})$ must exist and be finite.

D.2 Concavity of the Value Function

Following Acemoglu (2009), Theorem 6.4, the value function $J(a, w_{i0})$ is strictly concave in a if the profit function $\Pi^s(a, w_{i0})$ is concave and if the constraint correspondence $H(a)$ is convex. I first prove concavity of the profit function. Using equation (7) and the definition of $\tilde{a}_{t+1}$ and re-arranging yields

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

and therefore

$$\Pi^s(a, w_{i0}; \tilde{a}') = \left[\left[\frac{\left(\frac{\theta}{\theta-1}\right)^{-\theta}\rho A^{\theta-1}\Lambda}{(\tilde{a}' - (1-\delta)a)}\right]^{1/\theta} - c(a, w_{i0})\right]\frac{1}{\rho}(\tilde{a}' - (1-\delta)a). \tag{38}$$

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

$$\begin{aligned} H_{11} = &-\frac{1}{\rho}c''(a, w_{i0})\left[\tilde{a}' - (1-\delta)a\right] \\ &+ 2\frac{(1-\delta)}{\rho}c'(a, w_{i0}) - \frac{(\theta-1)(1-\delta)^2}{\rho\theta^2\left[\tilde{a}' - (1-\delta)a\right]}p, \end{aligned}$$

and

$$H_{12} = H_{21} = -\frac{1}{\rho}c'(a, w_{i0}) + \frac{(\theta-1)(1-\delta)}{\rho\theta^2\left[\tilde{a}' - (1-\delta)a\right]}p,$$

and

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

where $c'(a, w_{i0})$ and $c''(a, w_{i0})$ are the first and the second derivative of the marginal cost function with respect to a. Since $\tilde{a}' \geq (1-\delta)a$, $c'(a, w_{i0}) < 0$, and $c''(a, w_{i0}) > 0$, we have $H_{11} < 0$ and $H_{22} < 0$, and profits are concave in each of the two arguments separately. The determinant D of the Hessian is

$$D = \frac{\theta-1}{\rho^2\theta^2}pc''(a, w_{i0}) - \frac{1}{\rho^2}\left[c'(a, w_{i0})\right]^2.$$

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

$$p > \frac{\theta^2}{\theta-1}\frac{\left[c'(a, w_{i0})\right]^2}{c''(a, w_{i0})}. \tag{39}$$

As discussed in Lemma 2 in Section D.1, it is necessary for the existence of a solution that the cost function is sufficiently convex, i.e., $c''(a, w_{i0}) > (1+\theta)\frac{\left[c'(a, w_{i0})\right]^2}{c(a, w_{i0})}$. Equivalently,

$$p^* = \frac{\theta}{\theta-1}c(a, w_{i0}) > \frac{\theta(1+\theta)}{\theta-1}\frac{\left[c'(a, w_{i0})\right]^2}{c''(a, w_{i0})},$$

where $p^* = \frac{\theta}{\theta-1}c(a, w_{i0})$ is the optimal static price. This condition implies equation (39), and hence the profit function is strictly concave at the optimal static price and for a range of prices below this level.

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

D.3 Slope of the Policy Function

Using (7) and (6) in equation (9) and re-arranging, the first-order condition of the problem becomes

$$FOC = \left(\frac{\theta-1}{\theta}\right)\left[\frac{\rho\left(\frac{\theta}{\theta-1}\right)^{-\theta}A^{\theta-1}\Lambda}{(\tilde{a}'-(1-\delta)a)}\right]^{1/\theta} - c(a,w_{io}) + \beta\rho EJ_a(a',w'_{i0}) = 0.$$

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

$$\frac{\partial FOC}{\partial a} = \frac{1-\delta}{\theta}\left(\frac{\theta-1}{\theta}\right)\frac{p}{\tilde{a}'-(1-\delta)a} - c'(a,w_{i0}) > 0,$$

since $c'(a,w_{i0}) < 0$. Therefore, $d\tilde{a}'/da > 0$, and hence the policy function is strictly increasing in a.

D.4 Decreasing Price with Relationship Capital

Using equation (7) and the definition of $\tilde{a}' \equiv (1-\delta)a + \rho q(p)$ and re-arranging yields

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

Taking the derivative with respect to a gives

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

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

To see that this condition holds, note that we have from the definition of $\tilde{a}'$ at the static optimum price $p = \frac{\theta}{\theta-1}c(a,w_{i0})$, that

$$(\tilde{a}')^M = (1-\delta)a + \rho\left(\frac{\theta-1}{\theta}\right)^{2\theta}[c(a,w_{i0})]^{-\theta}A^{\theta-1}\Lambda,$$

and therefore

$$\frac{d(\tilde{a}')^M}{da} = (1-\delta) - \rho\theta\left(\frac{\theta-1}{\theta}\right)^{2\theta}c'(a,w_{i0})[c(a,w_{i0})]^{-\theta-1}A^{\theta-1}\Lambda > 1-\delta \tag{40}$$

where $(\tilde{a}')^M$ is the implied policy from setting the static optimum price. The expression is greater than $1-\delta$ since $c'(a,w_{i0}) < 0$.

Since $J(a,w)$ is concave in a by D.2, increasing capital has a smaller and smaller value. Therefore $\frac{d\tilde{a}'}{da}|_{a=a_2} \leq \frac{d\tilde{a}'}{da}|_{a=a_1}$ for $a_1 < a_2$. Since $\frac{d\tilde{a}'}{da}$ is therefore decreasing in a and since p is converging to the static optimum price, and since by equation (40) we have $\frac{d(\tilde{a}')^M}{da} > 1-\delta$, it must be the case that $\frac{d\tilde{a}'}{da} > 1-\delta$ for all a.

D.5 Proof of Comparative Statics

Part a): The first-order condition of the problem is

$$FOC = \left(\frac{\theta-1}{\theta}\right)\left[\frac{\rho\left(\frac{\theta}{\theta-1}\right)^{-\theta}A^{\theta-1}\Lambda}{(\tilde{a}'-(1-\delta)a)}\right]^{1/\theta} - c(a,w_{i0}) + \beta\rho E J_a(a',w'_{i0}) = 0.$$

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

$$\frac{\partial FOC}{\partial \rho} = \left(\frac{\theta-1}{\rho\theta^2}\right)p + \beta E J_a(a',w'_{i0}) > 0.$$

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

Part b): We have

$$\frac{\partial FOC}{\partial \delta} = -\frac{a}{\theta}\left(\frac{\theta-1}{\theta}\right)\frac{p}{\tilde{a}'-(1-\delta)a} < 0.$$

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

D.6 First-Order Condition of Seller's Problem under LC

The FOC of the seller's problem is

$$\begin{aligned}
&\left[(1-\theta)p^{-\theta} + \theta c(a,w_{i0})p^{-\theta-1}\right] - \beta\theta\rho E\left[I' p^{-\theta-1} J_a(a',\mathbf{w}'_{i0})\right] \\
&-\lambda p^{-\theta} - \beta\theta\rho\lambda E\left[I' p^{-\theta-1} W_a(a',\mathbf{w}'_{i0})\right] \\
&-\beta\theta\rho\lambda p^{-\theta-1} E\left[\frac{\partial I'}{\partial a'}\left\{W(a',\mathbf{w}'_{i0}) - U(\mathbf{w}'_{i0})\right\}\right] \\
&-\beta\theta\rho p^{-\theta-1} E\left[\frac{\partial I'}{\partial a'}\left\{J(a',\mathbf{w}'_{i0}) - V(\mathbf{w}'_{i0})\right\}\right] = 0.
\end{aligned}$$

Since a marginal increase in relationship capital only affects the break-up decision for states in which $J(a',\mathbf{w}'_{i0})$

is very close to $V(\mathbf{w}'_{i0})$, the last term is zero. Re-arranging yields (12).

D.7 Proof of $J_{aw}(a, w_{i0}) \leq 0$

Since an increase in w_{i0} strictly decreases profits in every period, we have that $J_w(a, w_{i0}) < 0$ for all a. Fix the level of capital at a, and consider two levels of costs, w_{i0} and $w_{i0} + \varepsilon$, where $\varepsilon > 0$ is assumed to be arbitrarily small. I will show that, since J is a continuous function, an increase in relationship capital from a to $a + \xi$ cannot raise J by more under $w_{i0} + \varepsilon$ than under w_{i0}. If that were the case then we would have $J(a, w_{i0}) > J(a, w_{i0} + \varepsilon)$ but $J(a + \xi, w_{i0}) \leq J(a + \xi, w_{i0} + \varepsilon)$, since ε can be chosen arbitrarily small, a contradiction.

Assume for contradiction that $J_{aw}(a, w_{i0}) > 0$. Then $J_a(a, w_{i0} + \varepsilon) > J_a(a, w_{i0})$. Choose a $\delta(\varepsilon)$ small enough so that $J_a(a, w_{i0} + \varepsilon) > J_a(a, w_{i0}) + \delta(\varepsilon)$, and define $\delta(\varepsilon) \equiv -\frac{\varepsilon}{\xi} J_w(a, w_{i0})$, which can be made arbitrarily small for any ε by choosing ξ appropriately since $J_w(a, w_{i0})$ is finite and continuous for $w_{i0} \geq \underline{e}\omega_i > 0$ from (35). Plugging in yields

$$\frac{J_a(a, w_{i0} + \varepsilon) - J_a(a, w_{i0})}{\varepsilon} > -\frac{J_w(a, w_{i0})}{\xi}.$$

Re-arranging this expression gives

$$\begin{aligned} J_{aw}(a, w_{i0}) > -\frac{J_w(a, w_{i0})}{\xi} &\Leftrightarrow J_w(a + \xi, w_{i0}) - J_w(a, w_{i0}) > -J_w(a, w_{i0}) \\ &\Leftrightarrow J_w(a + \xi, w_{i0}) > 0, \end{aligned}$$

which is a contradiction since it must be the case that $J_w(a, w_{i0}) < 0$ for all a. Therefore, $J_{aw}(a, w_{i0}) \leq 0$.

E Alternative Models

E.1 Demand-Side Mechanism

Consider an alternative setup in which the build-up of a relationship does not lower costs, as in my model, but instead affects the effective quantity obtained by the buyer, for example due to quality. The buyer's production function is then

$$y = a^{\gamma} A q,$$

where $\gamma < 1/\theta$ is a concavity parameter and the cost function of the seller depends only on w, $c(a, w_{i0}) \equiv c(w_{i0})$. In this setup, the buyer's price in the final goods market is

$$p^{f} = \left(\frac{\theta}{\theta-1}\right)\left(\frac{p}{a^{\gamma}A}\right).$$

Increases in a lead to higher sales to final consumers, and therefore a higher quantity demanded from the seller,

$$q(p) = \left(\frac{\theta}{\theta-1}\right)^{-\theta} p^{-\theta} a^{\gamma\theta} A^{\theta-1} \Lambda.$$

The seller's problem is then the same as in (8), which yields

$$p = \frac{\theta}{\theta-1}\left[c(w_{i0}) - \beta\rho E J_a(a', w'_{i0})\right],$$

where the key difference to before is that costs are no longer declining in a. The same intuition as before now holds. As the relationship is built up and a increases, $J_a(a', w'_{i0})$ declines due to the concavity of the value function. As a result, the mark-up rises. At the same time, however, costs are no longer declining and hence the rise in the mark-up also raises the overall price. This outcome is at odds with the data.

E.2 Variable Markup Model

I describe an alternative setup with variable mark-ups in which sellers accumulate market share, rather than relationship capital, and prices are set as in Atkeson and Burstein (2008). There exists a continuum of sectors i, which produce intermediate goods. The sectors are aggregated into final U.S. output 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. 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.

Demand for each sector i is then

$$q_t(i) = \left(\frac{p_t^f(i)}{P_t} \right)^{-\theta} Q_t, \tag{41}$$

where $p_t^f(i)$ is sector i's input price, 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 $k = 1, ..., K_1$ and the foreign firms are indexed by $k = K_1 + 1, ..., K_1 + K_2$. 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

$$q_t(i) = \left[\sum_{k=1}^{K_1+K_2} (m_t(i,k))^{(\eta-1)/\eta} \right]^{\eta/(\eta-1)}, \tag{42}$$

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

$$m_t(i,k) = \left(\frac{p_t(i,k)}{p_t^f(i)} \right)^{-\eta} q_t(i), \tag{43}$$

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

The firms in each sector employ a similar production technology as in the main text. Each firm has a production function of the form

$$m = ax, \tag{44}$$

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, $a_{t+1} = a_t + \zeta_{t+1}$, where $\zeta \sim (\mu, \sigma^2)$ are independent shocks across sellers. The input x is subject to marginal input cost w. Foreign firms' input cost evolves stochastically over time, reflecting exchange rate fluctuations, while domestic sellers' input costs are constant. The cost is identical for all firms of a given origin. I assume that sellers have to pay a fixed cost $F > 0$ each period to produce, and may hence choose to shut down if their costs become too high. However, any exiting seller is immediately replaced by a new firm with a new draw of costs, so that the total number of sellers in each sector is always constant.

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

$$\Pi^s(a_t(i,k),w_t(k)) = \max_{p_t(i,k),m_t(i,k)} [p_t(i,k) - w_t(k)/a_t(i,k)]\, m_t(i,k) - F, \tag{45}$$

subject to (43), (42), P_t, and Q_t, where sector quantities are given by (42) and the firm takes all other firms' quantities as given.

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

$$p(i,k) = \frac{\varepsilon(s(i,k))}{\varepsilon(s(i,k)) - 1} \frac{w(k)}{a(i,k)}, \tag{46}$$

where

$$\varepsilon(s(i,k)) = \left[\tfrac{1}{\eta}(1-s) + \tfrac{1}{\theta}s\right]^{-1} \tag{47}$$

is the elasticity of substitution perceived by the seller, and s is the seller's market share given by

$$s(i,k) = p(i,k)m(i,k)/(\sum_{k=1}^{K} p(i,k)m(i,k)) = \left(\frac{p(i,k)^{1-\eta}}{\sum_{k=1}^{K} p(i,k)^{1-\eta}}\right). \tag{48}$$

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 model incorporates dynamics in the market share of each individual firm due to the stochastic shocks to the productivity component a and, for the foreign sellers, stochastic shocks to the input cost w. Firms that receive good shocks to productivity or costs lower their price and thereby gain market share, which leads them to charge higher mark-ups. Log-linearizing equation (46) and using the expression for market shares (48) gives a similar expression as in Atkeson and Burstein (2008):

$$\hat{p}(i,k) = \frac{1}{1 + (\eta - 1)\Gamma(s(i,k))} \left[\hat{w} - \hat{a}(i,k) + (\eta - 1)\Gamma(s(i,k))\hat{p}(i)\right], \tag{49}$$

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. In this setup, $\Gamma'(s(i,k)) > 0$, and therefore higher market share firms put a larger and larger emphasis on the sectoral price index as opposed to their own cost shocks.

Consider now a shock to a foreign seller's input cost w resulting from exchange rate movements. Due to selection, firms that have been participating in the market for longer on average have a higher productivity a, and therefore on average have a higher market share. High market share firms put a larger emphasis on the sectoral price index than on their own cost shock when setting price. Since the sectoral price index also includes domestic firms, it generally moves by less than w, as in Atkeson and Burstein (2008). As a result, older exporters on average change their export price in the importer's currency by less than new exporters in response to an exchange rate shock. These older exporters price more to market, placing a larger weight on the sectoral price index. Hence, pass-through of a shock to w into import prices falls with exporter age. This finding is at odds with my empirical findings. Therefore, a framework in which relationship capital accumulation is replaced by the build-up of market share cannot explain my results.

E.3 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. To simplify notation, I omit the country indices on costs. 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

$$M(u_b,u_s) = (u_b^{-\iota}+u_s^{-\iota})^{-\frac{1}{\iota}}. \tag{50}$$

The probability that an unmatched buyer meets a seller is then

$$\pi_b(\vartheta) = M(1,\vartheta) = (1+\vartheta^{\iota})^{-\frac{1}{\iota}}, \tag{51}$$

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

$$\pi_s(\vartheta) = \vartheta(1+\vartheta^{\iota})^{-\frac{1}{\iota}} = \vartheta\pi_b(\vartheta). \tag{52}$$

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 and 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 the value of 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:

$$U = -c+\beta\left[\pi_b(\vartheta)EW(a',w')+(1-\pi_b(\vartheta))U\right], \tag{53}$$

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

$$EW(a',w') = \frac{c}{\beta\pi_b(\vartheta)}. \tag{54}$$

An unmatched seller has value function

$$V(w) = \beta[\pi_s(\vartheta)EJ(a',w')+(1-\pi_s(\vartheta))EV(w')],. \tag{55}$$

where here the expectation with respect to w' is the conditional expectation given the seller's current cost w.

Once the buyer and the seller are in a relationship, given the demand function of final consumers the buyer's value function is

$$W(a,w) = (Aq)^{\frac{\theta-1}{\theta}} \Lambda^{\frac{1}{\theta}} - T + \beta E\left[\max\left\{W(a',w'),U\right\}\right], \tag{56}$$

where the continuation value depends on the evolution of costs and relationship capital, and the first term in equation (56) represents the revenues of a buyer purchasing quantity q from the seller. The seller's value function is

$$J(a,w) = T - \frac{w}{a^{\gamma}}q + \beta E\left[\max\left\{J(a',w'),V(w')\right\}\right], \tag{57}$$

where I assume here a specific cost function, w/a^{γ}, where γ is a parameter. Given weight ϕ on the buyer, under Nash bargaining the payment satisfies

$$T = \operatorname{argmax}\left(W(a,w)-U\right)^{\phi}\left(J(a,w)-V(w)\right)^{1-\phi}. \tag{58}$$

Taking the first-order condition with respect to T and re-arranging gives:

$$\phi\left(J(a,w)-V(w)\right) = (1-\phi)\left(W(a,w)-U\right). \tag{59}$$

From equations (53)-(57), I have that

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

I can use the fact that condition (59) has to hold at each point in time to simplify and obtain:

$$T = (1-\phi)\left[(Aq)^{\frac{\theta-1}{\theta}}\Lambda^{\frac{1}{\theta}} + c\right] + \phi\frac{w}{a^{\gamma}}q + (1-\phi)\beta\pi_b(\vartheta)(\vartheta-1)E\left[W(a',w')-U\right]. \tag{60}$$

Using the free entry condition (54) and re-arranging yields

$$p = \frac{T}{q} = (1-\phi)\left[A^{\frac{\theta-1}{\theta}}\Lambda^{\frac{1}{\theta}}q^{-\frac{1}{\theta}} + \frac{\vartheta c}{q}\right] + \phi\frac{w}{a^{\gamma}}. \tag{61}$$

Next, adding up (56) and (57), and deducting (55), I obtain a total match surplus over the outside value of

$$S(a,w) = (Aq)^{\frac{\theta-1}{\theta}}\Lambda^{\frac{1}{\theta}} - \frac{w}{a^{\gamma}}q + \beta E\left[\max\{S(a',w'),0\}\right] - \beta\vartheta\pi_b(\vartheta)\frac{1-\phi}{\phi}E\left[W(a',w')-U\right]. \tag{62}$$

Using the free entry condition (54) yields

$$S(a,w) = (Aq)^{\frac{\theta-1}{\theta}} \Lambda^{\frac{1}{\theta}} - \frac{w}{a^{\gamma}} q + \beta E\left[\max\{S(a',w'),0\}\right] - \frac{1-\phi}{\phi} c\vartheta. \tag{63}$$

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 increasing 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 (63) with respect to q, I obtain

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

where $I' = I(a',w')$ is an indicator that is equal to one if the relationship is continued in state (a',w'). Note that the derivative with respect to the indicator satisfies $E[\frac{dI(a',w')}{dq}(S(a',w')-0)] = 0$ 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 (61) yields the pricing equation

$$\begin{aligned} p = {} & (1-\phi)\left(\frac{\theta}{\theta-1}\right)\left[\frac{w}{a^{\gamma}} - \beta\rho E\left[I' S_a(a',w')\right]\right] + \phi\frac{w}{a^{\gamma}} \\ & + (1-\phi)\frac{\vartheta c}{A^{\theta-1}\Lambda}\left(\frac{\theta}{\theta-1}\right)^{\theta}\left[\frac{w}{a^{\gamma}} - \beta\rho E\left[I' S_a(a',w')\right]\right]^{\theta}. \end{aligned} \tag{64}$$

Pass-through is given by

$$\begin{aligned} \frac{d\ln(p)}{d\ln(w)} = {} & \frac{(1-\phi)\left(\frac{\theta}{\theta-1}\right)\left[\frac{w}{a^{\gamma}} - \beta\rho\Psi(a',w')\right] + \phi\frac{w}{a^{\gamma}}}{p} \\ & + \frac{(1-\phi)\frac{\vartheta c}{A^{\theta-1}\Lambda}\left(\frac{\theta}{\theta-1}\right)^{\theta}\theta\left[\frac{w}{a^{\gamma}} - \beta\rho\Psi(a',w')\right]\left[\frac{w}{a^{\gamma}} - \beta\rho E\left[I' S_a(a',w')\right]\right]^{\theta-1}}{p}, \end{aligned} \tag{65}$$

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

Consider the case of $E\left[I' S_a(a',w')\right]$ 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, if anything pass-through is declining with a.

Figure E.1: Pass-Through under Nash Bargaining

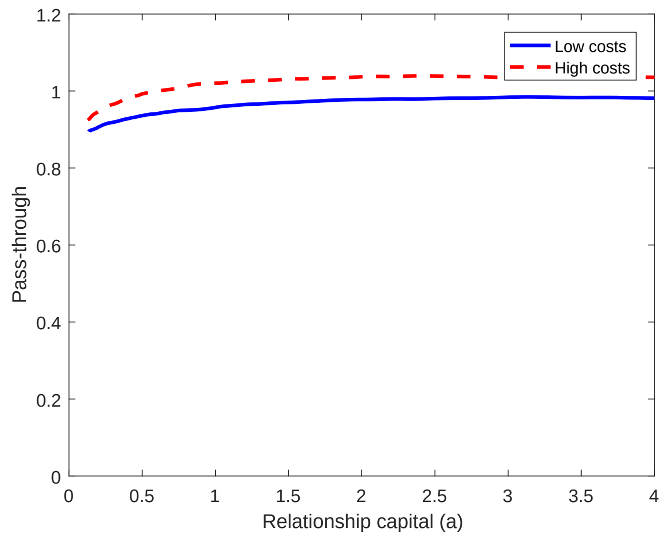


Figure E.1 presents a quantitative evaluation of pass-through in the fully specified model, where the matching probabilities are selected to match the exogenous matching probabilities from the main model. While the endogenous capital accumulation produces a small increase in pass-through at small levels of capital, pass-through is virtually flat, since this model lacks the occasionally binding participation constraints which in the main model generate a kink in pass-through.

F Analysis of Plausibly Exogenous Relationship Break-Ups

In this section, I show that plausibly exogenous relationship break-ups adversely affect the U.S. importer. Specifically, I show that 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 provide some statistics on relationship break-ups, 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.[40] 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 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.[41] 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 $d^b_{mh,i}$, 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.[42] Thus, I run:

$$\ln(q_{mht}) = \beta_0 + d^b_{mh,i} + \gamma_{mh} + \xi_t + \varepsilon_{mht}, \tag{66}$$

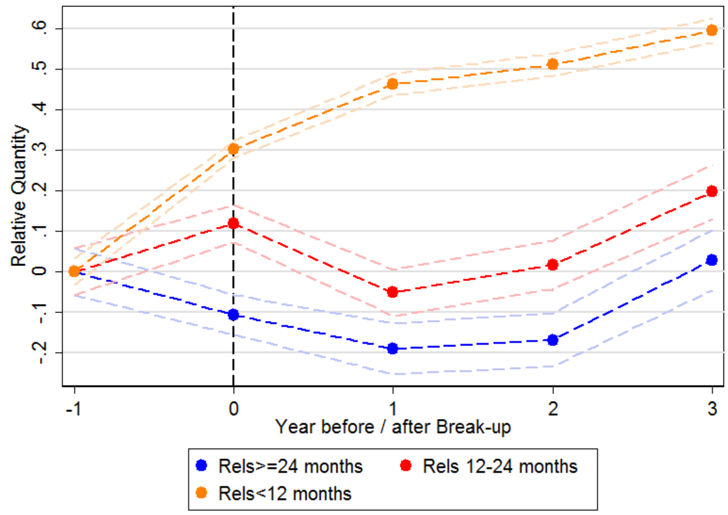
where γ_{mh} are importer-product fixed effects and ξ_t are year fixed effects. If relationships are valuable, the quan-

[40]"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.

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

[42]Note 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 F.1: Quantity Traded 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 F.1 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. 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 F.1 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 (66) for relationships lasting at least 24 months, and interact the break-up indicator with a dummy $d^{new}_{mh,t-1}$. 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

$$\ln(q_{mht}) = \beta_0 + d^b_{mh,t-1} + d^b_{mh,t-1} \cdot d^{new}_{mh,t-1} + \gamma_{mh} + \xi_t + \varepsilon_{mht}. \tag{67}$$

Column 6 of Table F.1 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 replaced with a new one. Column 7 redoes the regression with an interaction term measuring whether a new

Table F.1: Break-Up Regressions, Quantity

	Dependent variable: $\ln(q_{mht})$						
	$t+1$	t	$t-1$	$t-2$	$t-3$	$t-1$	$t-2$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
d^b_{mh}	.1166***	.0105	−.0736**	−.0517	.1451***	−.0812**	−.0750*
	(.0293)	(.0250)	(.0321)	(.0336)	(.0379)	(.0400)	(.0440)
$d^b_{mh} \cdot d^{new}_{mh}$						.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

Note: 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.

Table F.2: Break-Up Regressions, Employment

	Dependent variable: $\ln(e_{mht})$		
Rel. length	≥ 24	$12-24$	< 12
	(1)	(2)	(3)
d^b_{mh}	−.0149*	−.0126	−.0020
	(.0086)	(.0078)	(.0036)
Fixed effects	mh,t	mh,t	mh,t
Observations	9,542,000	9,542,000	9,542,000

Note: Number of observations has been rounded to the nearest 1000 as per U.S. Census Bureau Disclosure Guidelines.

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. Column 1 in Table F.2 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 (66) and (67) 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 F.3, for both quantities (columns 1-7) and employment growth (column 8). The results are strengthened compared to the baseline case.

Table F.4 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 F.3: Break-Up Regressions, Quantity, Robustness Specification

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

Note: Number of observations has been rounded to the nearest 1000 as per U.S. Census Bureau Disclosure Guidelines.

Table F.4: Break-Up Statistics

	$\geq 24 months$
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 found	0.9
Excess gap time between transactions	10.7

Note: The table provides statistics on the time needed to find a new supplier following a plausibly exogenous relationship break-up of a relationship that lasted at least 24 months.

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 of that good by on average 11 months. Thus, locating a supplier to replace a lost relationship takes a significant amount of time.

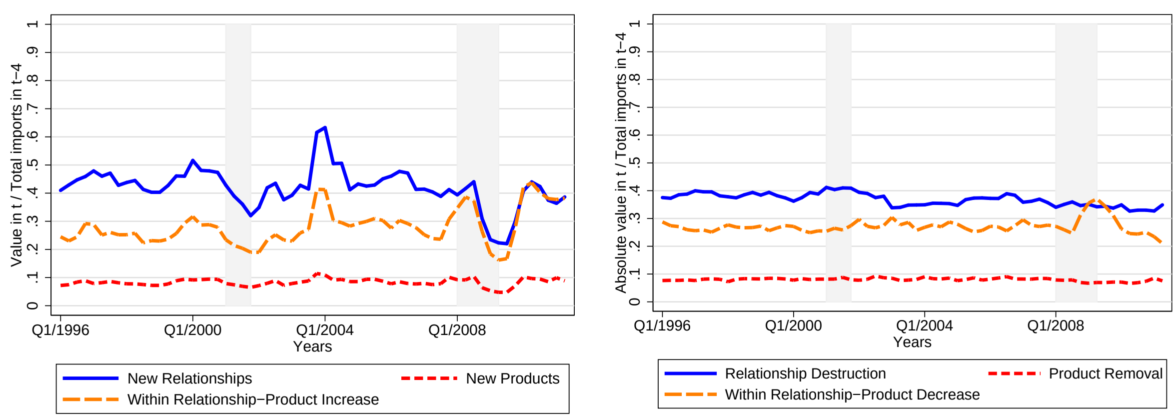
G Decomposition of Aggregate U.S. Imports

Naive Definition of Relationship Length

I perform the decomposition alternatively defining relationship length simply as the time passed since the first transaction of an importer-exporter pair in the data, regardless of time gaps between transactions. Thus, a relationship terminates at the last transaction of the importer-exporter pair in the data, a product is removed when it is traded for the last time by the relationship in the data, etc. Figure G.1a shows the creation margins and Figure G.1b presents the destruction margins under this definition. Relationship creation still accounts for 40% of the drop.

Figure G.1: Margins of Trade Changes under Naive Relationship Definition

(a) Creation Margins (b) Destruction Margins



Importer Entry and Exit

I perform a third decomposition into importer entry and exit, product additions and removals for existing importers, and value changes within importer-products. Let M_t be the set of importers that exist in quarter t. Similarly, let $H_{m,t}$ be the set of products traded by importer m in quarter t. Define $y_{mh,t}$ as the total value transacted by importer m or product h in quarter t. Then the aggregate change in U.S. imports between $t-4$ and t

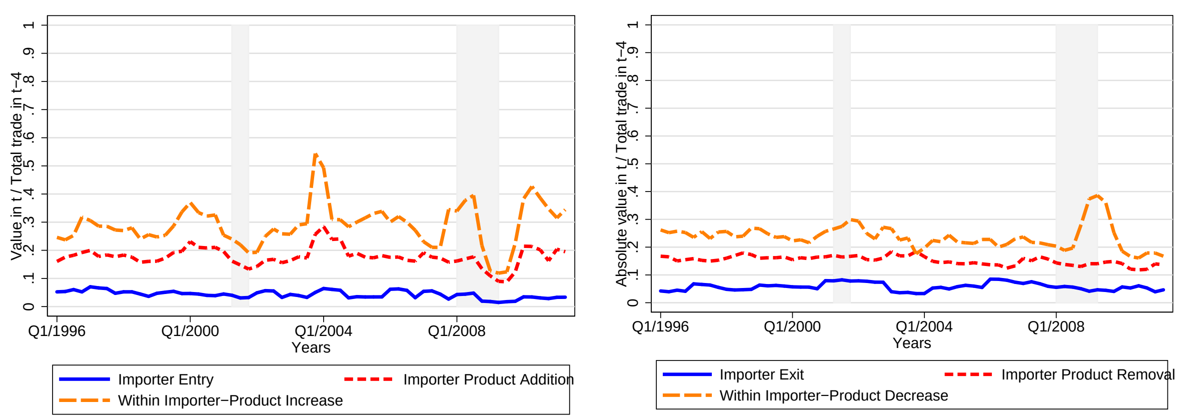
can be decomposed as

$$\begin{aligned}
\Delta y_{t-4,t} &= \sum_{m\in M_t}\sum_{h\in H_{m,t}} y_{mh,t} - \sum_{m\in M_{t-4}}\sum_{h\in H_{m,t-4}} y_{mh,t-4} \\
&= \left[\sum_{m\in M_t, m\notin M_{t-4}}\sum_{h\in H_{m,t}} y_{mh,t} - \sum_{m\notin M_t, m\in M_{t-4}}\sum_{h\in H_{m,t-4}} y_{mh,t-4}\right] \\
&+ \left[\sum_{m\in M_t\cap M_{t-4,t}}\sum_{h\in H_{m,t}, h\notin H_{m,t-4}} y_{mh,t} - \sum_{m\in M_t\cap M_{t-4}}\sum_{h\notin H_{m,t}, h\in H_{m,t-4}} y_{mh,t-4}\right] \\
&+ \sum_{m\in M_t\cap M_{t-4}}\sum_{h\in H_{m,t}\cap H_{m,t-4}} \left[\{y_{mh,t}-y_{mh,t-4}\}^{+} + \{y_{mh,t}-y_{mh,t-4}\}^{-}\right].
\end{aligned} \tag{68}$$

Figure G.2a shows the value of the creation margins from this decomposition, scaled by the total value of imports at $t-4$, y_{t-4}. The figure illustrates that within importer-product adjustments are the most important quantitatively to account for the variation of trade over the business cycle. Together with the finding in the main text that relationship creation is cyclical, this result suggests that new relationships for products that the importer already traded before are the most important adjustment margin. On the other hand, entry of new importers is relatively constant and accounts for less than 10% of trade. Figure G.2b presents the analogous destruction margins. During the Great Recession, the within importer-product margin rose significantly, suggesting that importers reduced trade within a given product without dropping the product entirely. Again, using the findings from the main text, this adjustment occurred mainly by destroying relationships at the usual pace and not forming new ones.

Figure G.2: Margins of Aggregate Trade Changes

(a) Creation Margins (b) Destruction Margins



H Additional Figures

Figure H.1: Trade distribution by industry

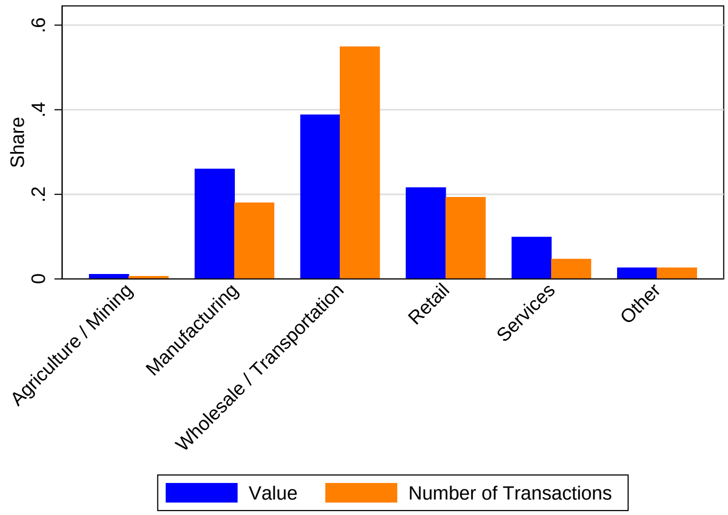
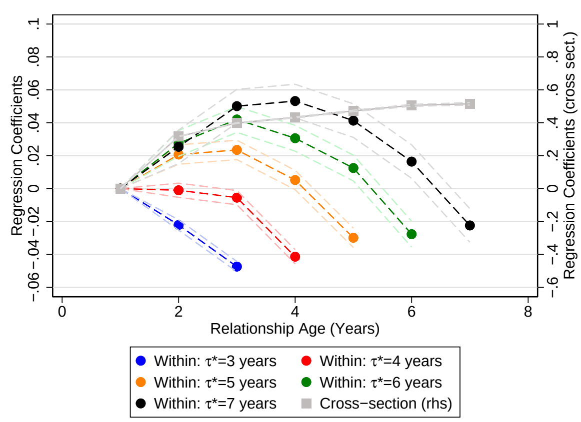


Figure H.2: Relationship Life Cycle

(a) Number of Products Traded



(b) Number of Transactions per Year

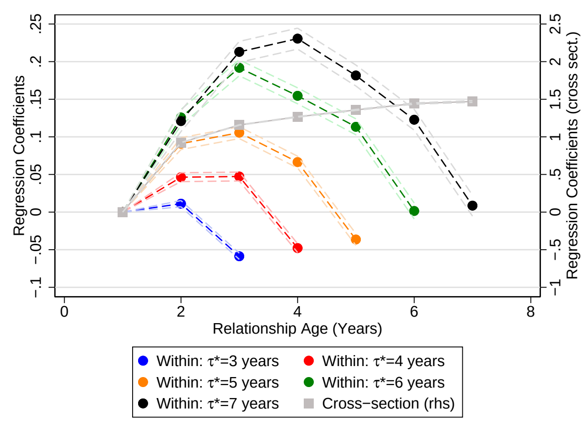
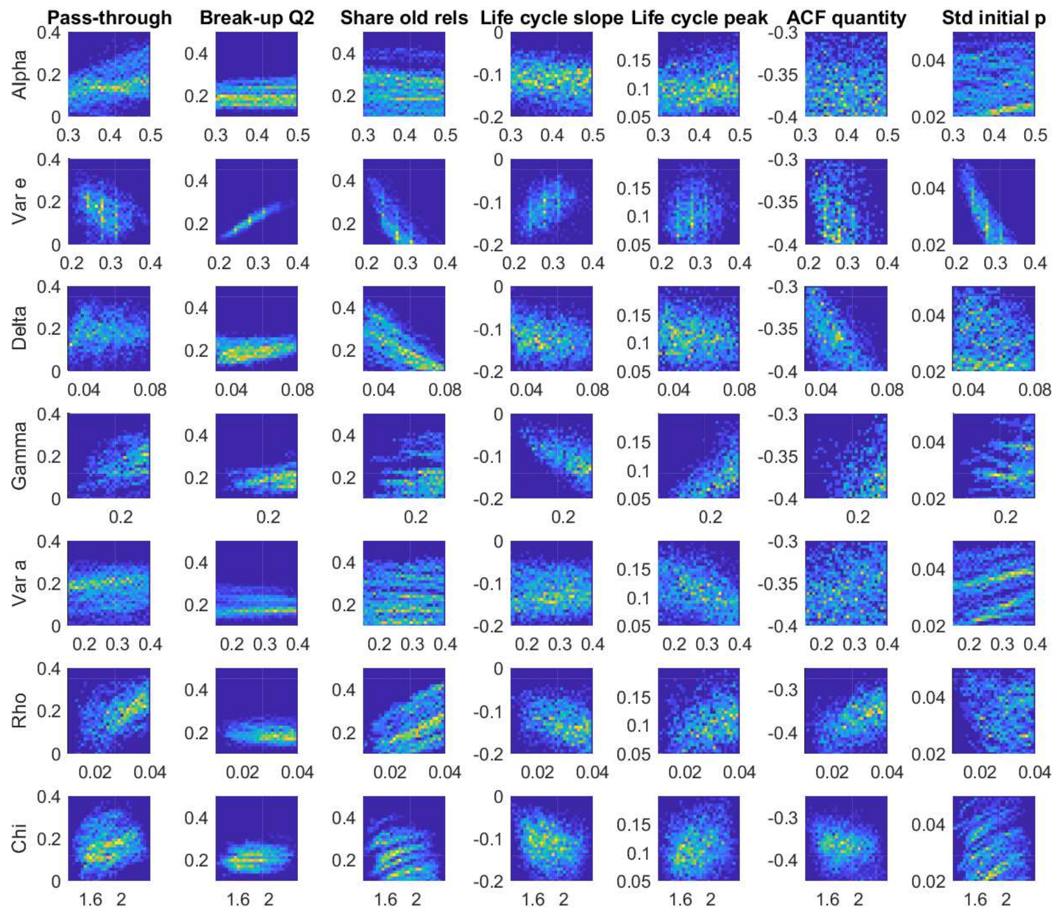
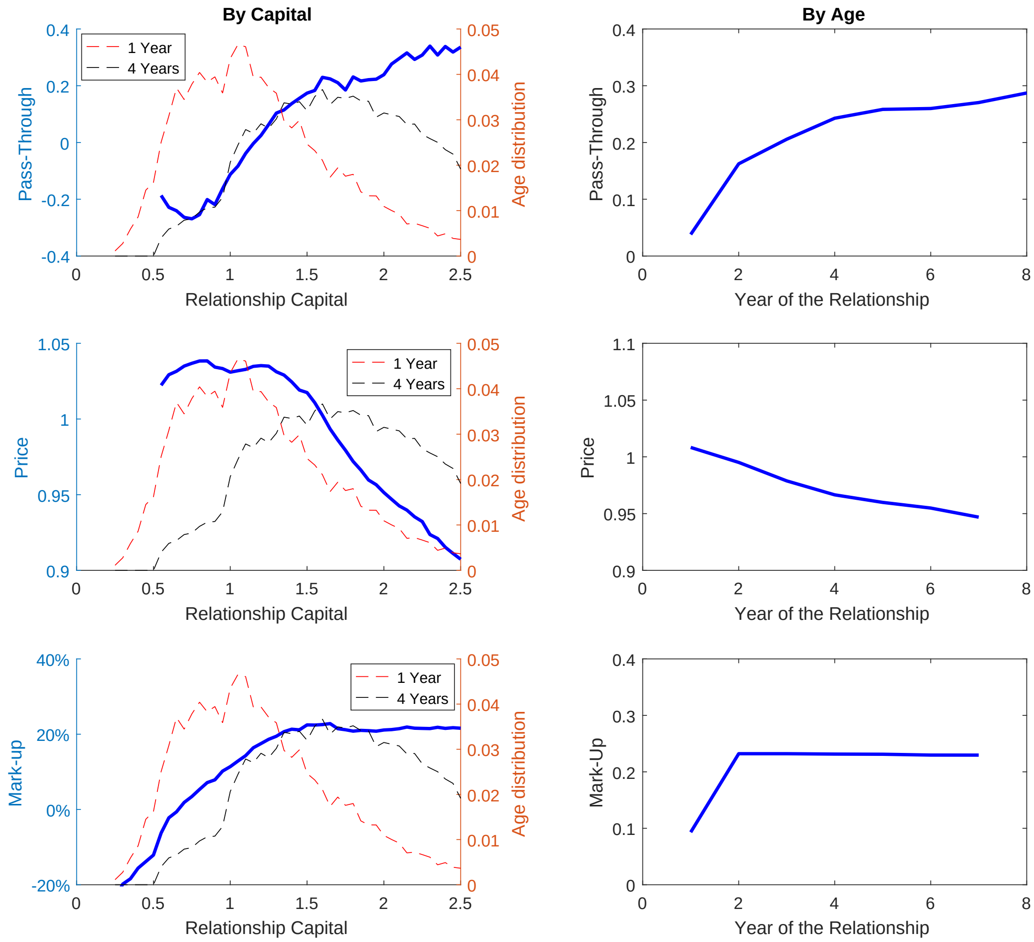


Figure H.3: Identification of Parameters



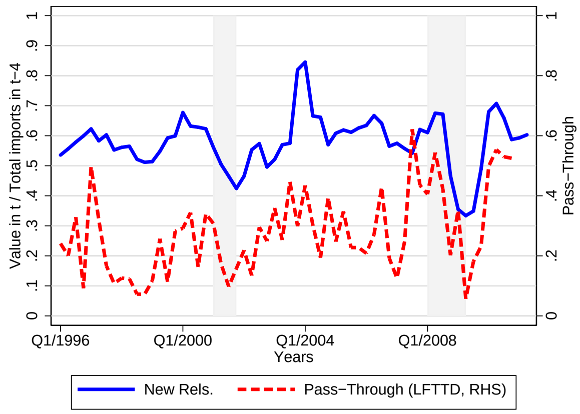
Note: The figure shows bin scatter plots of each of the seven parameters against each of the seven main moments used. The plot is constructed by first taking 100 initial random draws of all parameters to initiate 100 chains. Starting from these initial points, I then vary the row parameter along a linear grid for each chain, holding fixed the other parameters, and plot the value of the moment in the column against the value of the row parameter. Column 1 shows the parameters against the average pass-through of a three-year relationship, estimated from regression (1) with dummies in the simulated data. Column 2 shows the break-up hazard of a relationship in quarter two. Column 3 is the share of relationships that are older than four years. Column 4 presents the difference in the value traded between year five and year three in a relationship lasting five years in total. Column 5 shows the value traded in year three of a five year relationship relative to year one. Column 6 is the autocorrelation of a relationship's annual quantity traded. Column 7 is the standard deviation of the residuals of a regression of prices of new relationships on the cost draw. Repeated parameter/moment value pairs lead to lighter colors in a given location.

Figure H.4: Relationship Capital versus Age



Note: The left set of panels shows average pass-through, prices, and mark-ups in the simulated panel as a function of relationship capital (solid blue lines). The dashed lines plot the distributions of capital for relationships currently in their first year and for relationships currently in their fourth year, respectively. The right set of panels shows pass-through, prices, and mark-ups as a function of relationship age, obtained by integrating pass-through, prices, and mark-ups in the left panel over the relationship age distribution of the corresponding year. Due to the shift of the relationship capital distribution to the right in older relationships, their pass-through and mark-ups are higher and their prices are lower compared to young relationships.

Figure H.5: Pass-Through in the LFTTD



I Additional Tables

Table I.1: Summary Statistics

		All relationships	> 12 months
		(1)	(2)
(1)	Arms' length trade	38%	32%
(2)	Arms' length trade (always unrelated)	27%	21%
	Arms' length trade		
(3)	Exporters per importer-HS10, per year	2.7	2.2
(4)	Importers per exporter-HS10, per year	1.2	1.2
(5)	HS per importer-exporter, per year	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

Note: Column 1 shows statistics for all relationships, while column 2 shows statistics for only those relationships that last in total for more than 12 months. Row 1 shows the share of value transacted at arms' length. Row 2 shows the share of value transacted by relationships that are always arms' length. Rows 3-11 focus on arms' length trade only. Rows 3-5 present some matching statistics. Row 6 shows the average gap time between transactions based on my definition. Row 7 presents the average of maximum gap times (a product-level statistic) across HS10 products. Rows 8-11 present the average relationship length for overall and for different industries based on my relationship definition.

Table I.2: Domestic Relationships in the Management Literature

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.3: List of countries with exchange rates

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

Table I.4: Pass-Through Robustness - Number of Transactions ($Trans_{mxt}$)

$\Delta\ln(p)$	Every qtr	Selection	Annual	Size	Trans Val	GDP/Law	Country FE	Pos	Neg	Length	Exp FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\Delta\ln(e)$	$.4424^{***}$	$.5600^{***}$	$.5203^{***}$	$.8603^{***}$	$.3830^{***}$	$.2528^{***}$	.1588	$.5282^{**}$	$.3130^{**}$	$.5703^{***}$	$.5800^{***}$
	(.1469)	(.1475)	(.1487)	(.1961)	(.1140)	(.0915)	(.3572)	(.2011)	(.1373)	(.1617)	(.1650)
$\text{Trans} \cdot \Delta\ln(e)$	$.0042^{***}$	$.0035^{***}$	$.0168^{***}$	$.0053^{***}$	$.0026^{***}$	$.0026^{**}$	$.0014^{***}$	$.0027^{*}$	$.0028^{**}$	.0015	$.0042^{***}$
	(.0011)	(.0006)	(.0030)	(.0006)	(.0007)	(.0013)	(.0005)	(.0014)	(.0012)	(.0015)	(.0006)
$\text{Time Gap} \cdot \Delta\ln(e)$		$.0093^{***}$	$.0353^{**}$	$.0080^{***}$	$.0067^{***}$	$.0072^{***}$	$.0046^{***}$	.0019	$.0053^{*}$	$.0067^{***}$	$.0056^{***}$
		(.0024)	(.0144)	(.0021)	(.0021)	(.0021)	(.0015)	(.0089)	(.0031)	(.0020)	(.0020)
$\text{Avg Size} \cdot \Delta\ln(e)$	$-.0277^{**}$	$-.0392^{***}$	$-.0321^{***}$			$-.0203^{**}$	$-.0079^{**}$	$-.0317^{*}$	$-.0218^{**}$	$-.0408^{***}$	$-.0393^{***}$
	(.0108)	(.0108)	(.0100)			(.0079)	(.0033)	(.0161)	(.0103)	(.0121)	(.0124)
$\text{Imp Size} \cdot \Delta\ln(e)$				$-.0137^{***}$							
				(.0029)							
$\text{Exp Size} \cdot \Delta\ln(e)$				$-.0321^{***}$							
				(.0094)							
$\text{Trans Val} \cdot \Delta\ln(e)$					$-.0237^{***}$						
					(.0077)						
$\text{Trans} \cdot \Delta\ln(e) \cdot d^{GDP}_{\text{med}}$						.0002					
						(.0020)					
$\text{Trans} \cdot \Delta\ln(e) \cdot d^{GDP}_{\text{high}}$						$-.0008$					
						(.0020)					
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Rel-product FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	–
GDP/Law FE $\cdot\Delta\ln(e)$	–	–	–	–	–	Y	–	–	–	–	–
Country FE $\cdot\Delta\ln(e)$	–	–	–	–	–	–	Y	–	–	–	–
Total Length $\cdot\Delta\ln(e)$	–	–	–	–	–	–	–	–	–	Y	–
Exp-product FE	–	–	–	–	–	–	–	–	–	–	Y
Observations	6,113,000	26,560,000	2,717,000	13,850,000	13,850,000	13,850,000	13,850,000	7,422,000	5,196,000	13,850,000	15,290,000

Note: Number of observations has been rounded to the nearest 1000 as per U.S. Census Bureau Disclosure Guidelines. Standard errors are clustered at the country-level. Level coefficients are omitted for brevity. All regressions use the number of transactions completed by the relationship as intensity measure. Column (1) runs on the sample of only relationship-product triplets that transact in every quarter. Column (2) is estimated via the selection model described in in Appendix B. Column (3) re-runs the regression on data aggregated to the annual level rather than quarterly. Column (4) controls for importer and exporter size separately, and Column (5) controls for the actual value transacted of the product in the quarter. Column (6) includes two dummies d^{GDP}_{med} and d^{GDP}_{high}, respectively, capturing whether a country's average GDP per capita over the sample period was in the second or third tercile, respectively, and two average Rule of Law dummies from Kaufmann et al. (2010). Column (7) has a fixed effect for each country interacted with the exchange rate change. Columns (8) and (9) re-run the regression on the sample of positive (including zero) and negative exchange rate changes, respectively. Column (10) includes a control for how long the relationship is going to last in total. Column (11) contains exporter-product fixed effects.

Table I.5: Pass-Through Robustness - Value Change Since Year One ($\Delta\ln(YValue_{mxt})$)

$\Delta\ln(p)$	Every qtr	Selection	Annual	Size	Trans Val	GDP/Law	Country FE	Pos	Neg	Length	Exp FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\Delta\ln(e)$	.4390***	.5474***	.5503***	.8347***	.4190***	.2503**	.1517	.5632***	.3075**	.5702***	.5700***
	(.1469)	(.1597)	(.1488)	(.1916)	(.1130)	(.0972)	(.3570)	(.2045)	(.1363)	(.1630)	(.1670)
Trade Chg Since Y1 $\cdot\Delta\ln(e)$	.0107	.0148**	.0064	.0173***	.0134***	.0023	.0059	.0611***	−.0087	.0069	.0127***
	(.0068)	(.0058)	(.0049)	(.0050)	(.0049)	(.0046)	(.0044)	(.0174)	(.0092)	(.0042)	(.0043)
Time Gap $\cdot\Delta\ln(e)$		.0099***	.0569***	.0088***	.0071***	.0075***	.0047***	.0026	.0059**	.0066***	.0065***
		(.0027)	(.0139)	(.0021)	(.0020)	(.0021)	(.0015)	(.0089)	(.0033)	(.0020)	(.0019)
Avg Size $\cdot\Delta\ln(e)$	−.0245**	−.0360***	−.0305***			−.0184**	−.0067**	−.0333*	−.0195*	−.0405***	−.0357***
	(.0104)	(.0119)	(.0100)			(.0080)	(.0033)	(.0165)	(.0102)	(.0121)	(.0123)
Imp Size $\cdot\Delta\ln(e)$				−.0139***							
				(.0029)							
Exp Size $\cdot\Delta\ln(e)$				−.0273***							
				(.0091)							
Trans Val $\cdot\Delta\ln(e)$					−.0251***						
					(.0078)						
Trade Chg $\cdot\Delta\ln(e)\cdot d^{GDP}_{\text{med}}$						.0116					
						(.0113)					
Trade Chg $\cdot\Delta\ln(e)\cdot d^{GDP}_{\text{high}}$						.0186					
						(.0111)					
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Rel-product FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	–
GDP/Law FE $\cdot\Delta\ln(e)$	–	–	–	–	–	Y	–	–	–	–	–
Country FE $\cdot\Delta\ln(e)$	–	–	–	–	–	–	Y	–	–	–	–
Total Length $\cdot\Delta\ln(e)$	–	–	–	–	–	–	–	–	–	Y	–
Exp-product FE	–	–	–	–	–	–	–	–	–	–	Y
Observations	6,113,000	26,560,000	2,717,000	13,850,000	13,850,000	13,850,000	13,850,000	7,422,000	5,196,000	13,850,000	15,290,000

Note: Number of observations has been rounded to the nearest 1000 as per U.S. Census Bureau Disclosure Guidelines. Standard errors are clustered at the country-level. Level coefficients are omitted for brevity. All regressions use the annual trade value relative to the first year of the relationship as intensity measure. Column (1) runs on the sample of only relationship-product triplets that transact in every quarter. Column (2) is estimated via the selection model described in in Appendix B. Column (3) re-runs the regression on data aggregated to the annual level rather than quarterly. Column (4) controls for importer and exporter size separately, and Column (5) controls for the actual value transacted of the product in the quarter. Column (6) includes two dummies d^{GDP}_{med} and d^{GDP}_{high}, respectively, capturing whether a country's average GDP per capita over the sample period was in the second or third tercile, respectively, and two average Rule of Law dummies from Kaufmann et al. (2010). Column (7) has a fixed effect for each country interacted with the exchange rate change. Columns (8) and (9) re-run the regression on the sample of positive (including zero) and negative exchange rate changes, respectively. Column (10) includes a control for how long the relationship is going to last in total. Column (11) contains exporter-product fixed effects.

Table I.6: Pass-Through Robustness - Cumulative Value Traded ($\ln(CumValue_{mxt})$)

$\Delta\ln(p)$	Every qtr	Selection	Annual	Size	Trans Val	GDP/Law	Country FE	Pos	Neg	Length	Exp FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\Delta\ln(e)$	.3982***	.5263***	.5100***	.7898***	.3600***	.2131***	.1312	.4905**	.2788**	.5522***	.5410***
	(.1420)	(.1631)	(.1503)	(.1910)	(.1190)	(.0866)	(.3575)	(.2066)	(.1355)	(.1678)	(.1650)
Cum Value $\cdot\Delta\ln(e)$	.0345***	.0305***	.0452***	.0497***	.0240***	.0280**	.0179***	.0242	.0302***	.0126	.0360***
	(.0111)	(.0063)	(.0104)	(.0076)	(.0085)	(.0113)	(.0060)	(.0169)	(.0111)	(.0132)	(.0074)
Time Gap $\cdot\Delta\ln(e)$		.0095***	.0366**	.0083***	.0068***	.0073***	.0046***	.0022	.0055*	.0066***	.0059***
		(.0023)	(.0157)	(.0021)	(.0021)	(.0021)	(.0015)	(.0088)	(.0031)	(.0020)	(.0020)
Avg Size $\cdot\Delta\ln(e)$	−.0269**	−.0391***	−.0306***			−.0200**	−.0079**	−.0306*	−.0222**	−.0408***	−.0391***
	(.0107)	(.0120)	(.0099)			(.0078)	(.0033)	(.0156)	(.0102)	(.0120)	(.0124)
Imp Size $\cdot\Delta\ln(e)$				−.0137***							
				(.0029)							
Exp Size $\cdot\Delta\ln(e)$				−.0312***							
				(.0093)							
Trans Val $\cdot\Delta\ln(e)$					−.0240***						
					(.0077)						
Cum Value $\cdot\Delta\ln(e)\cdot d^{GDP}_{\text{med}}$						−.0020					
						(.0201)					
Cum Value $\cdot\Delta\ln(e)\cdot d^{GDP}_{\text{high}}$						−.0118					
						(.0259)					
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Rel-product FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	–
GDP/Law FE $\cdot\Delta\ln(e)$	–	–	–	–	–	Y	–	–	–	–	–
Country FE $\cdot\Delta\ln(e)$	–	–	–	–	–	–	Y	–	–	–	–
Total Length $\cdot\Delta\ln(e)$	–	–	–	–	–	–	–	–	–	Y	–
Exp-product FE	–	–	–	–	–	–	–	–	–	–	Y
Observations	6,113,000	26,560,000	2,717,000	13,850,000	13,850,000	13,850,000	13,850,000	7,422,000	5,196,000	13,850,000	15,290,000

Note: Number of observations has been rounded to the nearest 1000 as per U.S. Census Bureau Disclosure Guidelines. Standard errors are clustered at the country-level. Level coefficients are omitted for brevity. All regressions use the cumulative value traded up to the current year relative to the average trade value of the relationship as intensity measure. Column (1) runs on the sample of only relationship-product triplets that transact in every quarter. Column (2) is estimated via the selection model described in in Appendix B. Column (3) re-runs the regression on data aggregated to the annual level rather than quarterly. Column (4) controls for importer and exporter size separately, and Column (5) controls for the actual value transacted of the product in the quarter. Column (6) includes two dummies d^{GDP}_{med} and d^{GDP}_{high}, respectively, capturing whether a country's average GDP per capita over the sample period was in the second or third tercile, respectively, and two average Rule of Law dummies from Kaufmann et al. (2010). Column (7) has a fixed effect for each country interacted with the exchange rate change. Columns (8) and (9) re-run the regression on the sample of positive (including zero) and negative exchange rate changes, respectively. Column (10) includes a control for how long the relationship is going to last in total. Column (11) contains exporter-product fixed effects.

Table I.7: Pass-Through Robustness - Months Since First Trade of Product h ($PLength_{mxht}$)

$\Delta \ln(p)$	Every qtr	Selection	Annual	Size	Trans Val	GDP/Law	Country FE	Pos	Neg	Length	Exp FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\Delta \ln(e)$	.4422***	.5472***	.5206***	.8238***	.3890***	.2480**	.1533	.5485**	.2951**	.5595***	.5610***
	(.1479)	(.1845)	(.1472)	(.1917)	(.1100)	(.0975)	(.3571)	(.1352)	(.1350)	(.1613)	(.1650)
Prod Length $\cdot \Delta \ln(e)$	.0020***	.0015***	.0211***	.0021***	.0017***	.0009*	.0009***	.0012**	.0011**	.0012***	.0019***
	(.0005)	(.0003)	(.0033)	(.0003)	(.0003)	(.0005)	(.0002)	(.0005)	(.0005)	(.0003)	(.0004)
Time Gap $\cdot \Delta \ln(e)$		.0084***	.0259*	.0072***	.0061***	.0068***	.0042***	.0069	.0036	.0063***	.0048***
		(.0026)	(.0132)	(.0021)	(.0020)	(.0021)	(.0015)	(.0087)	(.0029)	(.0021)	(.0019)
Avg Size $\cdot \Delta \ln(e)$	−.0276**	−.0378***	−.0311***			−.0195**	−.0075**	−.0335**	−.0198*	−.0401***	−.0375***
	(.0110)	(.0131)	(.0101)			(.0082)	(.0033)	(.0166)	(.0101)	(.0121)	(.0125)
Imp Size $\cdot \Delta \ln(e)$				−.0130***							
				(.0028)							
Exp Size $\cdot \Delta \ln(e)$				−.0302***							
				(.0096)							
Trans Val $\cdot \Delta \ln(e)$					−.0254***						
					(.0078)						
Prod Length $\cdot \Delta \ln(e) \cdot d^{GDP}_{\text{med}}$						.0009					
						(.0006)					
Prod Length $\cdot \Delta \ln(e) \cdot d^{GDP}_{\text{high}}$						.0000					
						(.0006)					
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Rel-product FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	–
GDP/Law FE $\cdot \Delta \ln(e)$	–	–	–	–	–	Y	–	–	–	–	–
Country FE $\cdot \Delta \ln(e)$	–	–	–	–	–	–	Y	–	–	–	–
Total Length $\cdot \Delta \ln(e)$	–	–	–	–	–	–	–	–	–	Y	–
Exp-product FE	–	–	–	–	–	–	–	–	–	–	Y
Observations	6,113,000	26,560,000	2,717,000	13,850,000	13,850,000	13,850,000	13,850,000	7,422,000	5,196,000	13,850,000	15,290,000

Note: Number of observations has been rounded to the nearest 1000 as per U.S. Census Bureau Disclosure Guidelines. Standard errors are clustered at the country-level. Level coefficients are omitted for brevity. All regressions use the number of months since the relationship's first transaction of the given product as intensity measure. Column (1) runs on the sample of only relationship-product triplets that transact in every quarter. Column (2) is estimated via the selection model described in in Appendix B. Column (3) re-runs the regression on data aggregated to the annual level rather than quarterly. Column (4) controls for importer and exporter size separately, and Column (5) controls for the actual value transacted of the product in the quarter. Column (6) includes two dummies d^{GDP}_{med} and d^{GDP}_{high}, respectively, capturing whether a country's average GDP per capita over the sample period was in the second or third tercile, respectively, and two average Rule of Law dummies from Kaufmann et al. (2010). Column (7) has a fixed effect for each country interacted with the exchange rate change. Columns (8) and (9) re-run the regression on the sample of positive (including zero) and negative exchange rate changes, respectively. Column (10) includes a control for how long the relationship is going to last in total. Column (11) contains exporter-product fixed effects.

Table I.8: Pass-Through - Heterogeneity by Frequency of Trade, Size, and Products

$\Delta \ln(p_{mxht})$	Frequency		Size		Products	
	High	Low	Small	Large	Single Prod	Multi Prod
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln(e)$	.4124***	.6134***	.4000***	.6578***	.6825***	.5074***
	(.1427)	(.1687)	(.1492)	(.1964)	(.2445)	(.1415)
Length $\cdot \Delta \ln(e)$	.0012***	.0017***	.0014***	.0020***	.0018***	.0016***
	(.0003)	(.0002)	(.0002)	(.0003)	(.0005)	(.0002)
Time Gap $\cdot \Delta \ln(e)$	.0265**	.0056***	.0048*	.0099***	.0136***	.0046**
	(.0104)	(.0018)	(.0024)	(.0031)	(.0045)	(.0021)
Avg Size $\cdot \Delta \ln(e)$	−.0306**	−.0429***	−.0248**	−.0512***	−.0527**	−.0335***
	(.0116)	(.0129)	(.0107)	(.0177)	(.0200)	(.0099)
Time FE	Y	Y	Y	Y	Y	Y
Rel-product FE	Y	Y	Y	Y	Y	Y
Observations	6,338,000	7,515,000	9,412,000	4,441,000	2,774,000	11,080,000

Note: Number of observations has been rounded to the nearest 1000 as per U.S. Census Bureau Disclosure Guidelines. Standard errors are clustered at the country level. Columns (1) and (2) present the baseline regression for the sample of relationship-product triplets where the average time gap between transactions is above the median and below the median, respectively. Columns (3) and (4) present the baseline regression for the sample of importer-exporter relationships whose summed trade value is below and above the median, respectively. Columns (5) and (6) present the baseline regression for the sample of importer-exporter relationships that trade only one product and that trade several products, respectively.

Table I.9: Pass-Through Robustness: Specifications with Lags

$\Delta \ln(p_{mxht})$	Full Sample			Every Quarter		
	$K=2$	$K=3$	$K=4$	$K=2$	$K=3$	$K=4$
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln(e_{c,t-1,t})$	$.5945^{***}$	$.5921^{***}$	$.5993^{***}$	$.4485^{***}$	$.4481^{***}$	$.4475^{***}$
	(.1722)	(.1810)	(.2005)	(.1466)	(.1448)	(.1449)
$\Delta \ln(e_{c,t-2,t-1})$	$.0499^{***}$	$.0505^{**}$	.0318	$.0379^{***}$	$.0382^{***}$	$.0411^{***}$
	(.0140)	(.0194)	(.0227)	(.0081)	(.0084)	(.0095)
$\Delta \ln(e_{c,t-3,t-2})$		$-.0013$	.0128		$-.0026$	$-.0018$
		(.0184)	(.0226)		(.0121)	(.0117)
$\Delta \ln(e_{c,t-4,t-3})$			$.0496^{**}$			.0153
			(.0220)			(.0106)
$\Delta \ln(e_{c,t-1,t}) \cdot Length$	$.0016^{***}$	$.0015^{***}$	$.0013^{***}$	$.0013^{***}$	$.0013^{***}$	$.0013^{***}$
	(.0002)	(.0002)	(.0002)	(.0004)	(.0004)	(.0004)
$\Delta \ln(e_{c,t-2,t-1}) \cdot Length$	.0000	.0000	.0001	.0002	.0002	.0002
	(.0002)	(.0003)	(.0003)	(.0002)	(.0003)	(.0003)
$\Delta \ln(e_{c,t-3,t-2}) \cdot Length$		.0001	$-.0001$		.0001	.0000
		(.0002)	(.0003)		(.0002)	(.0002)
$\Delta \ln(e_{c,t-4,t-3}) \cdot Length$			.0000			.0001
			(.0003)			(.0003)
Time FE	Y	Y	Y	Y	Y	Y
Rel-product FE	Y	Y	Y	Y	Y	Y
Obs	$9,981,000$	$7,651,000$	$6,070,000$	$6,113,000$	$6,113,000$	$6,113,000$

Note: Number of observations has been rounded to the nearest 1,000 as per Census Bureau disclosure guidelines. Standard errors are clustered at the country level. $\Delta \ln(e_{c,t-k,t-(k-1)})$ is the change in the exchange rate between quarter $t-k$ and $t-(k-1)$. Columns (1)-(3) present the results of regression (2) using up to four lags. Columns (4)-(6) present the results of the same regressions for the sample restricted to relationship-HS10 triplets that trade in every quarter. Level coefficients on *Length* and on Time $\text{Gap}_{mx,t-k,t-(k-1)}$, as well as on the interaction terms Time $\text{Gap}_{mx,t-k,t-(k-1)} \cdot \Delta \ln(e_{c,t-k,t-(k-1)})$ and Avg $\text{Size}_{mx} \cdot \Delta \ln(e_{c,t,t-1})$ are not shown for brevity.

Table I.10: Pass-Through - Country Groups

$\Delta \ln(p_{mxht})$	GDP			OECD		Country Groups				
	Low	Medium	High	Non-Member	Member	Europe	China	Rest Asia	Mexico	Canada
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta \ln(e)$	.0542	$.5744^{***}$	$.7500^{**}$	.0110	$.6171^{***}$	$.9090^{***}$	$-.0342$	.1160	$-.0670$	$-.6000^{**}$
	(.0770)	(.1902)	(.3247)	(.0871)	(.1639)	(.0136)	(.2390)	(.0820)	(.1330)	(.2560)
$\text{Length} \cdot \Delta \ln(e)$	$.0008^{**}$	$.0012^{***}$	$.0012^{***}$	$.0007^{**}$	$.0014^{***}$	$.0010^{**}$	$.0021^{*}$	$.0009^{***}$	.00004	$.0024^{*}$
	(.0004)	(.0004)	(.0004)	(.0003)	(.0003)	(.0005)	(.0013)	(.0003)	(.0007)	(.0014)
$\text{Time Gap} \cdot \Delta \ln(e)$	$.0089^{**}$	$.0084^{**}$	.0031	$.0092^{*}$	$.0076^{**}$	.0034	$.0335^{***}$	.0029	.0070	.0039
	(.0043)	(.0039)	(.0041)	(.0045)	(.0030)	(.0029)	(.0057)	(.0024)	(.0090)	(.0135)
$\text{Avg Size} \cdot \Delta \ln(e)$	$-.0038$	$-.0353^{***}$	$-.0396$	$-.0001$	$-.0395^{***}$	$-.0577^{***}$	.0261	$-.0056$	.0095	$.0431^{**}$
	(.0060)	(.0107)	(.0256)	(.0074)	(.0121)	(.0114)	(.0200)	(.0069)	(.0089)	(.0200)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Rel-product FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	7,310,000	4,020,000	2,522,000	8,175,000	5,678,000	3,649,000	4,941,000	3,802,000	394,000	550,000

Note: Number of observations has been rounded to the nearest 1000 as per U.S. Census Bureau Disclosure Guidelines. Standard errors are clustered at the country level except for the single-country regressions. Columns (1)-(3) show results from the baseline regression for groups of countries based on their tercile in terms of average GDP per capita throughout the sample period. Columns (4)-(5) show results for countries that are not in the OECD and that are in the OECD, respectively. Columns (6)-(10) show the results for different countries and geographical regions.

Table I.11: Pass-Through - Currency Groups

$\Delta\ln(p_{mxht})$	Countries				Products					
Foreign Currency Share	Low		High		Low		Medium		High	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta\ln(e)$	.0988***	.0716	.4250***	.7444***	.2450***	.9054***	.1770***	.4881***	.2090***	.3940**
	(.0214)	(.0667)	(.0431)	(.2029)	(.0585)	(.2505)	(.0492)	(.1418)	(.0531)	(.1689)
Length $\cdot\,\Delta\ln(e)$		.0010***		.0008*		.0015***		.0015***		.0016***
		(.0002)		(.0004)		(.0002)		(.0003)		(.0005)
Time Gap $\cdot\,\Delta\ln(e)$		.0084***		.0036		.0029		.0090***		.0023
		(.0029)		(.0031)		(.0037)		(.0023)		(.0046)
Avg Size $\cdot\,\Delta\ln(e)$		−.0040		−.0369***		−.0626***		−.0357***		−.0229*
		(.0057)		(.0149)		(.0194)		(.0102)		(.0119)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Rel-product FE	N	Y	N	Y	N	Y	N	Y	N	Y
Observations	9,636,000	9,636,000	4,217,000	4,217,000	2,814,000	2,814,000	7,459,000	7,459,000	3,580,000	3,580,000

Note: Number of observations has been rounded to the nearest 1000 as per U.S. Census Bureau Disclosure Guidelines. Standard errors are clustered at the country level. Columns (1)-(2) show the baseline regression for countries that have a low share of non-U.S. dollar pricing, without controls and with controls, respectively. Columns (3)-(4) present analogous results for countries with high non-U.S. dollar pricing. High non-U.S. dollar pricing countries are those listed in Table 1 of Gopinath et al. (2010). All others are low non-U.S. dollar pricing. Columns (5)-(10) present the results for products that have a low, medium, and high share of non-U.S. dollar pricing based on Gopinath et al. (2010). The ”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.

Table I.12: Pass-Through - Network of the Firms

$\Delta \ln(p_{mcxht})$	Types of Relationships					
	One Supplier	Several Suppliers	One Customer	Several Customers	One-to-One	Not One-to-One
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln(e)$	$.6176^{***}$	$.5691^{***}$	$.5795^{***}$	$.5620^{***}$	$.8266^{***}$	$.5632^{***}$
	(.2040)	(.1647)	(.1583)	(.1724)	(.2436)	(.1644)
Length $\cdot \Delta \ln(e)$	$.0013^{*}$	$.0016^{***}$	$.0018^{***}$	$.0015^{***}$	$.0020^{***}$	$.0016^{***}$
	(.0007)	(.0002)	(.0003)	(.0002)	(.0007)	(.0002)
Time Gap $\cdot \Delta \ln(e)$	$-.0062$	$.0069^{***}$	$.0053^{*}$	$.0067^{***}$	.0037	$.0063^{***}$
	(.0056)	(.0022)	(.0029)	(.0022)	(.0060)	(.0021)
Avg Size $\cdot \Delta \ln(e)$	$-.0421^{***}$	$-.0392^{***}$	$-.0392^{***}$	$-.0389^{***}$	$-.0642^{***}$	$-.0386^{***}$
	(.0154)	(.0122)	(.0112)	(.0129)	(.0203)	(.0121)
Time FE	Y	Y	Y	Y	Y	Y
Rel-product FE	Y	Y	Y	Y	Y	Y
Observations	645,000	13,210,000	4,796,000	9,056,000	288,000	13,560,000

Note: Number of observations has been rounded to the nearest 1000 as per U.S. Census Bureau Disclosure Guidelines. Standard errors are clustered at the country level. Column (1) shows the baseline regression for the subset of relationship-product triplets where the buyer only has one supplier. Column (2) presents the results for triplets where the buyer has more than one supplier. Column (3) presents the results for suppliers that have only one customer for a given product, and column (4) shows the regression results for suppliers that have several customers. Column (5) presents the baseline regression for the set of relationship-product triplets where the buyer has only one supplier, and this supplier only has the buyer as its customer. Column (6) presents the complement of this set.

Table I.13: Pass-Through - Fixed Length

$\Delta \ln(p_{mcxht})$	Fixed length (in months)		
	$[2-3)$ years	$[3-4)$ years	$[4-5)$ years
	(1)	(2)	(3)
$\Delta \ln(e)$	$.5797^{***}$	$.4502^{***}$	$.6289^{***}$
	$(.1669)$	$(.1877)$	$(.2023)$
Length $\cdot \Delta \ln(e)$	$-.0009$	$.0016^{**}$	$.0010^{*}$
	$(.0011)$	$(.0008)$	$(.0005)$
Time Gap $\cdot \Delta \ln(e)$	$.0135^{**}$	$.0109^{**}$	$.0064^{*}$
	$(.0059)$	$(.0042)$	$(.0036)$
Avg Size $\cdot \Delta \ln(e)$	$-.0396^{***}$	$-.0289^{**}$	$-.0414^{***}$
	$(.0114)$	$(.0141)$	$(.0147)$
Time FE	Y	Y	Y
Rel-product FE	Y	Y	Y
Observations	$2,402,000$	$1,780,000$	$1,392,000$

Note: Number of observations has been rounded to the nearest 1000 as per U.S. Census Bureau Disclosure Guidelines. Standard errors are clustered at the country level. Columns (1)-(3) show the baseline regression for relationships of a fixed total length until termination.

Table I.14: Im-Paseran-Shin Test for Unit Roots

	e_{mxht}	p_{mxht}
	(1)	(2)
$\bar{\bar{Z}}$	266.3661	-403.2720
p-value	1.0000	0.0000
Panels	$65,100$	$65,100$
Obs	$1,676,000$	$1,676,000$

Note: $\bar{\bar{Z}}$ denotes the Im-Paseran-Shin test statistic of a unit root test in a panel dataset. Rejection of the test implies that no unit root is present. Only panels with at least 20 observations are used.

Table I.15: Pass-Through - "Naive" Relationship Definition

$\Delta \ln(p_{mcxht})$	No size	Baseline	Every qtr	Size	GDP/Law	Full FE
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln(e)$	$.1727^{***}$	$.6546^{***}$	$.3565^{**}$	$.8316^{***}$	$-.0135$	$.3109^{***}$
	(.0557)	(.1578)	(.1670)	(.1720)	(.3117)	(.0409)
Length $\cdot \Delta \ln(e)$	$.0013^{***}$	$.0014^{***}$	$.0013^{***}$	$.0017^{***}$	$.0007^{***}$	$.0004^{***}$
	(.0002)	(.0002)	(.0005)	(.0002)	(.0002)	(.0001)
Time Gap $\cdot \Delta \ln(e)$	.0010	.0007		.0008	$.0014^{**}$	$.0014^{***}$
	(.0009)	(.0009)		(.0009)	(.0006)	(.0002)
Avg Size $\cdot \Delta \ln(e)$		$-.0431^{***}$	$-.0204$		$-.0201^{**}$	$-.0097^{***}$
		(.0113)	(.0127)		(.0080)	(.0027)
Imp Size $\cdot \Delta \ln(e)$				$-.0106^{***}$		
				(.0026)		
Exp Size $\cdot \Delta \ln(e)$				$-.0312^{***}$		
				(.0076)		
GDPpc $\cdot \Delta \ln(e)$					.0380	
					(.0374)	
Time FE	Y	Y	Y	Y	Y	Y
Rel-product FE	Y	Y	Y	Y	Y	Y
Law FE $\cdot \Delta \ln(e)$	–	–	–	–	Y	–
Country FE $\cdot \Delta \ln(e)$	–	–	–	–	–	Y
Observations	18,080,000	18,080,000	3,724,000	18,080,000	18,080,000	18,080,000

Note: Number of observations has been rounded to the nearest 1000 as per U.S. Census Bureau Disclosure Guidelines. Standard errors are clustered at the country level. Table presents some of the key pass-through regressions using a naive definition of relationship length, computed as the time passed since the first ever transaction of the importer-exporter pair. Column (1) shows the baseline regression excluding the control for relationship size. Column (2) shows the baseline pass-through regression. Column (3) presents the regression for only those relationship-product triplets that trade in every quarter. Column (4) controls for importer and exporter size separately, using the total value of shipments of the buyer and of the seller. Column (5) includes GDP per capita and an interaction of the exchange rate change with GDP per capita, as well as two average Rule of Law dummies from Kaufmann et al. (2010). Column (6) has a fixed effect for each individual country interacted with the exchange rate change.

Table I.16: 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 I.17: Price Regression by Industry

	Animal	Vegetables	Fats	Food	Minerals	Chemicals	Plastics	Leather	Wood
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Length	−0.0001***	−0.0001***	−0.0001	−0.0001***	0.0001	−0.0004***	−0.0001*	−0.0002***	−0.0003***
	(0.00002)	(0.00003)	(0.0001)	(0.00002)	(0.0001)	(0.00007)	(0.00006)	(0.00004)	(0.00005)
d_6	−0.0016**	−0.0035***	−0.0007	−0.0040***	−0.0028	−0.0032*	−0.0063***	−0.0025**	−0.0008
	(0.0007)	(0.0007)	(0.0039)	(0.0008)	(0.0028)	(0.0017)	(0.0018)	(0.0011)	(0.0013)
d_{11}	−0.0012	−0.0053***	0.0013	−0.0035***	0.0018	−0.0038*	−0.0061***	−0.0010	−0.0041***
	(0.0008)	(0.0008)	(0.0051)	(0.0010)	(0.0034)	(0.0022)	(0.0022)	(0.0015)	(0.0017)
d_{16}	−0.0011	−0.0073***	−0.0015	−0.0033***	0.0040	−0.0058**	−0.0063***	−0.0007	−0.0057***
	(0.0009)	(0.0009)	(0.0061)	(0.0011)	(0.0039)	(0.0026)	(0.0026)	(0.0017)	(0.0020)
d_{21}	−0.0015*	−0.0122***	−0.0085	−0.0067***	0.0012	−0.0088***	−0.0084***	−0.0019	−0.0063***
	(0.0008)	(0.0008)	(0.0062)	(0.0011)	(0.0034)	(0.0025)	(0.0024)	(0.0016)	(0.0019)
d_{41}	−0.0029***	−0.0095***	−0.0047	−0.0073***	0.0081*	−0.0121***	−0.0048	−0.0040*	−0.0123***
	(0.0010)	(0.0010)	(0.0083)	(0.0014)	(0.0043)	(0.0034)	(0.0031)	(0.0021)	(0.0024)
Rel-product FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
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
Length	−0.00004***	−0.0004***	−0.0003***	−0.0002**	−0.0005***	−0.0013***	−0.0010***	−0.0009***
	(0.00001)	(0.00002)	(0.00005)	(0.0001)	(0.00003)	(0.00004)	(0.00006)	(0.00005)
d_6	0.0008***	0.0002	−0.0046***	−0.0051	−0.0066***	−0.0107***	−0.0073***	−0.0029**
	(0.0003)	(0.0006)	(0.0013)	(0.0038)	(0.0008)	(0.0011)	(0.0017)	(0.0015)
d_{11}	0.0007*	−0.0011*	−0.0069***	−0.0145***	−0.0090***	−0.0136***	−0.0086***	−0.0028
	(0.0004)	(0.0007)	(0.0017)	(0.0048)	(0.0010)	(0.0014)	(0.0020)	(0.0019)
d_{16}	0.0004	−0.0011	−0.0065***	−0.0180***	−0.0123***	−0.0182***	−0.0095***	−0.0098***
	(0.0005)	(0.0009)	(0.0020)	(0.0055)	(0.0012)	(0.0016)	(0.0023)	(0.0022)
d_{21}	−0.0010**	−0.0035***	−0.0086***	−0.0171***	−0.0146***	−0.0239***	−0.0078***	−0.0094***
	(0.0004)	(0.0008)	(0.0019)	(0.0052)	(0.0011)	(0.0015)	(0.0020)	(0.0021)
d_{41}	−0.0024***	−0.0089***	−0.0098***	−0.0202***	−0.0170***	−0.0307***	−0.0096***	−0.0136***
	(0.0006)	(0.0010)	(0.0026)	(0.0067)	(0.0014)	(0.0019)	(0.0024)	(0.0027)
Rel-product FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	20,890,000	3,526,000	2,612,000	543,000	5,553,000	8,680,000	2,347,000	2,387,000

Note: Number of observations has been rounded to the nearest 1000 as per U.S. Census Bureau Disclosure Guidelines.