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

Theory and Evidence

Sebastian Heise*

Federal Reserve Bank of New York

March 27, 2024

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)

*33 Liberty Street, New York, NY 10045. Email: sebastian.heise@ny.frb.org. This paper was previously circulated under the title "Firm-to-Firm Relationships and Price Rigidity" and was part of my doctoral dissertation. I thank Eduardo Engel, Pinelopi Goldberg, Giuseppe Moscarini, Peter Schott, and Aleh Tsyvinski for their advice and support throughout this project. I am also thankful to Costas Arkolakis, Oleg Itskhoki, Davide Melcangi, Michael Peters, and Tommaso Porzio, as well as to seminar participants at Bocconi, Deutsche Bundesbank, UIUC, Colorado Boulder, UT Austin, Edinburgh, Toronto, EIEF, Minneapolis Fed, New York Fed, Richmond Fed, UNC Chapel Hill, and USC Marshall for their comments. I thank Joseph Vavra for sharing his pass-through data, and René Chalom and Julia Wu for excellent research assistance. This material is based upon work supported by the National Science Foundation under Grant Number 1427027. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author and do not necessarily reflect the views of the National Science Foundation, the Federal Reserve Bank of New York, or the U.S. Census Bureau. The Census Bureau has reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1883 (CBDRB-FY23-P1883-R11057, CBDRB-FY23-P1883-R11122) and FSRDC Project Number 2407 (CBDRB-FY24-P2407-R11266).

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 – which presumably are 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 relationships' life cycle. My findings suggest that the responsiveness of prices to shocks co-varies 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 approximately 260 million arms' length import transactions conducted by U.S. firms between 1992 and 2017. As in the domestic economy, long-term relationships are common in U.S. imports – in an average quarter, about 43% of U.S. arms' length imports are sourced within

[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.

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

[4] Recent work by, e.g., Duprez and Magerman (2018), Tintelnot et al. (2021), and Bernard et al. (2022) uses annual VAT data to study domestic linkages in Belgium. However, these data are not at the transaction-level. Huneeus (2018) uses within-country transaction-level data, for Chile.

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. In a new relationship, price movements on average reflect 13% 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, such as the number of transactions and the cumulative value traded.

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, and is less likely to separate compared to when the relationship was young. Individual relationships follow a life cycle: new relationships start small, 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 four 12% more than in year one.

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)). 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.

[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.

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 foreign 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, such relationships' outside options are less likely to bind. Consequently, high-capital relationships have on average higher pass-through and higher mark-ups.

My model links relationship capital and age via selection. By virtue of having survived for longer, the average old relationship must have received relatively good idiosyncratic shocks. Thus, it has relatively high capital. 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.

I estimate the model structurally and show that it 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]

[6] I assume that some inputs are priced in dollars and 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.

Literature. My paper contributes to several strands of literature. First, I show that an economy's average relationship length may affect macroeconomic outcomes of interest, such as aggregate pass-through and mark-ups. Prior work studying the evolution of buyer-seller relationships has mostly analyzed relationships' micro-level properties, such as matching patterns (Eaton et al. (2021)), relationships' ability to relax limited commitment constraints (Macchiavello and Morjaria (2015)), and the value and duration of relationships (Monarch and Schmidt-Eisenlohr (2023)). 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.

Second, I point out an additional source of heterogeneity in exchange rate pass-through. Prior work has documented local costs (Goldberg and Verboven (2001)), imported inputs (Amiti et al. (2014)), imperfect competition (Atkeson and Burstein (2008)), or firm size (Berman et al. (2012)) as factors influencing pass-through. I show that, even conditional on firm size and country, pass-through rises as a relationship's length and intensity increase. Heterogeneity in relationship length across countries could thus 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). While the learning-by-doing literature finds increasing mark-ups, it has not investigated how learning affects pass-through. My mechanism also relates to the literature on price setting under customer base concerns (Phelps and Winter (1970), Kleshchelski and Vincent (2009), Gourio and Rudanko (2014), Foster et al. (2016), Paciello et al. (2019)). In contrast to this literature, I use transaction-level data to follow firm-to-firm relationships over time, and document life cycle properties that are not present in consumer markets.

Finally, the paper is related to the literature on firm-to-firm networks (e.g., Chaney (2014), Lim (2018), Huneeus (2018), Tintelnot et al. (2021)), and in particular to recent work studying heterogeneity in firms' mark-ups (Kikkawa et al. (2022)). My work is complementary to this literature by examining one layer of the supply chain in more detail with transaction-level data.

My finding of a larger price response in longer relationships is of relevance for the transmission of shocks throughout a network more generally.

This paper proceeds as follows. Section 2 presents the empirical analysis. 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. Second, I study the dynamics of a relationship to understand the potential mechanism. I show that (i) the value traded in relationships follows a life cycle; (ii) prices decline with relationship age; and (iii) old relationships are less likely to separate.

2.1 Data

Due to the lack of transaction-level data on buyer-supplier relationships in the U.S. domestic economy, I study relationships between U.S. firms and their overseas suppliers using customs data from the *Longitudinal Firm Trade Transactions Database (LFTTD)* of the U.S. Census Bureau. This dataset comprises the entire universe of import transactions in goods[8] made by U.S. firms since 1992. The data record for each import transaction an identifier of the U.S. importer as well as a foreign exporter ID (called "MID"), which is generated from components of the name, the address, and the city of the foreign supplier.[9] The data also contain the 10-digit Harmonized System (HS10) code of the product traded[10], the country of the foreign exporter, the quantity and the value

[8]Trade in goods accounted for more than 80% of all U.S. imports in 1992-2017.

[9]Specifically, the MID is generated as a combination of the origin country's ISO2 code, six characters taken from the producer's name, the first three letters of the producer's city, and up to four numeric characters taken from its address. See Kamal and Monarch (2018) for details.

[10]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".

shipped (in U.S. dollars), the date of the shipment, and an identifier for whether the two transaction parties are related firms.[11] I focus on the period 1992-2017.

I perform several standard data cleaning operations, such as dropping observations with missing importer or exporter ID and dropping warehouse entries. I deflate import values with the quarterly GDP deflator to make them comparable across years. I use the deflated values for all analyses except for the pass-through regressions, which use the nominal, non-deflated import prices. I compute (log) prices as unit values by dividing the shipment value by the quantity shipped, as in Monarch and Schmidt-Eisenlohr (2023). I focus on arms' length relationships only and exclude related party transactions, which include for example intra-firm trade, by dropping all importer-exporter pairs that record at least one related party transaction.[12] Prices in related party transactions are possibly non-allocative, for example due to profit shifting motives (see Bernard et al. (2006)), and hence I cannot accurately analyze pass-through for these. Appendix A.1 provides more detail on the data preparation steps and provides sample statistics.

An important requirement for my analysis is that I can reliably identify foreign exporters using the MID. Earlier work by Kamal and Monarch (2018) shows that the MID is a reasonably accurate identifier of foreign suppliers, and Redding and Weinstein (2017) find that using the MID as exporter identifier recovers many salient features of exporting activity, such as the high rates of product and firm turnover. I therefore follow Pierce and Schott (2016), Monarch (2021), Eaton et al. (2021), and Monarch and Schmidt-Eisenlohr (2023), who have all used the reported MID to study foreign exporters to the U.S, and use the MID as my baseline identifier of foreign suppliers. However, to gauge the sensitivity of my definition of foreign firms, I perform two sets of robustness checks. First, I identify foreign exporters using a "shortened MID" where I combine MIDs with the same address and city component into one. Kamal et al. (2015) show that this treatment of MIDs leads to a better match of the number of exporters with the number of sellers in the World

[11] 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".

[12] 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.

Bank's Exporter Dynamics Database. Second, I develop a new concordance that combines MIDs with similar strings and transaction patterns into one. This method extends previous work by Kamal and Monarch (2018) to the entire LFTTD. I show below that these three different definitions of a foreign supplier lead to similar results for all my analyses. Appendix A.1 provides more details on how the different treatments of the MID affect the sample, and Appendix A.2 describes the construction of my new MID concordance.

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 previously, 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.[13] 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 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 are traded within their 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 this end date, I treat it as a new relationship.[14] 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 allows me to determine more clearly whether relationships that have last traded near the end of the

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

[14] 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.

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. Appendix B provides summary statistics on matching and relationship length.[15]

Figure 1a presents the distribution of value traded by relationship length based on my definition. The blue bars show that 9% of the value traded in arms' length transactions is accounted for by relationships that have been together for more than four years, and 43% is due to pairs that have been together for more than 12 months. However, most matches are actually quite short-lived. The orange bars show that 33% of all pairs observed in an average quarter are less than one month old. However, such new matches account for only 20% of the value traded.[16]

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.[17] 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.

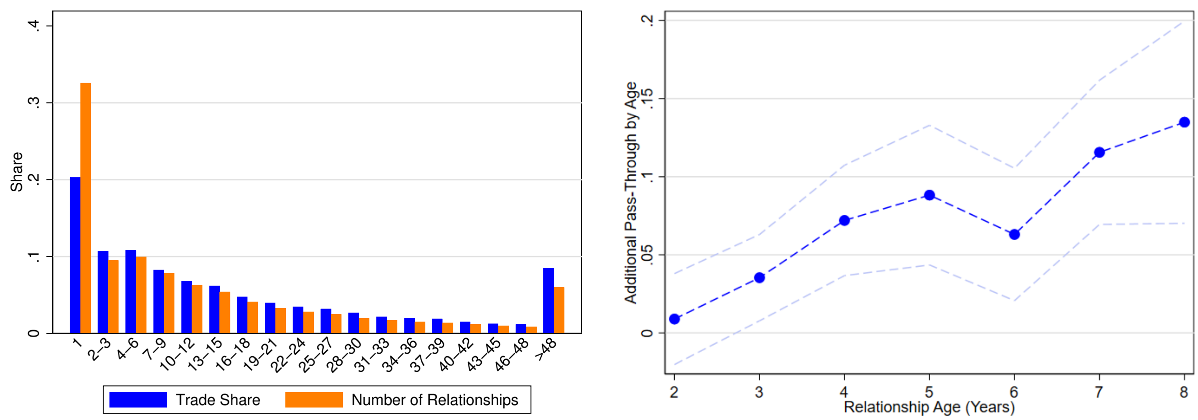
[15]Figure B.1 in Appendix B shows the overall distribution of trade by importer industry.

[16]In Appendix A.3, 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. Table B.3 in Appendix B 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.

[17]The LFTTD does not contain information on the type of contract used, e.g., fixed-price versus price-indexed. I can therefore only indirectly test whether long-term relationships use more fixed-price contracts by examining whether they adjust their prices less in response to shocks.

Figure 1: Relationship Age and Pass-Through

(a) Relationships by Length (in Months) (b) Pass-Through Relative to Year One



Notes: The left panel shows the distribution of relationships across different relationship length buckets for arms' length relationships between 1995-2017. The blue bars show the share of value traded in an average quarter by relationships with the current length in months indicated on the x-axis. The orange bars display the equally-weighted distribution of buyer-seller relationships by length (i.e., the count of relationships). The right panel is based on a version of regression (1), where the continuous variable $Length_{mxt}$ has been replaced by annual dummies for relationship length. I plot the coefficients on the interactions between annual relationship length dummies and exchange rate changes, $d^i_{mxt} \cdot \Delta \ln(e_{mxht})$, where d^i_{mxt} are dummies that are equal to one if the relationship is currently i years old.

Baseline. Let m index an importer, x the exporter, c the exporter's country, h the 10-digit Harmonized System (HS10) product code, and t the quarter. A relationship, which may trade one or several products, is indexed by mx. I aggregate the data to the quarterly level to smooth out noise in the unit values. My baseline specification is

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

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. Exchange rates are measured in U.S. dollar per foreign currency unit.[18] 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 price changes. 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 relationship length.

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 due to, e.g., 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.[19] I control for this channel by adding the

[18] Appendix A.1 provides further information on the sources of the exchange rate data. In total, my data cover 45 countries listed in Table A.4 in Appendix A.1.

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

number 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 may have lower pass-through into import prices for example because they 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, $\ln(\text{Avg Size}_{mx})$. 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, 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 0.13. The third column shows the full specification. For each additional month a relationship has lasted, the responsiveness of prices to exchange rate shocks rises by 0.0015. Thus, pass-through in a relationship that is four years old is about 7.2 percentage points higher than when the relationship was new. Coefficients on the interactions with Time Gap_{mxht} and Avg Size_{mx} show that pass-through is higher when more time has passed and lower when the relationship is larger.

Figure 1b 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.[20]

The positive correlation between pass-through and relationship age could arise via two forces: (i) relationships with greater total duration have higher average pass-through throughout their life,

[20] One might interpret this result as consistent with previous work showing higher exchange rate pass-through between related partners than in arms' length trade (Neiman (2010)) if firms that are related parties are interpreted as having a very close relationship, subject to the caveat that related party prices may also reflect other motives.

Table 1: Pass-Through Regressions

	Length			Intensity		
				Trans	Cum value	Prod months
$\Delta \ln(p)$	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln(e)$	0.2081***	0.1327***	0.4816**	0.4969**	0.4513**	0.4723**
	(0.0475)	(0.0398)	(0.1858)	(0.1885)	(0.1844)	(0.1848)
Length $\cdot \Delta \ln(e)$		0.0012***	0.0015***			
		(0.0001)	(0.0002)			
Time Gap $\cdot \Delta \ln(e)$		0.0067***	0.0056***	0.0066***	0.0069***	0.0058***
		(0.0021)	(0.0016)	(0.0017)	(0.0017)	(0.0016)
Avg Size $\cdot \Delta \ln(e)$			−0.0315**	−0.0325**	−0.0319**	−0.0302*
			(0.0151)	(0.0152)	(0.0151)	(0.0151)
Intensity $\cdot \Delta \ln(e)$				0.0040***	0.0354***	0.0016***
				(0.0006)	(0.0061)	(0.0003)
Time FE	Y	Y	Y	Y	Y	Y
Rel-product FE (γ)	N	Y	Y	Y	Y	Y
R-Squared	.0007	.1055	.1055	.1054	.1055	.1055
Observations	27,120,000	27,120,000	27,120,000	27,120,000	27,120,000	27,120,000

Notes: 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 for brevity. 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 three alternative measures of relationship intensity described in the text.

generating a positive correlation between pass-through and age via selection; (ii) pass-through could increase dynamically within a given relationship as it ages. To investigate these channels, in Appendix C.1 I study the evolution of pass-through as a relationship ages for fixed total relationship length groups. I find that both channels are present: relationships that last longer tend to start off with a higher baseline level of pass-through, and pass-through increases dynamically with relationship age. As the relationship nears termination pass-through tends to decline again, suggesting a life cycle of pass-through.

The remaining columns of Table 1 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, $Trans_{mxt}$. In column (5), 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 (6), I 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 three measures. I show in Section 2.4 that trade volume and relationship age 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 examining whether differences in the trading frequency of old versus new relationships drive my results. First, I re-run the baseline regression for only those relationship-product triplets that transact in every quarter of their existence, hence all triplets have the same frequency of trade in this sample. I still find increasing pass-through with relationship age (column (1) of Table 2). Tables C.2-C.4 in Appendix C.2 replicate this table separately for each of the three alternative measures of relationship intensity discussed above, and show that my findings also hold for these measures. Second, 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, such as the exchange rate, and estimate a selection model for panel data.[21] It yields similar results. Third, Table C.5 in Appendix C.2 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. Fourth, to assess whether the difference in pass-through between new and old relationships disappears over longer time horizons, I aggregate the dataset to the annual level and then re-run regression (1), where $Length_{mxt}$ is now measured in years (Column (3) of Table 2). Finally, in Table C.6 I include lagged exchange rate changes and their interactions. The results are similar in all cases.

I next examine whether heterogeneity in firm size affects my findings. In Column (4) of Table 2 (and in Table C.2-C.4), I include controls for the importer's and 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. 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}. In both cases I find similar results. I next split the sample into relationships with above and below median relationship size 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. Table C.5 shows that pass-through increases with relationship length in all specifications, but most strongly for large relationships.

In the third set of robustness checks, I study the impact of exporter country heterogeneity. In Column (6) of Table 2, I add to my baseline specification two dummies for the country's average GDP per capita 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,

[21] Appendix D provides more details on the selection model.

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
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta\ln(e)$	.2412	.3485*	.4511**	.7443***	.3867***	$-.2950$	.1050***	.5037*	.3807**
	(.1577)	(.1994)	(.1876)	(.1856)	(.1176)	(.2716)	(.0342)	(.2537)	(.1714)
Length $\cdot\,\Delta\ln(e)$	.0010***	.0012***	.0130***	.0018***	.0012***	.0010***	.0006***	.0012***	.0011***
	(.0004)	(.0003)	(.0036)	(.0002)	(.0001)	(.0002)	(.0001)	(.0003)	(.0003)
Time Gap $\cdot\,\Delta\ln(e)$		.0148***	.0871***	.0053***	.0056***	.0059***	.0040***	.0103**	.0031
		(.0041)	(.0155)	(.0018)	(.0017)	(.0016)	(.0010)	(.0045)	(.0023)
Avg Size $\cdot\,\Delta\ln(e)$	$-.0103$	$-.0257$	$-.0268^{*}$			$-.0136$	$-.0041$	$-.0323$	$-.0253^{*}$
	(.0126)	(.0164)	(.0144)			(.0096)	(.0029)	(.0209)	(.0137)
Imp Size $\cdot\,\Delta\ln(e)$				$-.0033$					
				(.0041)					
Exp Size $\cdot\,\Delta\ln(e)$				$-.0364^{***}$					
				(.0096)					
Trans Val $\cdot\,\Delta\ln(e)$					$-.0246^{***}$				
					(.0088)				
Length $\cdot\,\Delta\ln(e)\cdot d^{GDP}_{\text{med}}$						.1037			
						(.0902)			
Length $\cdot\,\Delta\ln(e)\cdot d^{GDP}_{\text{high}}$						.0757			
						(.1321)			
λ		.0128***							
		(.0026)							
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Rel-product FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
GDP/Law FE $\cdot\Delta\ln(e)$	–	–	–	–	–	Y	–	–	–
Country FE $\cdot\Delta\ln(e)$	–	–	–	–	–	–	Y	–	–
Observations	9,061,000	53,550,000	6,326,000	27,120,000	27,120,000	27,120,000	27,120,000	13,530,000	11,150,000

Notes: 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 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 Appendix D. 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 (8) re-run the regression on the sample of positive (including zero) and negative exchange rate changes, respectively.

I continue to find rising pass-through with relationship age and intensity, although the coefficients become smaller and noisier. Next, in Table C.7 I run the baseline regression separately for different groups of countries based on GDP per capita, for OECD and non-OECD members, and for different geographical regions. Table C.8 analyzes the effect of the currency of invoice.[22] 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 with age for all groups.

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

I provide several additional robustness exercises in Appendix C.2. First, I replicate Tables 1 and 2 when relationships are defined using exporters with the shortened MID (Tables C.9 and C.10) and the concorded MID (Tables C.11 and C.12). The findings are similar. Second, the findings are robust to adding an additional control for how long a relationship is going to last in total (Table C.13). Third, pass-through could be affected by a firm's network. Kikkawa et al. (2022) find that firms that account for a larger share of a customer's inputs set higher mark-ups, and Tintelnot et al. (2021) show that a firm's unit cost change in response to a foreign cost shock depends on the economy's network structure. While I do not observe firms' full network, I show in Table C.14 that pass-through increases with relationship age for sellers with one or multiple customers and for buyers with one or multiple suppliers. Fourth, I show in Table C.15 that my results hold for different fixed effect configurations. Fifth, I show in Table C.16 that cointegration is not an issue. Finally, I find in Table C.17 that my results hold when 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, regardless of the time gaps between transactions.

[22] 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.

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 price declines with age; (iii) old relationships are less likely to separate than new relationships.

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 0-11 of the relationship, months 12-23, etc., up to the relationship's end. Since many relationships do not trade in every year, I assume that the value purchased is equally distributed across intermittent years with zero trade.[23] 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 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

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

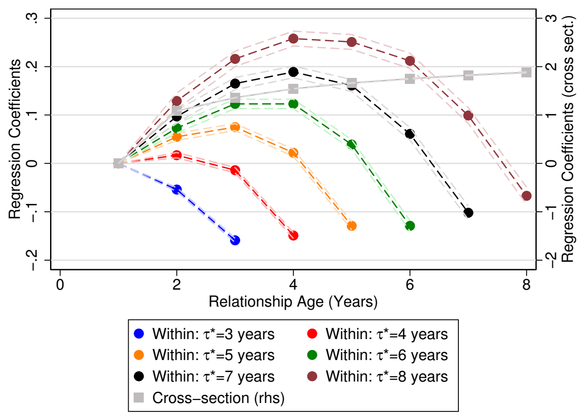
where $y_{mx\tau}$ is the total trade value of relationship mx in relationship year τ and $d_{mx,i}$ are dummies for the relationship's age in years. The gray squares in Figure 2a plot the coefficients and 95% confidence bands from this regression, with year one normalized to zero. There is a clear positive correlation between relationship age and trade, consistent with a framework in which older relationships on average trade more. Figures E.1a-E.1b in Appendix E 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. To address this

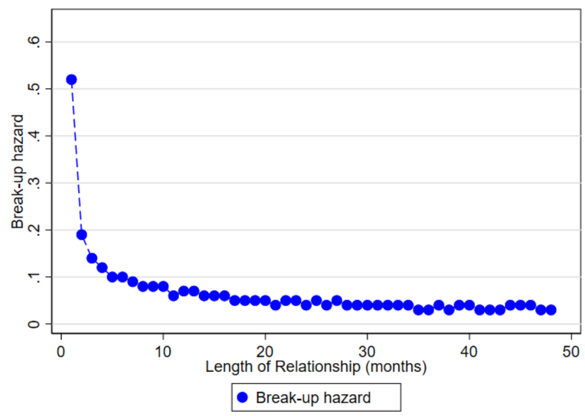
[23] This is consistent with a linear inventory policy with repurchase once the inventory level hits zero.

Figure 2: Relationship Dynamics

(a) Life Cycle of Value Traded



(b) Relationship Break Up Hazard



Notes: The left panel shows the relationship life cycle of value traded. The gray line plots the estimated coefficients on the relationship year dummies from regression (2) against the right-hand side y-axis. On the x-axis, relationships are in year one when they are 0-11 months old, relationships are in year two when they are 12-23 months old, and so on. The colored lines present the regression results when I condition on how long the relationship lasts in total and include relationship fixed effects, against the left-hand side y-axis. $\tau^* = 3$ years means that the relationship lasts three full years but fewer than four full years, so 36-47 months. $\tau^* = 4$ years means that the relationship lasts four full years but fewer than five full years, so 48-59 months. The right panel presents the probability of separation, i.e., the maximum gap time has elapsed, by length of the relationship in months. In each month t I compute a weighted average share of relationships that separate at each age, where the weight is the relationships' trade value over the past 12 months. I then take a simple average of these separation rates across all months t in the sample.

concern, I sort relationships into groups based on how many complete years a relationship lasts in total, $\tau^* = \{3,4,5,6,7,8\}$. I then examine relationship dynamics within sets of relationships of equal total duration by running regression (2) within each of these groups separately, where I add relationship fixed effects γ_{mx} to control for relationship heterogeneity.[24] The circles in Figure 2a 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 increases over the first few years and then declines gradually until the relationship's end. For example, for relationships lasting six years in total, the value traded in year three is 12% 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. Figures E.2a and E.2b in Appendix E show similar life cycles when I use the shortened MID or the concorded MID.

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 in my model validation below, and develop a theory that incorporates both mechanisms. My findings are consistent with Fitzgerald et al. (2023), who show that exporters gradually increase their sales in a new destination. 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 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)). In the *build-up and maturity stage*, the benefits of being in

[24] 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)).

the relationship gradually increase as products become more customized and production more efficient. 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 now analyze relationship-product triplets because overall relationships may trade several products with different prices. Analogous to equation (2), for each transaction j I first run a simple cross-sectional regression of prices on dummies for relationship age:

$$\ln(\tilde{p}_{mxhj}) = \sum_{i \geq 2} \beta_i d^i_{mxj} + \varepsilon_{mx\tau}, \tag{3}$$

where d^i_{mxj} is a dummy equal to one if the relationship age at transaction j is i years. The left-hand side variable $\ln(\tilde{p}_{mxhj})$ is the *relative* log price, computed as the log transaction price minus the log average price for that product-country combination in that quarter. The use of relative prices removes product- or country-specific price trends, and hence captures how a relationship's prices compare to the product-country average.[25] Column 1 in Table 3 shows that older relationships have on average lower prices: an 8-year relationship's prices are on average about 11% below those of a new relationship.

As before, I re-run this regression separately for relationship groups based on how many complete years a relationship lasts, and include relationship-product fixed effects γ_{mxh} to control for relationship heterogeneity. The results, in columns 2-7 of Table 3, indicate that prices decline slightly with relationship age. For a relationship lasting six years in total, the price in year three is about 2% below its level in the first year. Tables E.1 and E.2 in Appendix E show a similar pattern when I use the shortened MID or the concorded MID instead of the reported one.

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

[25] Since prices are demeaned, time dummies are not needed.

Table 3: Price Setting by Relationship Length

$\ln \tilde{p}_{mxhj}$	Cross Section	3 Years Total	4 Years Total	5 Years Total	6 Years Total	7 Years Total	8 Years total
Rel. Age	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2 Years	$-.0672^{***}$	$-.0113^{***}$	$-.0085^{***}$	$-.0078^{***}$	$-.0098^{***}$	$-.0124^{***}$	$-.0146^{***}$
	(.0088)	(.0011)	(.0009)	(.0018)	(.0019)	(.0021)	(.0027)
3 Years	$-.0762^{***}$	$-.0200^{***}$	$-.0176^{***}$	$-.0171^{***}$	$-.0171^{***}$	$-.0183^{***}$	$-.0272^{***}$
	(.0111)	(.0018)	(.0016)	(.0023)	(.0032)	(.0024)	(.0033)
4 Years	$-.0832^{***}$		$-.0243^{***}$	$-.0229^{***}$	$-.0208^{***}$	$-.0251^{***}$	$-.0346^{***}$
	(.0127)		(.0022)	(.0034)	(.0040)	(.0042)	(.0032)
5 Years	$-.0862^{***}$			$-.0296^{***}$	$-.0315^{***}$	$-.0337^{***}$	$-.0432^{***}$
	(.0147)			(.0041)	(.0039)	(.0044)	(.0034)
6 Years	$-.0918^{***}$				$-.0375^{***}$	$-.0448^{***}$	$-.0541^{***}$
	(.0173)				(.0045)	(.0055)	(.0037)
7 Years	$-.0943^{***}$					$-.0502^{***}$	$-.0584^{***}$
	(.0170)					(.0064)	(.0046)
8 Years	$-.1066^{***}$						$-.0629^{***}$
	(.0198)						(.0046)
Rel-product FE	N	Y	Y	Y	Y	Y	Y
R-Squared	.0012	.7970	.7899	.7797	.7728	.7697	.7719
Observations	150,600,000	12,260,000	10,090,000	8,143,000	6,302,000	4,929,000	4,004,000

Notes: 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. Column 1 presents the regression coefficients of the cross-sectional specification (3). Columns 2-7 show the results of running this regression for relationships that last in total $\{3,4,5,6,7,8\}$ full years, where additionally relationship-product fixed effects γ_{mxh} have been added. $\tilde{p}_{mxhj}$ is the log transaction price of transaction j of importer-exporter-product triplet mxh minus the log average price of the product and country in that quarter. The coefficients on "2 years",... "8 years" are the coefficients on the dummies d^i_{mxj} that are equal to one if the relationship is i years old at transaction j.

Frankwick (2005)). In Appendix E, I examine to what extent the price declines are due to quantity discounts versus the direct productivity or learning effect. Using the demand of a firm's downstream industries as instrument for the quantity imported, I show that prices decline both due to quantity discounts and a direct effect. Price declines tend to be strongest for differentiated products such as chemicals, machinery, and transportation. 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:

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

Figure 2b shows the average hazard rate across all months t. It declines very rapidly: from 52% in the first month to 7% in month 12.[26] The finding that relationships are likely to break up early aligns well with the presence of an "exploration phase" of the relationship life cycle.

3 Model

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

[26] Eaton et al. (2021) and Monarch (2021) show similar results for Colombian and Chinese suppliers, respectively.

3.1 Setup

Environment. Let time t be discrete. There is a continuum of symmetric small open economies denoted by $i \in [0,1]$. Given symmetry, I will omit the country indices below. Each country is populated by a representative household, which aggregates a continuum of final goods $b \in [0,1]$

$$Y_t = \left(\int_0^1 y_t(b)^{(\theta-1)/\theta} db \right)^{\theta/(\theta-1)}, \tag{4}$$

where $y_t(b)$ is the quantity of good b and $\theta > 1$ is the demand elasticity. Given price $p_t^f(b)$, the household demand for good b is $y_t(b) = (\frac{p_t^f(b)}{P_t})^{-\theta} Y_t$, where $P_t = (\int p_t^f(b)^{1-\theta} db)^{1/(1-\theta)}$ is the final goods price index.

The final goods are non-tradeable and produced by a continuum of buyer firms in the same country according to $y_t(b) = Aq_t$. A buyer firm's input q_t is sourced from a *foreign* seller firm s with which the buyer is matched in a relationship r as described below. Given the seller's price $p_t(r)$, expressed in the destination country's currency, profit maximization implies that the buyer sets a standard mark-up over marginal costs for downstream consumers: $p_t^f(b) = \frac{\theta}{\theta-1} \frac{p_t(r)}{A}$.

Seller s produces input q_t with the production function $f(a_t, x_t)$, where a_t is a productivity shifter and x_t an input bundle. The input bundle combines two primary inputs l and z according to $x_t = l_t^{\alpha} z_t^{1-\alpha}$. Here, l_t is a foreign input, such as labor, and z_t is an input priced in destination country currency. Such an input could be local labor used to assemble or distribute the good in the destination, or an imported input.[27] The seller's input costs in destination currency are thus $w_t = (e_t \omega_l^*)^{\alpha} (\omega_z)^{1-\alpha}$, where ω_l^* is the price of the foreign input and ω_z is the price of the destination input. The exchange rate e_t transforms the cost of the foreign input into destination currency. I assume $\ln(e_{t+1}) = \varphi \ln(e_t) + \xi_{t+1}$, with $\varphi < 1$ and $\xi_{t+1} \sim N(0, \sigma_\xi^2)$ independent across countries and time, where e_t is expressed in buyer country currency per foreign currency unit.

The seller's marginal costs depend on how the production function $f(a_t, x_t)$ combines x_t and a_t. I assume a general marginal cost function $c(a_t, w_t)$, and assume that $\partial c / \partial a < 0$ and $\partial^2 c / \partial a^2 > 0$,

[27] Amiti et al. (2014) show that large exporters are also large importers.

i.e., costs decrease at a declining rate with a_t.[28] An increase in a_t can reflect any process that reduces costs or that raises the amount of quality produced per unit of input. Marginal costs increase in the cost of the seller's input bundle, $\partial c/\partial w > 0$: increases in the exchange rate e_t, i.e., foreign currency appreciations, act as cost shocks for the seller in destination currency.

Relationship Capital. Previous work has suggested that long-term relationships allow the seller to learn about the buyer's requirements (e.g., Rauch and Watson (2003)) or about the seller's reliability (Macchiavello and Morjaria (2015)), to collaborate more efficiently (Defever et al. (2016)), or to customize outputs (Bernard et al. (2018)). To capture these mechanisms in a reduced-form way, I interpret the productivity shifter a_t as specific to the relationship, $a_t(r)$, and refer to it as *relationship capital*. I assume that relationship capital evolves according to

$$a_{t+1}(r) = (1-\delta)a_t(r) + \rho q_t(p_t(r)) + \varepsilon_{t+1}, \tag{5}$$

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. I show in Appendix F.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. 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)).[29] 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: first, the hump-shaped relationship life cycle indicates that a relationship's value is not simply increasing over time, and hence I need a mechanism that allows relationships to deteriorate. Second, the fact that prices decrease with relationship age motivates the introduction of a productivity shifter,

[28] For concreteness, in the quantitative estimation below, I will assume $c(a_t, w_t) = \frac{w_t}{a_t^\gamma}$.

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

rather than a demand-side mechanism. I therefore introduce relationship capital as a stochastic productivity term. While empirically I only observe relationship age, I show in Section 4 that a relationship's age is tightly correlated with its level of relationship capital due to selection.

Matching. Buyers and sellers meet in a frictional international matching market. There exists a unit mass of buyers and a mass S of seller firms in each country. Let v_i be the mass of unmatched buyers in country i, with $v \equiv \int_0^1 v_i di$ the total mass of unmatched buyers. Similarly, denote by u_i the mass of sellers in country i that are not matched with a buyer, with $u \equiv \int_0^1 u_i di$. Buyers and sellers meet through a CES matching function $M(v,u) = (v^{-\iota} + u^{-\iota})^{-(1/\iota)}$. Given market tightness $\vartheta_t = v_t/u_t$, the probability that an unmatched buyer finds a seller is $\pi_b(\vartheta_t) = (1+\vartheta_t^{\iota})^{-(1/\iota)}$, and the probability that an unmatched seller finds a buyer is $\pi_s(\vartheta_t) = \vartheta_t(1+\vartheta_t^{\iota})^{-(1/\iota)}$. Once a match is formed, initial relationship capital is drawn from a distribution $G(a)$. Unmatched sellers obtain zero profits. Unmatched buyers purchase the input from a domestic spot market at price $p_t(\emptyset) = \frac{\chi}{A}$. I assume that buyers and sellers can unilaterally terminate the relationship at any time.[30]

Price Setting Problem. I will solve the model in steady state below, where the aggregate variables (P_t, ϑ_t) are fixed. Since countries are atomistic and symmetric, and exchange rates are stationary and i.i.d., each firm faces the same steady state distribution of exchange rates with respect to the other countries by the law of large numbers. Consequently, each country has the same steady state distribution of relationships and the same price level P.[31]

I assume that the seller sets prices, subject to the buyer's participation constraint. Given the fixed aggregate state variables (P, ϑ), a seller's pricing decision depends on the two state variables specific to her current relationship: relationship capital a, and the exchange rate e with her buyer's country. I therefore index the relationship by (a,e) from now on. Given price p in destination

[30] For example, Rauch and Watson (2003) provide evidence that buyers abandon a relationship if they find a better match. See also Defever et al. (2016), Bernard et al. (2018), and Monarch (2021).

[31] To be clear, steady state does not mean that each individual relationship stays unchanged, but only that the distribution of relationships is stationary.

currency, a seller's profits in destination currency are

$$\Pi_s(a,e) = [p - c(a,e)]\, q(p), \tag{6}$$

where $q(p)$ is a function of household demand $y(b)$ and hence of the seller's price p:

$$q(p) = \frac{y(b)}{A} = (\tfrac{p^f(b)}{P})^{-\theta}\frac{Y}{A} = \left(\frac{\theta}{\theta-1}\right)^{-\theta} P^{\theta}A^{\theta-1}Yp^{-\theta}. \tag{7}$$

Exchange rate fluctuations act as a cost shock for the seller: her inputs are partially priced in foreign currency, but her output price is in destination currency.[32] Under standard static profit maximization, the seller would maximize (6) by setting $p = \frac{\theta}{\theta-1}c(a,e)$.

In my model, there are dynamic considerations since the seller can increase the amount of relationship capital in the next period by setting a lower price today (see (5)). The seller therefore maximizes the present discounted value of present and future profits, $J(a,e)$, rather than static profits. Since (a,e) follow first-order Markov processes, I write the problem recursively as[33]

$$J(a,e) = \max_p\, [p - c(a,e)]\, q(p) + \beta E\left\{\max\left\{J(a',e'),V\right\}\right\}, \tag{8}$$

where β is the discount factor, (a',e') are next period's relationship capital and exchange rate of the relationship, and the expectation is taken with respect to the evolution of these two variables. When the relationship is terminated, the seller receives an "outside option" value equal to

$$V = \beta[\pi_s(\vartheta)EJ(a,e) + (1-\pi_s(\vartheta))V]. \tag{9}$$

The outside option reflects that in the next period with probability $\pi_s(\vartheta)$ an unmatched seller draws a new relationship from the steady state distribution of (a,e) with expected value $EJ(a,e)$, and remains unmatched for another period otherwise.

The buyer's relationship value is

$$W(a,e) = \left[p^f(a,e) - \tfrac{p(a,e)}{A}\right] y(p^f(a,e)) + \beta E\left[I'(a',e')W(a',e') + (1-I'(a',e'))U\right], \tag{10}$$

where $I'(a',e')$ is a dummy variable that is equal to one if the relationship is continued in state

[32] This assumption mirrors pricing in the U.S., since around 90% of U.S. imports are priced in U.S. dollars (Gopinath et al. (2010)).

[33] In Appendix G.1, I prove formally that a recursive representation of the problem and an optimal policy exist, provided that the marginal cost function is sufficiently convex in relationship capital.

(a', e'). The buyer's outside option is

$$U = \Pi_b^o + \beta [\pi_b(\vartheta) EW(a, e) + (1 - \pi_b(\vartheta)) U], \tag{11}$$

where $\Pi_b^o = \frac{1}{\theta-1}(\frac{\theta}{\theta-1})^{-\theta}(\frac{\chi}{A})^{1-\theta} P^\theta Y$ are the buyer's profits when purchasing on the spot market at price χ/A. The seller maximizes (8) subject to the buyer's *participation constraint* $W(a, e) \geq U$.

Note that the relationship is continued as long as the suplus is non-negative: $I'(a', e') = 1 \Leftrightarrow W(a, e) + J(a, e) - U - V \geq 0$. Intuitively, if there exists a price at which $W(a, e) \geq U$ and $J(a, e) > V$, then the seller will set such a price, since setting a price such that $W(a, e) < U$ will lead the buyer to separate, leaving the seller strictly worse off.

3.2 Characterization

Full Commitment. I first solve the problem under full commitment and study limited commitment below. Taking the first-order condition of problem (8) with full commitment, I obtain

$$p = \frac{\theta}{\theta - 1} \left[c(a, e) - \beta \rho E J_a(a', e') \right], \tag{12}$$

where $EJ_a(a', e')$ is the derivative of the expected value function with respect to relationship capital.[34] This equation highlights that the seller sets a lower price than the static optimum $\frac{\theta}{\theta-1} c(a, e)$, 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)). I prove in Appendix G.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 $J(a, e)$ is concave in a, the price therefore becomes closer to the monopoly price as capital increases and the incentive to accumulate more capital diminishes.

The solid line in Figure 3a 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 mark-up $\frac{\theta}{\theta-1}$ over marginal costs. As shown in Appendix G.4, the seller's optimal price is strictly decreasing in a. It approaches the static optimum from below as a

[34] In Appendix G.2 I show that under the assumption of sufficient convexity of the cost function the value function is concave and the optimal policy is unique.

becomes large.[35] Since the price approaches the static optimum from below, the seller's mark-up, $\mu = p/c(a,e)$, rises with capital. The dotted line in Figure 3a plots on the right axis a typical mark-up schedule.

The pricing schedule illustrates that while the seller's price falls as capital rises, she increases her share of the joint profits by raising her mark-up towards $\theta/(\theta-1)$. 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 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. Consistent with this view, Doney and Cannon (1997) document that firms' choice of new suppliers is significantly influenced by price, but that prices become less important as the relationship develops. Jap (1999) shows that long-term relationships increase profits for both the buyer and the seller, consistent with higher mark-ups and falling costs.

Figure 3b shows the pass-through of a positive shock to costs $c(a,e)$ into the seller's price, $PT \equiv \frac{\Delta \ln p}{\Delta \ln c(a,e)}$. An increase in costs raises the price both due to a static effect, as costs increase today, and due to a dynamic effect, as the expected marginal value of additional capital declines when costs go up (see Appendix G.6). The lower value of additional relationship capital means that the seller raises the price by more than the cost change due to the diminished accumulation motive, pushing pass-through above one. Pass-through marginally declines with capital since capital accumulation is most affected by costs at low capital levels.

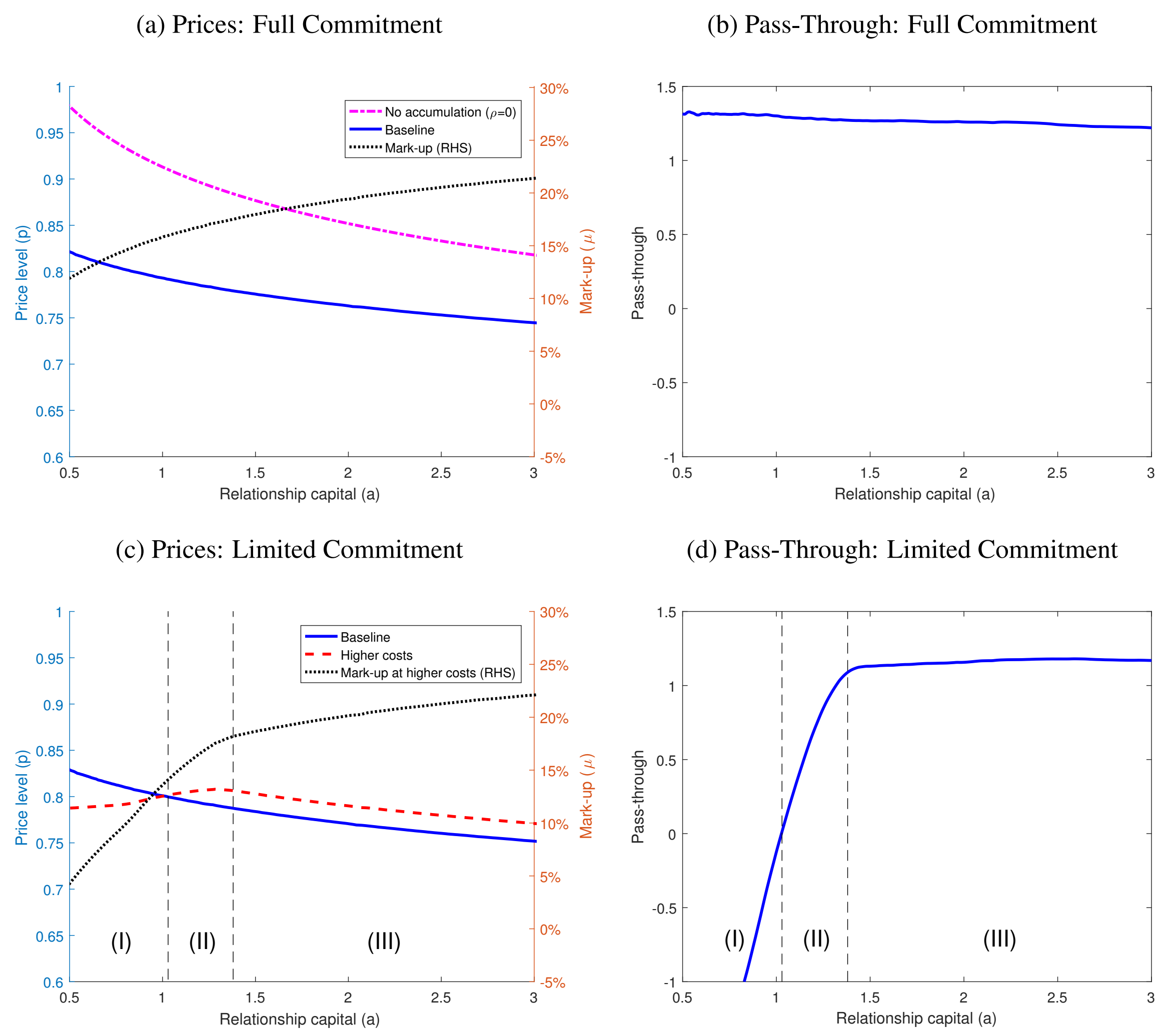
Limited Commitment. I now examine the seller's problem allowing for separations. The first-order condition of maximizing (8) subject to $W(a,e) \geq U$ is

$$p = \frac{\theta}{\theta-1+\lambda}\left\{c(a,e) - \beta\rho E\left\{I'(a',e')\left[J_a(a',e') + \lambda W_a(a',e')\right] + \lambda \frac{\partial I'}{\partial a'}\left[W(a',e') - U\right]\right\}\right\}, \quad (13)$$

(see Appendix G.7), where λ is the Lagrange multiplier on the buyer's participation constraint $W(a,e) \geq U$. Since the seller's price falls with a if the buyer is not constrained, as shown above,

[35] Appendix G.5 shows that i) $dp/d\rho < 0$ and ii) $dp/d\delta > 0$.

Figure 3: Prices and Pass-Through vs Relationship Capital



Notes: The top left panel shows the policy function of prices and mark-ups as a function of relationship capital in the model with full commitment. The blue line shows the price in the baseline model with relationship capital accumulation. The pink dashed and dotted line shows the price in a model without capital accumulation ($\rho = 0$); here, the price is just a constant markup over marginal costs, $\frac{\theta}{\theta-1}c(a,e)$. The black dotted line (on the right-hand axis) is the mark-up in the model with relationship capital accumulation. The top right panel shows the estimated pass-through of a change in costs, $\Delta \ln c(a,e)$, in the model with relationship capital accumulation and full commitment as a function of relationship capital, $PT \equiv \frac{\Delta \ln p}{\Delta \ln c(a,e)}$. The bottom left panel shows the policy function of prices for low costs (blue) and high costs (red dashed) as a function of relationship capital under limited commitment. The black dotted line (on the right-hand axis) presents the mark-up for the high-cost case. The three areas highlighted in the figure represent the case of unconstrained prices in the high-cost case (area III), constrained prices under high costs where the price is still higher than under low costs (area II), and constrained prices under high costs where the price is lower than under low costs (area I). The bottom right panel shows the estimated pass-through of a change in costs from low to high under limited commitment.

the buyer's value increases with relationship capital, $\partial W(a,e)/\partial a > 0$. Consequently, the buyer's participation constraint is more likely to bind ($\lambda > 0$) when capital is low. In that case, the seller lowers the price to provide additional surplus to the buyer to incentivize her to stay in the relationship, via three terms. First, the seller lowers her mark-up to $\frac{\theta}{\theta-1+\lambda}$. Second, the $\lambda W_a(a',e')$ term shows that the price is lower when the slope of the buyer's value function $W_a(a',e')$ is higher, since in that case small increases in relationship capital 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's outside option binds, the seller's price may be significantly below its unconstrained level.

Figure 3c presents an example of a pricing schedule for two levels of exchange rates e. At the baseline level of e (solid line) the buyer is unconstrained for all values of a in the figure and prices fall with relationship capital as before. By contrast, at a higher level of e (red dashed line), the seller's costs and hence price are higher, and the buyer's outside option becomes binding at low levels of capital (regions (I) and (II)). In these regions, the seller's pricing schedule is increasing in a.[36] Intuitively, consider an a at which the buyer is indifferent between staying and leaving, and imagine that capital declines to $a' < a$. This decrease in capital raises the seller's marginal costs in the relationship today and, due to the persistence of relationship capital, implies higher expected costs and a greater likelihood of separation in the future, making the relationship less valuable. The decline in the relationship's value causes the buyer to prefer termination to staying. To keep the buyer in the relationship, the seller has to lower her price to $p' < p$, transferring additional value to the buyer to keep $W(a,e) = W(a',e) = U$. Since the overall value of the relationship has fallen, the seller's value of the relationship declines, $J(a',e) < J(a,e)$. Separation occurs when relationship capital falls below some lower bound $\underline{a}(e)$ at which the relationship surplus becomes zero.

The intuition for an increase in the exchange rate e is similar. When e increases, the buyer's value of the relationship falls because of the higher costs and because termination becomes more

[36]See Appendix G.8 for proof.

likely. If the buyer's outside option becomes binding, the seller has to cut her price 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 compensate for the low relationship continuation value. 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. As costs rise with e, the relationship surplus falls and the separation bound $\underline{a}(e)$ increases in e, making relationship termination more likely.

Figure 3d shows that pass-through is 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 3c. The presence of negative pass-through in low-capital relationships is a key feature of my model, which I will verify empirically below. 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 show that new relationships start with on average low relationship capital close to the separation bound (regions (I) or (II) in Figure 3d). 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 3d). This mechanism will generate increasing pass-through with relationship age.

Discussion of 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 captures, in a reduced form, the features that have been emphasized in the literature, such as customization (e.g., Rauch and Watson (2003), Bernard et al. (2018)), learning (Macchiavello and Morjaria (2015)) and efficiency gains over time (e.g., Defever et al. (2016)). The setup is also motivated by two stylized facts. First, relationships' value traded follows a hump shape. This pattern cannot be explained by a mechanism where the relationship improves perpetually, such as learning about supplier quality as in Monarch and Schmidt-Eisenlohr (2023), without negative shocks, e.g., due to staff turnover. Instead, it matches survey evidence of a relationship life cycle (Dwyer et al. (1987)). Second, prices are decreasing (or at least not rising) with relationship age. This finding rules out a 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 H.1). Instead, it is in line with survey evidence that production costs in relationships fall, e.g, due to productivity improvements (Kalwani and Narayandas (1995)).[37]

The second assumption is that sellers set prices. This assumption is less restrictive than it appears because buyers' limited commitment implies that the model can accommodate different degrees of pricing power. If the buyer's separation value U is sufficiently valuable, then the seller may have to set prices close to marginal costs to prevent the buyer from leaving. Buyers such as Wal-Mart could have very good outside options and thus force sellers to set low prices (region (I) in Figure 3c). The key assumption of my theory is that the seller adjusts her markup in response to a binding participation constraint of the buyer. By lowering her markup in response to a shock, the seller reduces her pass-through. 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. I show in Appendix H.3 that this requirement rules out a standard Nash bargaining model, which always splits relationship surplus in a fixed proportion and therefore has constant pass-through.

Third, my theory focuses on one-to-one relationships. Recent work by Duprez and Magerman (2018) and Kikkawa et al. (2022) stresses the relevance of a firm's network for its price setting. As shown by Table C.14 in Appendix C.2, pass-through indeed differs based on the network. Importantly, however, the baseline finding of increasing pass-through with relationship age is robust to the firm's network configuration in my trade data.

[37] 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 H.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.

4 Quantitative Analysis

I now structurally estimate the model. The estimation serves two purposes: first, I show that the relationship capital channel can generate the empirical facts and quantitatively match the increase in pass-through with relationship age observed in the data. Second, I show that the model provides a micro foundation for countercyclical variation in pass-through, as documented by Berger and Vavra (2019), through variation in the relationship creation rate, which falls in recessions.

Since the countries are symmetric, I solve the value functions and policies for one representative buyer country. I make one change relative to the model introduced in Section 3 and assume that in the first period after matching the buyer cannot switch to an alternative spot market supplier, $\Pi_b^o = 0$, due to the time needed to set up the relationship and to learn a.[38] This extension implies that the value functions and policies in the first period take a slightly different form than in all other periods of the relationship. However, the same insights as before hold. I list the extended value functions in Appendix I.

A steady state equilibrium consists of a set of value functions, prices, break-up policies, a distribution of relationships across states $\Gamma(a,e)$, and tightness ϑ such that sellers maximize (8) subject to $W(a,e) \geq U$, buyers set prices $p^f(a,e)$ to maximize their profits, the final goods market clears, and $\Gamma(a,e) = \bar{\Gamma}(a,e)$, $u = \bar{u}$, and $v = \bar{v}$ are constant.

4.1 Simulations

Parametrization and Estimation. I fix total income in each country exogenously, $PY = 1$, and parametrize the relationship cost function as $c(a,e) = \frac{1}{a^{\gamma}}(e\omega_l^*)^{\alpha}(\omega_z)^{1-\alpha}$, where I require $\gamma < 1/\theta$.[39] I will estimate γ below. The shape of $c(a,e)$ implies that exchange rate pass-through into the seller's costs in destination currency is approximately α in the unconstrained region,

[38]This feature helps the model to better match two empirical facts: (i) many relationships with a bad draw of a will trade at least once before separating, generating the high initial separation rate; (ii) the seller can set a relatively high price in the first period since the buyer's outside option is low, generating a greater average price difference between relationships in year one and year two.

[39]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.

$\Delta\ln(c(a,e)) = \alpha\Delta\ln(e)$. This assumption provides a simple way to generate the observed average level of pass-through.[40] I will examine how pass-through rises with relationship age around this average.

I set some of the parameters outside of the model and estimate the remainder by simulated method of moments. The top part of Table 4 shows the externally calibrated parameters with their values and a brief description of how these parameters are set. The remaining parameters are estimated via MCMC using the procedure by Chernozhukov and Hong (2003). I list the values of the estimated parameters α, δ, σ_ε, γ, σ_a, ρ, and χ with the main moments providing identification in the bottom part of Table 4. I provide details on the calibrated parameters in Appendix J.1, on moments and identification in Appendix J.2-J.3, and on the estimation procedure in Appendix J.4.

Simulation Results. To visualize the model's performance, the top panels of Figure 4 show the model-generated cross-sectional share of trade by relationship age (left), the life cycle of value traded (middle), and the hazard rate of break-ups (right). Overall, the model generates a similar age distribution, life cycle, and a sharply declining break-up hazard as the data.

The bottom part of Table 4 provides more information on the model's fit. The first row shows that fully unconstrained relationships have pass-through of $\alpha = 44\%$, leading to an average pass-through of 29% in the model for relationships in their third year, a bit higher than in the data. Shocks to capital play a large role in driving the model: a one standard deviation positive shock would raise relationship capital by $\sigma_\varepsilon = 32.0\%$ 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, $\gamma = .231$ 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 9.6%. The large decreasing returns are needed to generate the relatively

[40] A more general model could generate incomplete pass-through for example through oligopolistic competition as in Atkeson and Burstein (2008). Since my theory is about the increase in pass-through with relationship length rather than its level, I choose this simple assumption to keep the model more tractable.

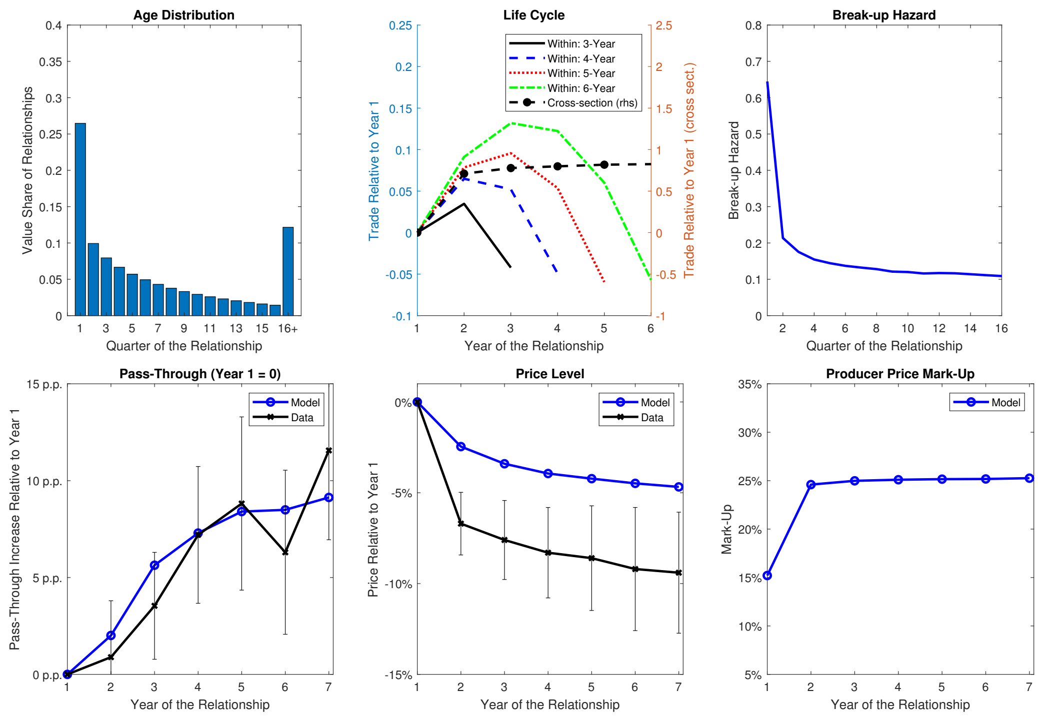
Table 4: Parameters and Moments

Panel a: Calibrated Parameters			
	Parameter	Value	Source
β	Quarterly discount factor	0.992	Assumption
θ	Elasticity of substitution	4	Nakamura and Steinsson (2008)
σ_ξ	Sd exchange rate shocks	0.066	Average quarterly log exchange rate change
φ	Persistence exchange rate process	0.99	Persistence of exchange rates
A	Productivity	1	Normalization
μ_a	Mean of new rel. capital	0	Assumption
ϑ	Matching market tightness	0.66	Time buyer needs to find supplier after exogeneous break-up
ι	Matching market elasticity	0.45	and time seller needs to find an additional buyer

Panel b: Estimated Parameters					
	Parameter		Moment		
	Value	s.e.		Model	Data
α	.444	(.060)	Pass-through in year 3	.282	.168
σ_ε	.320	(.032)	Break-up hazard Q1	.645	.667
			Break-up hazard Q2	.214	.287
δ	.063	(.014)	Value share of rels in Q1	.265	.310
			Value share of rels in >Q16	.122	.085
γ	.231	(.016)	Value traded in Year 5 - Value traded in Year 3 (for 5y rel)	$-.155$	$-.204$
σ_a	.389	(.062)	Value traded in Year 3 relative to Year 1 (for 5y rel)	.096	.075
			Price in Year 2 / Price in Year 1	$-.025$	$-.067$
ρ	.019	(.006)	Autocorrelation of quantity	$-.415$	$-.356$
			Break-up hazard Q8/Q2	.599	.456
χ	2.792	(.404)	Std initial price (residual)	.042	.044
			J (objective)	.514	

Notes: Panel (a) shows the values of the calibrated parameters. The last column provides a summary of the source of the parameter' value. Details are in Appendix J.1. Panel (b) shows the values of the estimated parameters. Details on their construction are in Appendix J.2, identification is discussed in Appendix J.3, and the estimation procedure is described in Appendix J.4. The second column of panel (b) shows the estimated value of each parameter, obtained as the best estimate from 400 Markov chains of length 100 each. The third column shows the standard deviation of the parameter estimates across the best 20 Markov chains. The last two columns show the value of the simulated moment and its corresponding value in the data. The objective function is computed as $J = \min_{\hat{\Psi}} E\left[\left(\frac{G(\hat{\Psi})-G(\Psi)}{G(\Psi)}\right)'\left(\frac{G(\hat{\Psi})-G(\Psi)}{G(\Psi)}\right)\right]$, where Ψ is the true parameter vector, $\hat{\Psi}$ is a parameter vector used in the simulation, and $G(\Psi)$ and $G(\hat{\Psi})$ are the data moments and the model moments, respectively.

Figure 4: Model-Generated Moments



Notes: The top left panel shows the share of value traded by relationships of the age indicated on the x-axis, analogous to Figure 1a. The top middle panel shows the relationship life cycle of value traded, analogous to Figure 2a. The four inverse U-shaped lines represent the average value traded in year x relative to year one of the relationship, conditional on whether the relationship lasts $\{3,4,5,6\}$ years in total. The dashed line with dots is the cross-sectional value traded, i.e., the average value traded in relationships of age x relative to the average value traded in relationships of age one, without conditioning on total relationship duration. The top right panel shows the hazard rate of relationship break-ups, similar to Figure 2b. The bottom left panel replicates the pass-through coefficients from regression (1) with annual dummies, from Figure 1b, with their 95 percent confidence intervals (black line). The blue line runs the same regression in the simulated data and plots the estimated coefficients. The bottom middle panel shows the estimated coefficients from the price regression (3), from column 1 of Table 3 (black line), with their 95 percent confidence intervals against the estimated coefficients from running the same regression in the simulated data (blue line). The bottom right panel shows the average mark-up of relationships of age x years in the model.

muted life cycle of values. In contrast to the shocks, the depreciation rate of relationship capital δ is low, at about 6% 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.

The bottom panel of Figure 4 presents the non-targeted moments generated by the model. The left panel shows that the simulated pass-through coefficients lie within the 95% confidence interval of the data from Figure 1b. Thus, while the average level of pass-through is higher in the model than in the data, the slope of pass-through with age, which is my key object of interest, matches well. The middle panel shows that the model generates lower prices of older relationships in the cross-section, although the decline in the first year is not as pronounced as in column (1) of Table 3. The large price difference between one- and two-year old relationships in the data is due to the fact that relationships that trade only once have much higher prices than my model can generate through the relationship capital mechanism alone.[41] The bottom right panel shows that mark-ups rise from on average 15% for relationships in their first year to 25% for older relationships.

Mechanism. Figure J.3 in Appendix J.5 illustrates how the model generates the empirical results 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. As a result, the relationship capital distribution of older relationships stochastically dominates that of younger ones. Higher average relationship capital means that older relationships on average trade more and have higher pass-through. Relationships that experience bad shocks lose capital until they reach the termination bound, which generates a stochastic life cycle.

Model Tests. The model has several testable implications. First, pass-through should frequently be negative in young relationships, and negative pass-through should become rarer as the relation-

[41] See for comparison columns 2-7 of Table 3: the price decline is much smaller within relationships of a given length. It is possible that one-off transactions are essentially spot market transactions and never intended to form a relationship. In principle, I could match the relatively higher prices of very short relationships by introducing another parameter that governs costs for one-off transactions. I opted against adding a parameter just to match this moment.

ship ages and trades more. Second, pass-through should be lower when the buyer has a better outside option. Third, relationships with higher pass-through in the first year last longer, since higher initial pass-through is indicative of higher initial relationship capital. I verify that these implications hold empirically in Appendix L.

4.2 Aggregate Implications

In this final section, I show that the model provides a micro foundation for countercyclical pass-through through variation in relationship creation.

The top panels of Figure 5 decompose the change in U.S. real imports between quarter t and quarter $t-4$ into six margins.[42] The three margins in the left panel contribute positively to trade: trade can grow due to i) new relationships, ii) new products traded in continuing relationships, and iii) more trade within continuing relationship-product pairs. The three margins in the right panel contribute negatively to trade: trade can decline due to iv) relationship termination, v) fewer products traded in continuing relationships, and vi) less trade within continuing relationship-products. Figure 5a shows that relationship creation is by far the most important positive margin. On average, imports by new relationships in t amount to about 51% of total imports in $t-4$. Figure 5b shows that relationship destruction is similarly important: if no new trade were added, imports would fall by about 47% because relationships that existed in $t-4$ no longer trade in t.

The key observation from the figures is that relationship creation displays strong cyclicality, falling sharply in recessions.[43] Figures K.1 and K.2 in Appendix K show that this finding also holds for relationships using the shortened or concorded MID.[44] The lack of relationship creation shifts the relationship age distribution towards older relationships in recessions, which generates cyclicality in pass-through. Figure 5c plots the relationship creation rate against the pass-through

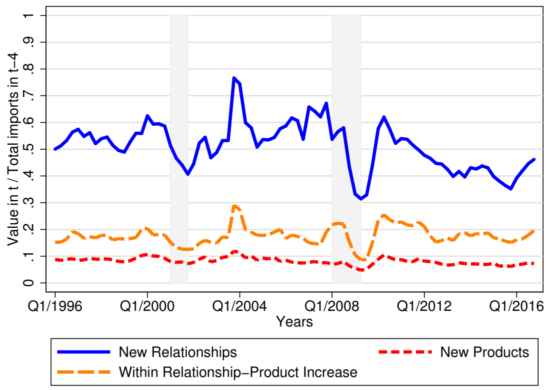
[42] Appendix K provides more details on how these margins are constructed.

[43] The HP-filtered relationship creation margin exhibits a correlation with filtered U.S. GDP of 0.46. While product additions and the intensive margins also display some cyclical behavior, the drop in net relationship creation explains about 57% of the fall in total U.S. imports in the Great Recession and 61% of the drop in the recession of 2001.

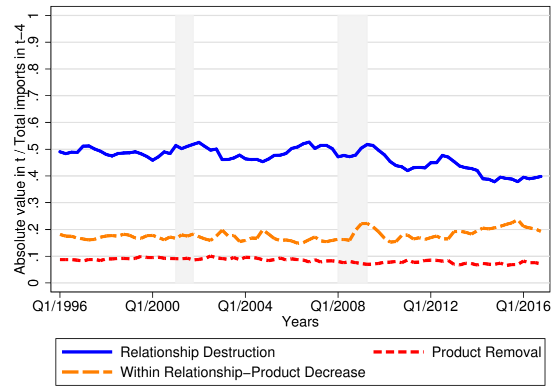
[44] Figure K.3 shows that the result is similar using a "naive" definition of relationships that does not rely on the maximum gap time. Figure K.4 shows that the drop in relationship creation is due to existing importers not forming relationships rather than variation in importer entry.

Figure 5: Decomposition of Trade and Pass-Through

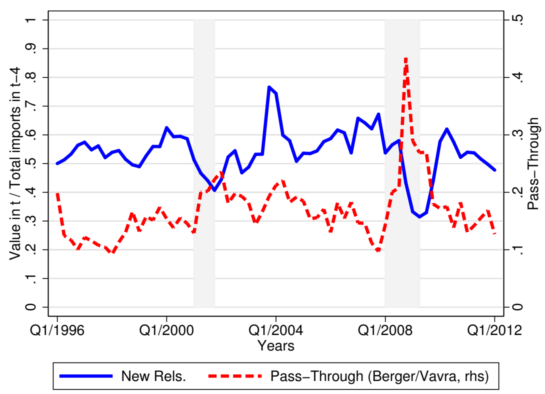
(a) Creation Margins as Share of Total Imports



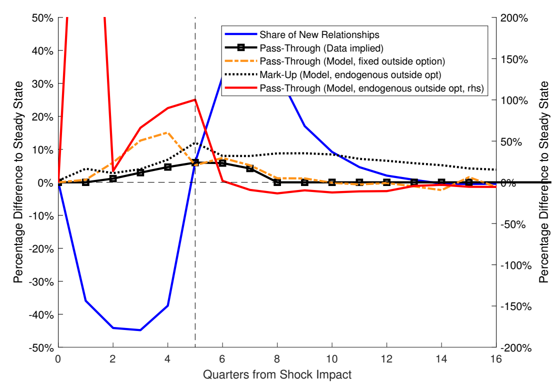
(b) Destruction Margins as Share of Total Imports



(c) Pass-Through and Relationship Creation in the Data



(d) Impact of Shock on Pass-Through and Mark-Ups



Notes: The top panels show the change in U.S. imports between quarters $t-4$ and t decomposed into six margins. The margins are constructed by taking the change in trade between $t-4$ and t for every importer-exporter-product triplet and by assigning this change in trade to one of the six categories based on my definition of whether a relationship or a product is no longer active. "New relationships" is trade by importer-exporter pairs that are new in t compared to $t-4$. "New products" is trade by importer-exporter-product triplets that are new in t compared to $t-4$ where the overall importer-exporter relationship already existed in t. "Within Relationship-Product Increase" is the change in trade for continuing importer-exporter-product triplets that trade more in t than in $t-4$. "Relationship destruction" is the (absolute value) of trade by relationships in $t-4$ that are terminated in t. "Product removal" is the (absolute value) of trade by importer-exporter-product triplets in $t-4$ that are no longer active in t while the overall relationship is still active. "Within Relationship-Product Decrease" is the (absolute value) change in trade for continuing importer-exporter-product triplets that trade less (possibly 0) in t than in $t-4$. The margins add up to the total change in imports. The bottom left panel shows the relationship creation margin (blue, left axis) against the estimated exchange rate pass-through in quarter t from Berger and Vavra (2019) (red, right axis). The bottom right panel shows the impulse response of pass-through and new relationships to an exit shock of firms. The black line with squares shows pass-through in the Great Recession from a simple empirical exercise: I compute steady state pass-through as the weighted mean of the age-specific pass-through from Figure 1b, using the value shares from Figure 1a 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 5a, and let the relationship age distribution evolve according to the steady state survival probabilities implied by the age distribution. The blue line shows the simulated value share of new relationships in the economy. The yellow dashed and red lines show the pass-through obtained from the model with fixed outside options and with adjusting outside options, respectively. The black dashed line shows the mark-ups generated by the model. All series are relative to their value in steady state.

coefficients estimated by Berger and Vavra (2019), using import price data from the Bureau of Labor Statistics.[45] As expected, the series are strongly negatively correlated.[46]

How much did the lack of relationship creation contribute to the increase in pass-through in the Great Recession? I first run a simple empirical exercise: starting in Q3/2008, I change the rate of relationship creation in the economy according to Figure 5a and compute the average pass-through in each quarter using the relationship age distribution and the estimated annual pass-through coefficients from Figure 1b. The black squares in Figure 5d show that the implied pass-through rises by 6% from its steady state before gradually falling back to the baseline. The smooth trajectory is somewhat at odds with the sharp spike in pass-through observed empirically.

I next perform the same exercise in the model. Starting in steady state in Q3/2008 ($t = 0$), I introduce a shock in $t = 1$ which exogenously causes a fraction κ_1 of currently unmatched buyers to become "inactive". 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 unmatched buyers back to zero to match the empirical change in the trade share of new relationships from the data (blue line). I hold the price level fixed at its steady state since there was no burst of deflation during the Great Recession, and assume that from $t = 1$ onwards firms have full information about the evolution of the economy. I 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 5d 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%, a bit more more than in the purely empirical exercise. This outcome arises because in the model pass-through rises a lot within a relationship's first year, i.e., between quarter two and four of a relationship, which is masked by using average annual pass-

[45] Berger and Vavra (2019) observe prices rather than unit values, and compute pass-through conditional on a firm changing price with a number of item and country controls.

[46] For comparison, Figure K.5 in Appendix K 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.

through coefficients in the empirical exercise. The solid red line (on the RHS) shows pass-through when I simulate the full model, allowing value and policy functions to vary. In this case, pass-through spikes in $t = 1$, and then stays about twice as high as its baseline level for several quarters, consistent with the data where pass-through also about doubles for several quarters. As some buyers drop out of the search market due to inactivity, the fraction of unmatched available buyers v falls, reducing market tightness. This lower tightness improves the buyers' relative outside option by raising their matching probability $\pi_b(\vartheta)$. 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, prices and costs fall simultaneously in most relationships, causing pass-through to spike as in the data.[47,48] The estimated mark-up rises by 12% during the recession due to the shift to older relationships and then declines slowly as the economy returns to its steady state.

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. I interpret this finding via a model in which buyers and sellers interact repeatedly under limited commitment and build up relationship capital to lower production costs, for example due to learning-by-doing. I estimate the model based on new facts about a relationship's life cycle and show that the model can quantitatively match the data. I then show that the model can rationalize the observed cyclicality in the pass-through of shocks via a new mechanism: variation in an economy's relationship age distribution. Since the average age of relationships increases in recessions when buyers' outside options improve relative to sellers', the model predicts a countercyclical responsiveness of prices to shocks and countercyclical mark-ups. These findings suggest that the relationship age distribution in an economy

[47]In both the baseline economy and the shocked economy I let the exchange rate process follow its law of motion plus a sequence of aggregate shocks such that my model matches the import-weighted average exchange rate of the U.S. against its major trading partners over the period Q3/2008-Q4/2009.

[48]Note that there was a smaller 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.

may be a relevant state variable for the transmission of shocks more generally.

Going beyond the cyclicality of pass-through, the model suggests that firms' outside options could be a relevant determinant of pass-through. For example, making it harder for U.S. buyers to form relationships with sellers from China due to higher tariffs may increase the prices and pass-through of shocks in relationships between U.S. buyers with Vietnamese sellers, by worsening U.S. buyers' ability to leave these relationships. Thus, trade policy may affect the transmission of shocks beyond the immediately affected countries. Additionally, policies that make it harder to form long-term relationships, such as an increase in trade policy uncertainty as suggested in Heise et al. (2024), will alter the transmission of shocks. Investigating these channels further is an interesting avenue for future research.

References

Amiti, M., O. Itskhoki, and J. Konings (2014). Importers, exporters, and exchange rate disconnect. *American Economic Review 104*(7), 1942–1978.

Anderson, E. and B. Weitz (1992). The use of pledges to build and sustain commitment in distribution channels. *Journal of Marketing Research 29*(1), 18–34.

Atkeson, A. and A. Burstein (2008). Pricing to market, trade costs and international relative prices. *American Economic Review 98*(5), 1998–2031.

Barro, R. J. (1977). Long-term contracting, sticky prices, and monetary policy. *Journal of Monetary Economics 3*(3), 305–316.

Berger, D. and J. Vavra (2019). Shocks vs responsiveness: What drives time-varying dispersion. *Journal of Political Economy 127*(5), 2104–2142.

Berman, N., P. Martin, and T. Mayer (2012). How do different exporters react to exchange rate changes? *Quarterly Journal of Economics 127*(1), 437–492.

Bernard, A. B., E. A. Bøler, and S. Dhingra (2018). Firm-to-firm connections in colombian imports. NBER Working Paper No. 24557.

Bernard, A. B., E. A. Bøler, R. Massari, J.-D. Reyes, and D. Taglioni (2017). Exporter dynamics and partial-year effects. *American Economic Review 107*(10), 3211–3228.

Bernard, A. B., E. Dhyne, G. Magerman, K. Manova, and A. Moxnes (2022). The origins of firm heterogeneity: A production network approach. *Journal of Political Economy 130*(7), 1765–1804.

Bernard, A. B., J. . B. Jensen, and P. K. Schott (2006). Transfer pricing by u.s.-based multinationals. NBER Working Paper No. 12493.

Bernard, A. B., A. Moxnes, and K. H. Ulltveit-Moe (2018). Two-sided heterogeneity and trade. *Review of Economics and Statistics 100*(3), 424–439.

Burstein, A. and G. Gopinath (2014). International prices and exchange rates. In G. Gopinath, E. Helpman, and K. Rogoff (Eds.), *Handbook of International Economics*, Volume 4. Elsevier.

Campa, J. M. and L. S. Goldberg (2005). Exchange rate pass-through into import prices. *Review of Economics and Statistics 87*(4), 679–690.

Cannon, J. P. and C. Homburg (2001). Buyer-supplier relationships and customer firm costs. *Journal of Marketing 65*(1), 29–43.

Cannon, J. P. and W. D. Perreault Jr. (1999). Buyer-seller relationships in business markets. *Journal of Marketing Research 36*(4), 439–460.

Carlton, D. W. (1986). The rigidity of prices. *American Economic Review 76*(4), 637–658.

Chaney, T. (2014). The network structure of international trade. *American Economic Review 104*(11), 3600–3634.

Chernozhukov, V. and H. Hong (2003). An mcmc approach to classical estimation. *Journal of Econometrics 115*(2), 293–346.

Claycomb, C. and G. L. Frankwick (2005). The dynamics of buyers' perceived costs during a relationship development process: An empirical assessment. *Journal of Business Research 58*(12), 1662–1671.

Dasgupta, P. and J. E. Stiglitz (1988). Learning-by-doing, market structure and industrial trade policies. *Oxford Economic Papers 40*(2), 246–268.

Defever, F., C. Fischer, and J. Südekum (2016). Relational contracts and supplier turnover in the global economy. *Journal of International Economics 103*, 147–165.

Doney, P. M. and J. P. Cannon (1997). An examination of the nature of trust in buyer-seller relationships. *Journal of Marketing 61*(2), 35–51.

Duprez, C. and G. Magerman (2018). Price updating in production networks. NBB Working Paper No. 352.

Dwyer, F. R., P. H. Schurr, and S. Oh (1987). Developing buyer-seller relationships. *Journal of Marketing 51*(2).

Dyer, J. H. (1996). Specialized supplier networks as a source of competitive advantage: Evidence from the auto industry. *Strategic Management Journal 17*(4), 271–291.

Eaton, J., M. Eslava, D. Jinkins, C. J. Krizan, and J. Tybout (2021). A search and learning model of export dynamics. NBER Working Paper No. 29100.

Egan, M. L. and A. Mody (1992). Buyer-seller links in export development. *World Development 20*(3), 321–334.

Fitzgerald, D., S. Haller, and Y. Yedid-Levi (2023). How exporters grow. *Review of Economic Studies*, forthcoming.

Foster, L., J. Haltiwanger, and C. Syverson (2016). The slow growth of new plants: Learning about demand? *Economica 83*(329), 91–129.

Ganesan, S. (1994). Determinants of long-term orientation in buyer-seller relationships. *Journal of Marketing 58*(2), 1–19.

Goldberg, P. K. and F. Verboven (2001). The evolution of price dispersion in the european car market. *Review of Economic Studies 68*(4), 811–848.

Gopinath, G. and O. Itskhoki (2010). Frequency of price adjustment and pass-through. *Quarterly Journal of Economics 125*(2), 675–727.

Gopinath, G., O. Itskhoki, and R. Rigobon (2010). Currency choice and exchange rate pass-through. *American Economic Review 100*(1), 304–336.

Gourio, F. and L. Rudanko (2014). Customer capital. *Review of Economic Studies 81*(3), 1102–1136.

Han, S.-L., D. P. Wilson, and P. Dant, Shirish (1993). Buyer-supplier relationships today. *Industrial Marketing Management 22*(4), 331–338.

Heise, S., J. Pierce, G. Schaur, and P. K. Schott (2024). Tariff rate uncertainty and the structure of supply chains. NBER Working Paper No. 32138.

Huneeus, F. (2018). Production network dynamics and the propagation of shocks. mimeo, Princeton University.

Jap, S. D. (1999). Pie-expansion efforts: Collaboration processes in buyer-supplier relationships. *Journal of Marketing Research 36*(4), 461–475.

Kalwani, M. U. and N. Narayandas (1995). Long-term manufacturer-supplier relationships: Do they pay off for supplier firms? *Journal of Marketing 59*(1), 1–16.

Kamal, F., C. J. Krizan, and R. Monarch (2015). Identifying foreign suppliers in us merchandise import transactions. *US Census Bureau Center for Economic Studies Paper No. CES-WP-15-11*.

Kamal, F. and R. Monarch (2018). Identifying Foreign Suppliers in U.S. Import Data. *Review of International Economics 26*(1), 117–39.

Kaufmann, D., A. Kraay, and M. Mastruzzi (2010). The worldwide governance indicators: Methodology and analytical issues. Policy Research Working Paper Series 4978, The World Bank 2010.

Kikkawa, A. K., G. Magerman, and E. Dhyne (2022). Imperfect competition in firm-to-firm trade. *Journal of the European Economic Association 20*(5), 1933–1970.

Kleshchelski, I. and N. Vincent (2009). Market share and price rigidity. *Journal of Monetary Economics 56*, 344–352.

Kocherlakota, N. R. (1996). Implications of efficient risk sharing without commitment. *Review of Economic Studies 63*(4), 595–609.

Liker, J. K. and T. Y. Choi (2004). Building deep supplier relationships. *Harvard Business Review 82*(12), 104–113.

Lim, K. (2018). Endogenous production networks and the business cycle. mimeo, University of Toronto.

Lyons, Thomas F., K., A. R. Krachenberg, and J. W. Henke Jr. (1990). Mixed motive marriages: What's next for buyer-supplier relations? *Sloan Management Review 31*(3), 29–36.

Macchiavello, R. and A. Morjaria (2015). The value of relationships: Evidence from a supply shock to kenyan rose exports. *American Economic Review 105*(9), 2911–2945.

Monarch, R. (2021). It's not you, it's me: Price, quality, and switching in u.s.-china trade relationships. *The Review of Economics and Statistics*, 1–49.

Monarch, R. and T. Schmidt-Eisenlohr (2023). Longevity and the value of trade relationships. *Journal of International Economics 145*.

Nakamura, E. and J. Steinsson (2008). Five facts about prices: A reevaluation of menu cost models. *Quarterly Journal of Economics 123*(4), 1415–1464.

Neiman, B. (2010). Stickiness, synchronization, and passthrough in intrafirm trade prices. *Journal of Monetary Economics 57*(3), 295–308.

Paciello, L., A. Pozzi, and N. Trachter (2019). Price dynamics with customer markets. *International Economic Review 60*(1), 413–446.

Phelps, E. S. and S. G. Winter (1970). Optimal price policy under atomistic competition. In *Microeconomic Foundations of Employment and Inflation Theory*, pp. 309–337.

Pierce, J. and P. K. Schott (2016). The surprisingly swift decline of u.s. manufacturing employment. *American Economic Review 106*(7), 1632–1662.

Rauch, J. E. and J. Watson (2003). Starting small in an unfamiliar environment. *International Journal of Industrial Organization 21*, 1021–1042.

Redding, S. J. and D. E. Weinstein (2017). Aggregating from micro to macro patterns of trade. NBER WP No. 24051.

Ring, P. S. and A. H. van de Ven (1994). Developmental processes of cooperative interorganizational relationships. *Academy of Management Review 19*(1), 90–118.

Rotemberg, J. J. and M. Woodford (1999). The cyclical behavior of prices and costs. In J. B. Taylor and M. Woodford (Eds.), *Handbook of Macroeconomics*, Volume 1B, Chapter 16, pp. 1051–1135. Elsevier, North Holland.

Tintelnot, F., A. K. Kikkawa, M. Mogstad, and E. Dhyne (2021). Trade and domestic production networks. *Review of Economic Studies 88*(2), 543–668.

Online Appendix (Not for Publication)

A Construction of the Datasets

A.1 LFTTD Data

Baseline Dataset

This section describes the preparation of the LFTTD dataset. I use version d201701 of the data, covering the years 1992-2017. The data contain for each import transaction an identifier of the U.S. importer, a 10-digit Harmonized System (HS10) product code, and a foreign manufacturer ID (or "MID"). As described in the main text, the MID combines characters of the origin country, exporter name, the address, and the city of the foreign supplier. Kamal and Monarch (2018) and Monarch (2021) 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. I therefore follow Pierce and Schott (2016), Monarch (2021), Eaton et al. (2021), and Monarch and Schmidt-Eisenlohr (2023) and use these MIDs as my baseline identifier of foreign firms.

Since HS10 codes change over time, I use the concordance by Pierce and Schott (2012) to make the HS10 codes time-consistent. I construct prices (unit values) as the reported import value divided by quantity of each transaction. Each transaction also contains the export date abroad and the import date in the U.S., reported as strings such as "05222006". I use the export date as the date of the transaction since that 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. The first row in Table A.1 presents some statistics for the full LFTTD data from 1992-2017, which includes about 1.18 billion transactions. The data cover about $43 trillion dollars of imports conducted by 1.4 million distinct U.S. firm IDs and 11.2 million distinct foreign manufacturer IDs. I observe about 28.3 million importer-exporter pairs (relationships) and 66.3 million importer-exporter-HS10 triplets.

I perform several data cleaning operations, and show in Table A.1 how these affect the data. In the first step, I transform the string export dates into machine readable dates. A few transactions with incorrectly reported dates, such as June 31 (e.g., "06312002"), are dropped in this step, as shown in row 2. Next, I deflate all import values with the quarterly GDP deflator from FRED (series GDPDEF, seasonally adjusted) and report the impact in row 3. The import value is in 2012 US dollars for this row and for all following rows. This step increases the import value from \$43 trillion nominal dollars to about \$45 trillion in constant 2012 dollars. I perform this step to make import values comparable across years. I use the deflated values for all analyses except for the pass-through regressions, which use the nominal, non-deflated import prices and exchange rates.

In the next step, I drop all transactions with a missing quantity or value. This step removes about 17% of the dataset by import value and reduces the number of relationships by nearly 8 million. I require both non-zero values and quantities to compute unit values (prices), which are the key object of interest in my pass-through regressions. Rows 5 and 6 drop observations with a missing U.S. firm ID or a missing MID. These identifiers are crucial to observe relationships between firms. Import transactions may not have a firm ID for example because they are conducted by consumers directly. I also drop MIDs that do not start with a letter (since they should start with a country's ISO code) or that have fewer than three characters. These steps reduce the import value included in my data from \$37 trillion to about \$31 trillion. Note that dropping missing firm IDs does, by definition, not change the number of firm IDs in the data, and similarly dropping observations with missing MID does not change the number of MIDs.

In row 7, I drop transactions that are warehouse entries rather than directly available for sale, using a variable indicating the purpose of the import in the data. For such transactions there is a time lag between the import and when the product is actually sold by the importer, which may affect the relationship between the import price and the exchange rate. This step only has a marginal effect on the data, dropping only about 1,000 firm IDs and almost no import value. Next, I remove transactions where the foreign manufacturer is a U.S. firm, based on an MID starting with "US" (row 8). The prices for these transactions include for example re-imports, and may not depend on the exchange rate. In row 9, I drop cases with a high likelihood of input error as indicated by a non-missing blooper flag. Row 10 then drops transactions with an export date before 1992, i.e., these are shipments that departed abroad prior to 1992 and only arrived in the U.S. in that year. Overall, the data cleaning steps up to this point drop about 36% of import value in 2012 dollars, 18% of U.S. firm IDs, and 28% of relationships.

In the next step, I remove transactions between related parties using the related party flag in the data. I focus on arms' length transactions because my interest is in price setting between two parties that are not part of the same firm. Prices in related party transactions are possibly non-allocative and could be set based on profit shifting motives (see Bernard et al. (2006)). I follow a conservative approach and completely drop all transactions of importer-exporter relationships that ever report a related party transaction throughout their life, since price setting of firms that become related in the future could already be affected prior to that event. I treat missing related party flags as related parties as well. Thus, the remaining dataset only includes importer-exporter pairs that report being at arms' length throughout their entire duration. Row 11 shows that this step removes about $21 trillion dollars of import value in 2012 dollars, leaving about $8 trillion. The number of firm IDs and relationships do not drop nearly as strongly, falling by only 2% and 10% compared to row 10, indicating that most of the related party relationships are relatively large.

I next set to missing cross sectional and time series outliers based on the transaction price. I define cross sectional outliers as prices that are below the 1st percentile or above the 99th percentile of the distribution of unit values within each HS10 by country by quarter bin. I define time series outliers as cases where the price (in absolute value) changes by more than 4 log points from one transaction to the next for a given importer-exporter-HS10 triplet. For these outlier transactions I set prices, values, and quantities to missing but keep the transaction record for the purposes of computing relationship length and time gaps between adjacent transactions. Row 12 reports statistics on the remaining dataset of non-missing prices. This resulting dataset is my baseline dataset for computing all empirical results in the paper, with the exception of the pass-through regressions, which require some additional restrictions. This dataset has an import value of $8 trillion dollars, covers 18 million relationships, and nearly 37 million relationship-product triplets.

For the pass-through regressions, I merge into the dataset for each quarter an average quarterly exchange rate between the U.S. and a foreign country for the set of countries listed in Table A.4 below. Exchange rates are obtained from the OECD's Monetary and Financial Statistics database, measured in U.S. dollar per foreign currency unit, and supplemented with rates from Datastream for Eurozone countries. 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. I then perform three additional data cleaning operations. First, I drop all observations with missing exchange rates since I cannot compute pass-through for these (row 13). Second, I drop the years 1992-1994 and use them only to compute relationship length (row 14).[49] Finally, due to the relationship-product fixed effects γ_{mxh} in the pass-through regression (1), importer-exporter-HS10 triplets that do not trade in at least two different quarters are singletons and are therefore not useful to identify the regression coefficients. Row 15 presents the dataset of non-singleton observations that is actually used to identify the coefficients in regression (1).[50] This final pass-through dataset has an import value of about $4 trillion dollars, contains 2.8 million relationships, and 4.7 million relationship-HS10 triplets.

[49] I apply a similar step to the baseline dataset and use 1992-1994 only to compute relationship length, but drop them from all analyses.

[50] Note that STATA drops these observations automatically when running the regression. The sample in row 15 corresponds to the sample obtained by the command "e(sample)" in the post-estimation analysis in STATA.

Table A.1: Baseline with Original MID

	Desc.	Value	Num. Firm IDs	Num. Exporters	Num. Pairs	Num. Triplets
	Baseline dataset					
(1)	Entire LFTTD	$4.28 \cdot 10^{13}$	1,440,000	11,200,000	28,300,000	66,300,000
(2)	Drop incorrect date	$4.27 \cdot 10^{13}$	1,440,000	11,200,000	28,300,000	66,300,000
(3)	Deflated with 2012 prices	$4.47 \cdot 10^{13}$	1,440,000	11,200,000	28,300,000	66,300,000
(4)	Drop missing or zero qty & value	$3.72 \cdot 10^{13}$	1,189,000	8,339,000	20,600,000	47,400,000
(5)	Drop missing firm ID	$3.32 \cdot 10^{13}$	1,189,000	7,661,000	20,600,000	47,400,000
(6)	Drop missing MID/MID shorter than 3 chars	$3.05 \cdot 10^{13}$	1,182,000	7,661,000	20,600,000	47,400,000
(7)	Drop warehouse entries	$3.05 \cdot 10^{13}$	1,181,000	7,644,000	20,600,000	47,300,000
(8)	Drop U.S. sellers	$2.89 \cdot 10^{13}$	1,181,000	7,600,000	20,500,000	47,100,000
(9)	Drop non-missing blooper flag	$2.89 \cdot 10^{13}$	1,181,000	7,598,000	20,500,000	47,100,000
(10)	Drop exports from before 1992	$2.88 \cdot 10^{13}$	1,180,000	7,588,000	20,500,000	47,100,000
(11)	Drop related-party trade	$7.99 \cdot 10^{12}$	1,152,000	7,018,000	18,500,000	37,000,000
(12)	Drop outlier prices	$7.89 \cdot 10^{12}$	1,145,000	6,962,000	18,300,000	36,600,000
	Pass-through regression dataset					
(13)	Drop missing exchange rate	$6.13 \cdot 10^{12}$	1,100,000	6,146,000	16,300,000	32,100,000
(14)	Drop period before 1995	$5.86 \cdot 10^{12}$	1,077,000	5,789,000	15,500,000	30,700,000
(15)	Regression dataset	$3.92 \cdot 10^{12}$	351,000	1,333,000	2,837,000	4,735,000

Notes: Numbers have been rounded per Census Bureau disclosure guidelines. “Value” refers to the import value (nominal in rows 1-2, in 2012 dollars in rows 3-15). “Num Firm IDs” is the number of distinct, non-missing U.S. firm identifiers. “Num Exporters” is the number of distinct MIDs. “Num Pairs” is the number of importer-exporter pairs, and “Num Triplets” is the number of importer-exporter-HS10 triplets. HS10 codes have been concorded using the concordance by Pierce and Schott (2012). The regression sample in row 15 corresponds to the sample obtained by the command “e(sample)” in the post-estimation analysis in STATA.

Alternative Foreign Exporter IDs

One issue with the foreign exporter IDs (MIDs) in the LFTTD data is that several MIDs might pertain to the same exporter. For example, a clerical error in inputting the exporter’s address would result in a new MID. Moreover, two plants with different addresses belonging to the same firm would also show up as different MIDs. Kamal et al. (2015) compare the number of MIDs in the Census data to the number of foreign exporters for 43 countries from the World Bank’s Exporter Dynamics Database (EDD), which is based on foreign national government statistics and private company data. They show that the number of MIDs in the Census data matches well with the number of sellers in the EDD when the street address or the city component are omitted. I therefore analyze the data using two alternative definitions of the foreign exporter. First, I drop the street address and the city component from the MID, and identify exporters using the remaining, shortened MID. This variable has been used in previous work, such as Amiti and Heise (2024). Second, I develop a new concordance procedure that combines MIDs with similar strings into one, building on the string merge algorithm by Kamal and Monarch (2018), to generate time-consistent concorded MIDs. I describe the concordance procedure in detail in Appendix A.2.

Tables A.2 and A.3 provide statistics on these alternative datasets. The first row in both tables reports the LFTTD after the cleaning steps of rows 1-10 in Table A.1, analogous to row 10 of that table. This dataset has exactly the same import value of $28.8 trillion as before and contains the same transactions. However, it contains significantly fewer distinct exporters due to the aggregation of some MIDs. When the city and address portion of the MID are eliminated, the dataset contains only 2.6 million distinct exporters compared to 7.6 million in the baseline. Using the concorded MIDs, I count only 634,000 exporters. I then drop related party trade in row 2 of tables A.2 and A.3. Since some of the original MIDs are combined together, a smaller set of importer-exporter pairs never report a related party transaction. Consequently, I drop a larger share of imports in this step, removing $22 trillion (Table A.2) and $24 trillion of imports (Table A.3), respectively. Row 3 shows the cleaned pass-through dataset (equivalent to row 14 of Table A.1), and row 4 shows the regression dataset excluding singleton observations (equivalent to row 15 of Table A.1). Overall, the non-singleton regression data using the shortened MID (in row 4 of Table A.2) has only 88% of the import value of the baseline dataset and 430,000 fewer relationships. Note, however, that the number of firm IDs actually increases slightly, since fewer firm IDs have only singleton transactions and are therefore dropped completely. The non-singleton regression data using the concorded MID (in row 4 of Table A.3) has 64% of the import value of the baseline dataset and about 1.5 million fewer relationships.

Table A.2: Shortened MID

	Desc.	Value	Num. Firm IDs	Num. Exporters	Num. Pairs	Num. Triplets
(1)	Cleaned LFTTD (row 10 from baseline)	$2.88 \cdot 10^{13}$	1,180,000	2,629,000	15,700,000	39,800,000
(2)	Drop related-party trade (row 11)	$6.93 \cdot 10^{12}$	1,148,000	2,467,000	14,200,000	30,400,000
(3)	Cleaned pass-through data (row 14)	$5.03 \cdot 10^{12}$	1,073,000	2,035,000	12,100,000	25,400,000
(4)	Pass-through regression dataset (row 15)	$3.45 \cdot 10^{12}$	359,000	572,000	2,407,000	4,159,000

Notes: Numbers have been rounded per Census Bureau disclosure guidelines. “Value” refers to the import value (in 2012 dollars). “Num Firm IDs” is the number of distinct, non-missing U.S. firm identifiers. “Num Exporters” is the number of shortened MIDs, where I drop the city and the address component. “Num Pairs” is the number of importer-exporter pairs, and “Num Triplets” is the number of importer-exporter-HS10 triplets. HS10 codes have been concorded using the concordance by Pierce and Schott (2012). The row references report the row in the baseline Table A.1.

Table A.3: Concorded MID

	Desc.	Value	Num. Firm IDs	Num. Exporters	Num. Pairs	Num. Triplets
(1)	Cleaned LFTTD (row 10 from baseline)	$2.88 \cdot 10^{13}$	1,180,000	634,000	7,264,000	23,400,000
(2)	Drop related-party trade (row 11)	$4.81 \cdot 10^{12}$	1,137,000	595,000	6,484,000	16,300,000
(3)	Cleaned pass-through data (row 14)	$3.44 \cdot 10^{12}$	1,063,000	520,000	5,502,000	13,500,000
(4)	Pass-through regression dataset (row 15)	$2.49 \cdot 10^{12}$	362,000	305,000	1,386,000	2,605,000

Notes: Numbers have been rounded per Census Bureau disclosure guidelines. “Value” refers to the import value (in 2012 dollars). “Num Firm IDs” is the number of distinct, non-missing U.S. firm identifiers. “Num Exporters” is the number of concorded MIDs, concorded as described in Appendix A.2. “Num Pairs” is the number of importer-exporter pairs, and “Num Triplets” is the number of importer-exporter-HS10 triplets. HS10 codes have been concorded using the concordance by Pierce and Schott (2012). The row references report the row in the baseline Table A.1.

Exchange Rate Data

The exchange rates are from the OECD’s Monetary and Financial Statistics database, supplemented with rates from Datastream for Eurozone countries. 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, my foreign exchange data cover the 45 countries listed in Table A.4.

Table A.4: 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

Notes: This table shows the list of foreign countries included in the pass-through regressions.

A.2 Details on the Concordance of MIDs

In this section, I describe how I construct the concorded MID as the exporters' identifier. I clean the LFTTD as described in Appendix A.1 and implement my procedure on the dataset described in row 10 of Table A.1. I generate a time-consistent concorded MID for the entire period 1992-2017.

The starting point for my approach is the procedure developed by Kamal and Monarch (2018). They propose a string matching algorithm that compares every MID to every other MID from the same country, and combine MIDs that are sufficiently similar based on their strings. This method is computationally burdensome because it requires the comparison of a large number of MID pairs. Kamal and Monarch (2018) therefore implement their methodology only for 2011, and do not extend it to other years. My procedure overcomes this challenge by using economic information on firms' transaction patterns to pre-select the MIDs that are compared with the string matching algorithm. The initial selection step significantly reduces the computational requirements of the procedure. Specifically, I choose three sets of comparison MIDs for each MID for the string comparison, based on three approaches.

My first approach compares each MID only to MIDs with similar pricing behavior. Two MIDs that set very different unit values in similar circumstances are likely to be distinct, and hence a string comparison is not necessary. Since prices in related party transactions are possibly non-allocative, for example due to profit shifting motives (see Bernard et al. (2006)), for each importer-exporter pair I drop all transactions in years in which the pair reports at least one related party transaction.[51] I collapse the data to the importer-exporter-HS10-mode of transportation-foreign port of departure-U.S. port of entry-year level, and construct the average price (unit value) for each collapsed observation. I then generate an exporter-product-specific pricing component that is purged of buyer and transaction characteristics in two steps. First, I residualize the log unit values by regressing them on the log quantity imported as well as on mode of transportation and foreign port of departure by U.S. port of entry fixed effects. This step removes price variation that arises due to differences in the quantity purchased (for example quantity discounts), the mode of transportation (airplane, vessel, etc.), or the departure country of the good. Prices might be higher for example for air shipments because these are correlated with higher quality, and a greater shipping distance might lead to higher prices. In the second step, I remove price variation that arises because of different buyers, for example due to differences in bargaining power. Specifically, I implement an AKM estimation based on Abowd et al. (1999). I collapse the residualized prices to the importer-exporter-HS10-year level, and run in each year t and for each exporter country c a regression of the form

$$\ln(\tilde{p}_{mxhct}) = \alpha_{mt} + \beta_{xhct} + \varepsilon_{mxhct},$$

where m denotes the importer, x the exporter, h the HS10 product, c the exporter country, and t the year, $\tilde{p}_{mxhct}$ is the residualized log price from the first stage, α_{mt} are importer-year fixed effects, and β_{xhct} are exporter-product-year fixed effects. Given the large number of importers and exporters, I estimate the model using sparse matrices in Matlab. As is standard, I implement the regression procedure on the largest connected set of importers and exporters in each country. The estimated exporter-product fixed effects $\hat{\beta}_{xhct}$ in each year reflect the supplier component of prices that is cleaned of importer characteristics. I then select the comparison set for each MID in each year

[51] This approach is less stringent than the one used in the main text since I keep years in which the pair is completely arms'-length.

by comparing the supplier component of each MID-HS10 to the supplier component of each other MID-HS10 from the same country. I select for the string comparison any MID that has a supplier component that is within 5% of the target MID's supplier component for the same HS10, or that has a supplier component closer than 10% for a different HS10.

The second approach selects as comparison set for each MID only those MIDs that share the same customer in a given year. If an MID is slightly different from another one because of a clerical error, I should still observe it selling to the same customers as the correct MID. My third approach uses as comparison set for each MID the MIDs that share the same port of entry in a given year. Since these two approaches do not rely on price information, I keep here also the related party transactions.

In the second stage I perform the string matching procedure by Kamal and Monarch (2018), which uses the probabilistic record linkage algorithm by Wasi and Flaaen (2015). Within each comparison set constructed in the first step, I compare each MID to every other MID, and obtain a similarity score for each pair of strings. Since the comparison is only within each set, the computational demands are significantly reduced compared to the original method of comparing all MIDs. I retain all matched MID pairs with similarity scores above a cut-off of 0.98.

I also implement a "brute force" approach where each MID is compared to every other MID from the same country in each year. Using parallelization techniques, it was feasible to execute this approach within a finite period of time for all years. Overall, I thus end up with four lists of matched MID pairs, one for each of the comparison sets used.

In the third step, I retain as final matches only those MID pairs that appear in at least three of the four approaches. For example, an MID pair that is flagged under the "brute force" approach as having very similar strings would be discarded if it did not also share the same buyer, port, or similar pricing. I perform this step to retain only MID pairs that share similarities based on their transaction patterns. I do not require an MID pair to appear in all four lists because that appeared to be too restrictive, in particular since the AKM algorithm can only be performed on the largest connected set of firms for each country and discards related party trades. Overall, I thus obtain a list of matched MID pairs for each exporter country and each year.

In the final step of the procedure, I generate a time-consistent grouped ID from the set of matched MID pairs. Starting from the list of matched MID pairs across all years and countries from the previous step, I run an iterative algorithm. First, for each MID pair, I find whether one of the pair's members appears in another MID pair. If that is the case, I join these pairs together into a group. I then keep combining groups that have shared members until no further groups can be combined. I assign each group a new grouped ID, which is an arbitrary string that is the same for all MIDs that are in a group. I set it equal to the alphabetically first member of the group. I use this grouped ID for all analyses using the concorded MIDs.

A.3 Bloomberg Data

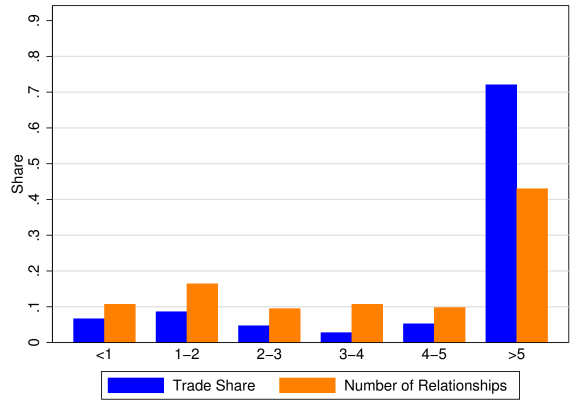
The "SPLC" function in Bloomberg displays the customers and suppliers of a given firm that are active at a specific date. These data are obtained from two main sources. First, under U.S. accounting rules, firms are required to report any customer that accounts for at least 10% of revenues. For example, 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.

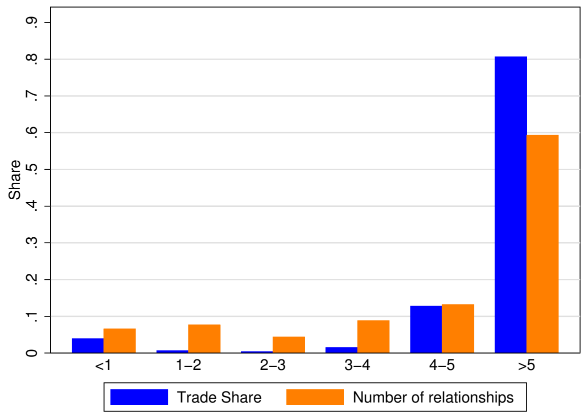
Figure A.1 presents the resulting distributions. Since the data contain only relationships that Bloomberg discovered in public information, they are most likely biased towards larger, longer relationships. Nevertheless, the figure shows two interesting facts. First, almost 90% of relationships in the 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 the 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 to be not 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)

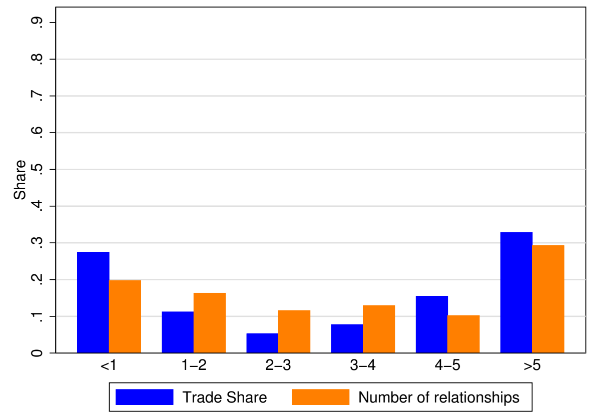


Source: Bloomberg SPLC function. Notes: Data are for 2012-2018. Figure shows the number of reported relationships and the share of value traded in the reported relationships by relationship length.

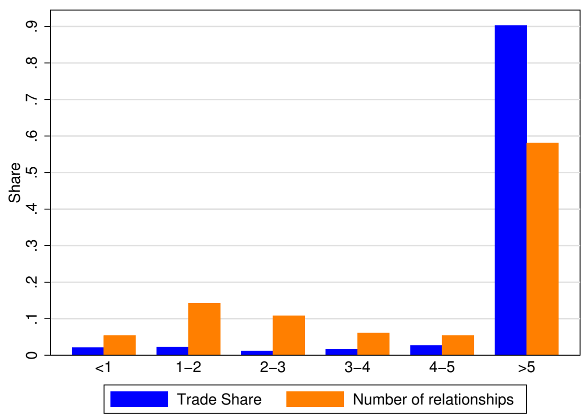
Figure A.2: Domestic Relationships



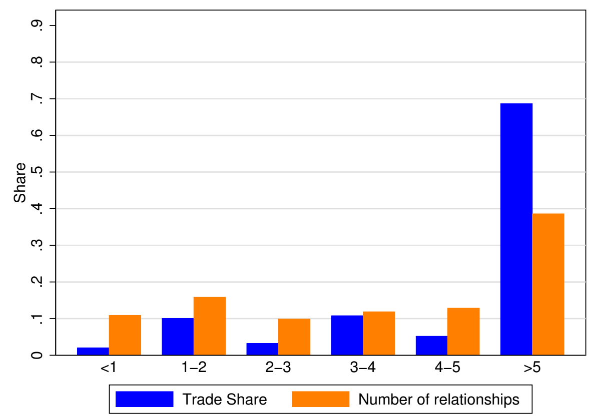
(a) Apple



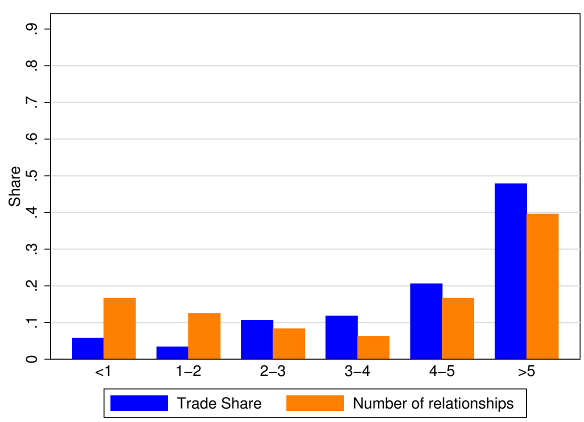
(b) Amazon



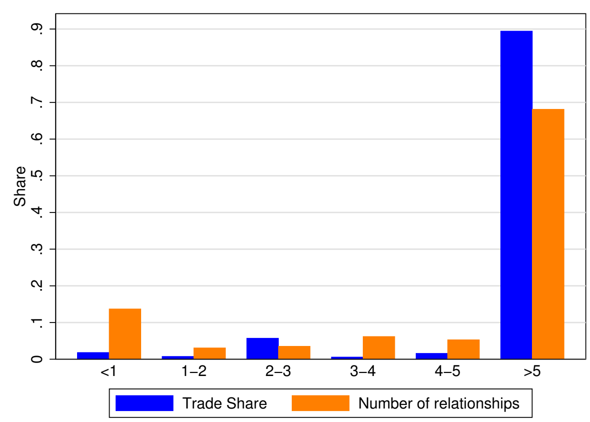
(c) Boeing



(d) General Motors



(e) Johnson & Johnson



(f) Wal-Mart

Source: Bloomberg SPLC function. Notes: Data are for 2012-2018. Figure shows the number of reported relationships and the share of value traded in the reported relationships by relationship length.

B Additional Summary Statistics of Relationships

In this section I provide some additional summary statistics on relationships and trade.

I first analyze the share of trade that occurs at arms' length in the cleaned LFTTD sample (which corresponds to row 10 of Table A.1). Row 1 of Table B.1 shows that about 38% of import value is at arms' length, defined as all transactions where the related party flag is not missing or indicates related party. As discussed in the main text, I use as baseline a more stringent definition and focus only on relationships that are always unrelated throughout their life. Row 2 shows that 28% of trade occurs in relationships that are always unrelated.[52]

I next examine some matching statistics for the sample of relationships that are always unrelated (from the sample in row 12 of Table A.1). The first column presents statistics for all these relationships, while column 2 shows statistics for only those importer-exporter relationships that last for more than 12 months in total. Rows 3 and 4 show that the average importer buys a given HS10 product from more than two exporters per year, while the average exporter transacts with only one U.S. importer for a given product. The number of partners in relationships that last more than 12 months is slightly smaller. Row 5 documents that the average importer-exporter relationship trades two HS10 products per year. This number rises to nearly three products for relationships that last for more than 12 months in total. Row 6 shows that the average importer-exporter-product triplet trades every two months (row 6). For comparison, the average time for which an importer-exporter-product triplet can go without trading before I define it as terminated is 13 months (row 7).

Table B.2 presents statistics on the distribution of relationship length in different sectors. I assign each relationship to the main sector of the U.S. importer. Specifically, I obtain the 6-digit NAICS code of each of an importer's establishments from the *Longitudinal Business Database* (LBD) in each year, where the 6-digit NAICS codes are the time-consistent codes constructed by Fort and Klimek (2018). I then assign to the importer the 6-digit NAICS code with the largest employment share in each year, and use the importer's modal NAICS code across all years. The

[52] This statistic corresponds to the ratio of the value traded in row 11 and row 10 in Table A.1.

first column shows the average relationship length in months for all arms' length relationships in different sectors, and the second column conditions on relationships that last more than 12 months in total. The last three columns present percentiles of the relationship length distribution. On average, relationships last about 5-6 months. However, this relatively low number is driven by the fact that many relationships are one-off, as shown in the main text. Conditioning on relationships that last more than 12 months, the average relationship length rises to around 30 months. The average relationship length is very similar for importers that are in manufacturing, wholesale trade, and retail trade, and slightly shorter when the importer is in mining/agriculture and in services.

Figure B.1 shows the distribution of arms' length trade by importer sector. About 40% of total arms' length imports are accounted for by buyers in the wholesale and transportation sector, with the remainder mostly in manufacturing and in retail (blue bars). In terms of the number of transactions, nearly 60% are in wholesale, highlighting that the average transaction size in that sector is relatively smaller than in manufacturing or in retail.

Table B.3 provides some further evidence on the average relationship length in domestic U.S. transactions from management surveys. These surveys suggest that the average relationship length in the U.S. is around one year, with some relationships being considerably longer.

Table B.1: Summary Statistics

(1)	Arms' length trade	38%
(2)	Arms' length trade (always unrelated)	28%

	Arms' length trade	All relationships	> 12 months
		(1)	(2)
(3)	Exporters per importer-HS10, per year	2.3	1.9
(4)	Importers per exporter-HS10, per year	1.3	1.2
(5)	HS per importer-exporter, per year	1.8	2.5
(6)	Average gap time between transactions (months)	2.2	–
(7)	Average maximum gap time (months)	12.6	–

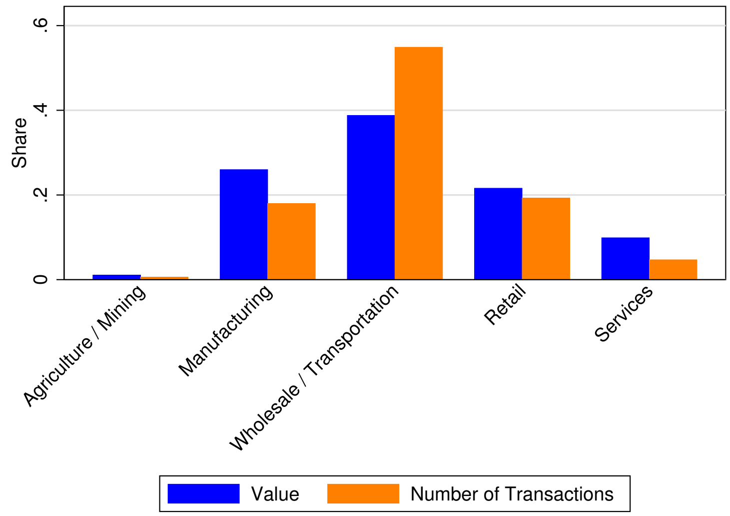
Notes: Row 1 shows the share of import value that is associated with transactions occuring at arms' length, defined as all transactions where the related party flag is not missing or indicates related party. Row 2 shows the share of value transacted by relationships that are always arms' length throughout their duration. In the following rows, I focus on always arms' length relationships only. Column 1 presents statistics for the entire sample of always arms' length relationships. Column 2 focuses on the subsample of arms' length relationships that last in total for more than 12 months. Rows 3-5 present some matching statistics. Row 6 shows the average gap time between transactions (in months) based on my definition. Row 7 presents the average of maximum gap times (a product-level statistic) across HS10 products. The maximum gap time is defined as the 95th percentile of the product-level distribution of gap times between subsequent trades of the same relationship-product.

Table B.2: Distribution of Relationship Length by Importer Sector

		All Relationships	> 12 months	P50 months	P75 months	P95 months
	Average Relationship Length in Months	(1)	(2)	(3)	(4)	(5)
(1)	... in Mining/Agriculture	5.3	29.0	1	4	25
(2)	... in Manufacturing	6.5	30.7	1	6	30
(3)	... in Services	4.7	28.1	1	3	21
(4)	... in Wholesale Trade	6.5	31.3	1	6	30
(5)	... in Retail Trade	6.4	29.8	1	6	29

Notes: Table shows the average arms' length relationship length by sector of the U.S. importer. I determine each importers sector by taking the importer's 6-digit NAICS industry with the largest employment share in the LBD in each year, and then find the modal industry across years. The 6-digit NAICS codes are from Fort and Klimek (2018). 6-digit NAICS codes starting with 11 or 21 are in Agriculture/Mining, 31-33 are Manufacturing, 42 and 48-49 are Wholesale Trade and Transportation, 44-45 are Retail, and codes starting with 5, 6, 7, or 8 are in Services. Column 1 shows average relationship length by importer sector. Column 2 conditions on relationships that last more than 12 months in total. Columns 3-5 present percentiles of the relationship length distribution.

Figure B.1: Trade Distribution by Importer Sector



Notes: Table shows the share of arms' length import value (blue) and the share of transactions (orange) by sector of the U.S. importer. I determine each importer's sector by taking the importer's 6-digit NAICS industry with the largest employment share in the LBD in each year, and then find the modal industry across years. The 6-digit NAICS codes are from Fort and Klimek (2018). 6-digit NAICS codes starting with 11 or 21 are in Agriculture/Mining, 31-33 are Manufacturing, 42 and 48-49 are Wholesale Trade and Transportation, 44-45 are Retail, and codes starting with 5, 6, 7, or 8 are in Services.

Table B.3: 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 Jr. (1999)	426 firms, mainly manufacturing and distributors	Main supplier of last purchasing decision	11
Kotabe et al. (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 et al. (2007)	373 automotive and electronics manufacturers, 75 matched suppliers	Firms have recently worked to improve performance	12.4

Notes: The table presents evidence on the average length of buyer-seller relationships in the domestic U.S. economy from management surveys. The first column indicates the authors of the study. The second column presents the sample of firms used. The third column shows how the relationships used in the analysis were chosen. The final column indicates the average relationship length across these relationships.

C Additional Robustness for the Pass-Through Results

C.1 Relationship Dynamics Versus Selection

In this section I study whether the positive correlation between pass-through and relationship age arises via a dynamic increase in pass-through as a given relationship ages or via selection because relationships of greater total duration have higher average pass-through. I sort relationships by total duration into groups of length 3-4 years, 5-6 years, 7-9 years, and so on. For each of these groups, I estimate a specification similar to the main pass-through regression (1):

$$\Delta\ln(p_{mxht}) = \beta_1\Delta\ln(e_{mxht}) + \sum_i \rho_i d^i_{mxt} + \sum_i \gamma_i d^i_{mxt}\cdot\Delta\ln(e_{mxht}) + \beta_4 X_{mxht} + \gamma_{mxh} + \omega_t + \varepsilon_{mxht}, \quad (14)$$

where X_{mxht} are the same controls as before and d^i_{mxt} are dummies for the current length of relationship mx in quarter t: 3-4 years, 5-6 years, 7-9 years, and so on. In contrast to the continuous variable $Length_{mxt}$, these dummies capture the effect of relationship length on pass-through non-parametrically. Current length of 1-2 years is the omitted category.

Column 1 of Table C.1 shows that for relationships with total duration 3 to 4 years, pass-through in year 3-4 is marginally higher than in year 1-2 but the effect is not statistically significant. Column 2 shows that for relationships of total duration 5-6 years, pass-through first increases relative to year 1-2 but then falls again slightly. Pass-through increases with time for relationships lasting 7-9 years (column 3) and increases with a decline in the last period for relationships of length 10-11 years (column 4). In column 5, I expand the group of relationships to those lasting 10-12 years in total to include three years as for the 7-9 year group. For these relationships, pass-through increases throughout (column 5). Finally, for relationships of total length 13-15 years, pass-through increases until year 5-6 and then declines again. Overall, these results suggest that pass-through dynamically increases with relationship age, and for many groups there is a life cycle pattern with declining pass-through towards the end. Moreover, pass-through unconditional on current age (in the first row) tends to be higher for relationships that last longer in total. Thus, the positive correlation between pass-through and relationship age appears to be driven both by a dynamic increase in pass-through with age and selection.

To test whether the life cycle is present in the average relationship, in column 7 I run a regression with two dummies for the first year (d_{mx}^{first}) and the last year (d_{mx}^{last}) of the relationship, both on their own and interacted with the exchange rate, for relationships lasting more than two years. The interaction terms with the exchange rate indicate that pass-through in the first year and in the last year is lower than in intermediate years, corroborating the idea that pass-through follows a life cycle.

Table C.1: Pass-Through by Total Length Groups

$\Delta \ln(p_{mcxht})$	$3-4$ years	$5-6$ years	$7-9$ years	$10-11$ years	$10-12$ years	$13-15$ years	>2 years
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta \ln(e)$	$.4536^{***}$	$.5834^{**}$	$.7107^{***}$	.4815	$.5868^{*}$	1.383^{***}	$.5890^{***}$
	(.1673)	(.2171)	(.2157)	(.3274)	(.3280)	(.2491)	(.2008)
Time Gap $\cdot \Delta \ln(e)$	$.0089^{***}$	$.0064^{**}$	.0023	.0024	.0018	.0002	$.0053^{***}$
	(.0026)	(.0025)	(.0020)	(.0038)	(.0034)	(.0033)	(.0015)
Avg Size $\cdot \Delta \ln(e)$	$-.0277^{**}$	$-.0380^{**}$	$-.0442^{**}$	$-.0296$	$-.0376$	$-.1015^{***}$	$-.0336^{**}$
	(.0137)	(.0170)	(.0172)	(.0237)	(.0235)	(.0199)	(.0155)
d(3-4 Years) $\cdot \Delta \ln(e)$	.0042	$.0486^{**}$	.0201	.0701	.0822	.0591	
	(.0100)	(.0185)	(.0192)	(.0509)	(.0535)	(.1028)	
d(5-6 Years) $\cdot \Delta \ln(e)$		.0281	$.0434^{**}$	.0636	.0776	$.1804^{**}$	
		(.0191)	(.0169)	(.0572)	(.0515)	(.0834)	
d(7-9 Years) $\cdot \Delta \ln(e)$			$.0827^{***}$	$.1019^{**}$	$.0944^{**}$	$.1753^{*}$	
			(.0225)	(.0416)	(.0415)	(.0894)	
d(10-11 Years) $\cdot \Delta \ln(e)$				.0866			
				(.0558)			
d(10-12 Years) $\cdot \Delta \ln(e)$					$.1001^{*}$	$.1464^{**}$	
					(.0557)	(.0705)	
d(13-15 Years) $\cdot \Delta \ln(e)$						.0736	
						(.0938)	
d(First year) $\cdot \Delta \ln(e)$							$-.0331^{***}$
							(.0111)
d(Last year) $\cdot \Delta \ln(e)$							$-.0297^{***}$
							(.0085)
Time FE	Y	Y	Y	Y	Y	Y	Y
Rel-product FE	Y	Y	Y	Y	Y	Y	Y
R-Squared	.0792	.0469	.0329	.0242	.0239	.0218	.0577
Observations	8,057,000	4,579,000	3,319,000	1,095,000	1,387,000	452,000	18,090,000

Notes: This table presents selected regression coefficients from specification (14). 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. d(x Years) denotes a dummy equal to one of the relationship has current age x. 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. FirstYear is a dummy equal to one if the relationship is in its first year, and LastYear is a dummy equal to one if the relationship is in its last year. Columns 1-6 are for relationships that last for the total number of years indicated in the column header. Last column is for all relationships that last longer than two years in total.

C.2 Additional Robustness

In this section, I provide additional robustness for my pass-through results in Section 2.3.

Tables C.2-C.4 replicate the pass-through analysis from Table 2 separately for each of the three alternative measures of relationship intensity: the number of transactions ($Trans_{mxt}$), the relationship's cumulative value traded ($CumValue_{mxt}$), and the time passed since the first transaction of product h in the relationship ($PLength_{mxht}$). I find that my results hold for all three alternative measures of relationship growth.

Table C.5 analyzes the heterogeneity in pass-through across different groups of relationships. One concern could be that my results only hold for a specific group of relationships based on the frequency of trade or size. Columns 1 and 2 examine the baseline regression (1) for the sample of relationship-product triplets where the average time gap between transactions is above the median and below the median, respectively. The results show that the increase of pass-through with relationship length is higher in the group of triplets that trade less frequently. Columns 3 and 4 present the baseline regression results for the sample of relationship-product triplets whose total trade value is below and above the median, respectively. I find that pass-through increases more strongly for triplets that trade more. In Columns 5 and 6 I split the sample into importer-exporter relationships that trade a single product and multiple products, respectively. The increase in pass-through with length is very similar across these two groups.

Another concern with the baseline pass-through regression is that the difference in pass-through between new and old relationships could disappear over longer time horizons. To examine this concern, I run the baseline regression with lags

$$\Delta \ln(p_{mxht}) = \sum_{k=1}^{K} \alpha_k \Delta \ln(e_{mxh,t(k),t(k-1)}) + \beta Length_{mxt} + \sum_{k=1}^{K} \theta_k \Delta \ln(e_{mxh,t(k),t(k-1)}) \cdot Length_{mxt}$$
$$+ \xi X_{mxht} + \gamma_{mxh} + \omega_t + \varepsilon_{mxht}, \tag{15}$$

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 in the baseline regression, 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. Table C.6 presents the results. Each column uses a different number of K lags. The first three columns run the regression using the full sample, while the last three columns only use relationship-product triplets that transact in every quarter of their existence. The results indicate that pass-through increases with relationship length for all lag lengths.

Table C.7 runs the baseline pass-through regression (1) for different samples based on the country of the seller. In principle, it is possible that pass-through increases with relationship length only for a specific group of countries. Columns 1-3 assign the countries to terciles based on their average GDP per capita throughout the sample period. Columns 4 and 5 assign countries based on whether they are an OECD member. Columns 6-7 analyze pass-through for different geographical groups. Overall, pass-through increases with relationship length for every country group, and most strongly for high-GDP OECD members.

Table C.8 assigns countries and products to groups based on their likelihood of foreign currency use from Gopinath et al. (2010). Odd columns run the baseline regression using only the change in the exchange rate and time fixed effects as controls to analyze average pass-through for each group. Even columns include all controls from the baseline regression. Columns 1-4 compare low versus high foreign currency countries, and columns 5-10 analyze low, medium, and high foreign currency use products. I find that pass-through increases with relationship age for all groups, and more strongly for high foreign currency countries than for low foreign currency ones.

I next examine whether my definition of exporters alters my findings. It is possible that my choice of using the reported MID to identify exporters systematically affects relationship length, thereby changing the pass-through results. Tables C.9 and C.10 replicate the main pass-through regression from Table 1 and the main robustness checks from Table 2 using the shortened MID as defined in Appendix A.1 to define relationships. Tables C.11 and C.12 replicate these tables for the concorded MID. The results are similar, indicating that the choice of exporter identifier does not drive the results.

Table C.13 provides another check for whether the overall duration of a 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. I therefore run the baseline regression (1) with an additional control for how long a relationship is going to last in total, $TotLength_{mx}$, both by itself and interacted with the exchange rate change. Column 1 presents the results using relationship length. While controlling for total relationship length lowers the effect, there is still a significant dynamic effect. Columns 2-4 shows the pass-through for the alternative measures of relationship growth and show similar effects.

Table C.14 analyzes whether a firm's network of suppliers or customers affects pass-through. 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, 2-5 foreign suppliers, and six or more foreign suppliers, respectively (columns 1-3). Similarly, I analyze pass-through for suppliers that have one, 2-5, and six or more U.S. customers (columns 4-6). Column 7 considers only relationships where neither the buyer nor the supplier have other partners, and column 8 analyzes the complement of this set. I find that the pass-through increases quite similarly with relationship age within each of these configurations, and even for pairs that have no other partners in the dataset.

Table C.15 replaces the importer-exporter-HS10 fixed effects in the baseline regression, 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. 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.

I next examine 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. Since the test requires a minimum number of exchange rate and price observations per panel, I drop all relationship-product triplets with fewer than 20 price changes. I then draw 100 random samples of 20% of the observations and perform the test on each of these samples.[53] Table C.16 reports the average test statistic and p-value across the 100 samples. The test strongly rejects the null that all panels contain a unit root for prices ($p < .0001$), and hence cointegration does not appear to be present.

Finally, if relationships are able to continue relatively seamlessly even after long breaks, then I might be mismeasuring relationship length by ending relationships when the maximum gap time has elapsed. To investigate this possibility, Table C.17 presents my key regressions where I do not use the procedure described in Section 2.2 to calculate relationship length. Instead, I 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 to my findings in the main text.

[53] Running the test on the entire sample was not feasible in a reasonable amount of time given the computing resources available. Drawing random samples repeatedly allowed me to run several tests in parallel, shortening the time requirements.

Table C.2: Pass-Through Robustness - Number of Transactions ($Trans_{mxt}$)

$\Delta\ln(p)$	Every qtr	Selection	Annual	Size	Trans Val	GDP/Law	Country FE	Pos	Neg
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta\ln(e)$	.2403	.3579**	.4379**	.7545***	.4000***	$-.2876$	.1090***	.4916*	.4059**
	(.1573)	(.1696)	(.1901)	(.1867)	(.1210)	(.2774)	(.0342)	(.2509)	(.1735)
Trans $\cdot\,\Delta\ln(e)$	.0028**	.0035***	.0153***	.0050***	.0026***	.0027***	.0014***	.0036***	.0027***
	(.0011)	(.0010)	(.0037)	(.0007)	(.0006)	(.0007)	(.0004)	(.0011)	(.0008)
Time Gap $\cdot\,\Delta\ln(e)$		.0155***	.0853***	.0065***	.0066***	.0067***	.0044***	.0069	.0043*
		(.0045)	(.0148)	(.0019)	(.0018)	(.0017)	(.0010)	(.0044)	(.0025)
Avg Size $\cdot\,\Delta\ln(e)$	$-.0103$	$-.0264^{*}$	$-.0269^{*}$			$-.0141$	$-.0043$	$-.0314$	$-.0270^{*}$
	(.0127)	(.0139)	(.0146)			(.0096)	(.0029)	(.0206)	(.0139)
Imp Size $\cdot\,\Delta\ln(e)$				$-.0034$					
				(.0910)					
Exp Size $\cdot\,\Delta\ln(e)$				$-.0367^{***}$					
				(.0096)					
Trans Val $\cdot\,\Delta\ln(e)$					$-.0252^{***}$				
					(.0089)				
Trans $\cdot\,\Delta\ln(e)\cdot d_{\text{med}}^{GDP}$						.1054			
						(.0041)			
Trans $\cdot\,\Delta\ln(e)\cdot d_{\text{high}}^{GDP}$						.0769			
						(.1331)			
λ		.0180***							
		(.0046)							
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Rel-product FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
GDP/Law FE $\cdot\Delta\ln(e)$	–	–	–	–	–	Y	–	–	–
Country FE $\cdot\Delta\ln(e)$	–	–	–	–	–	–	Y	–	–
Observations	9,061,000	53,550,000	6,326,000	27,120,000	27,120,000	27,120,000	27,120,000	13,530,000	11,150,000

Notes: 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. λ denotes the selection term in a Heckman model. 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 Appendix D. 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_{med}^{GDP} and d_{high}^{GDP}, 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. Column (8) and (9) re-run the regression on the sample of positive (including zero) and negative exchange rate changes, respectively.

Table C.3: Pass-Through Robustness - Cumulative Value Traded ($CumValue_{mxt}$)

$\Delta\ln(p)$	Every qtr	Selection	Annual	Size	Trans Val	GDP/Law	Country FE	Pos	Neg
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta\ln(e)$	.2137	.3269*	.4212**	.6883***	.3784***	$-.3291$	.0928***	.4523*	.3760**
	(.1494)	(.1983)	(.1859)	(.1790)	(.1239)	(.2807)	(.0347)	(.2479)	(.1709)
$\ln(\text{Cum Value})\cdot\Delta\ln(e)$	.0189	.0261**	.0395***	.0449***	.0230***	.0249***	.0134***	.0270*	.0238***
	(.0112)	(.0107)	(.0139)	(.0071)	(.0066)	(.0071)	(.0046)	(.0140)	(.0078)
Time Gap $\cdot\Delta\ln(e)$		.0153***	.0927***	.0069***	.0068***	.0069***	.0045***	.0073	.0045*
		(.0055)	(.0143)	(.0019)	(.0018)	(.0017)	(.0010)	(.0044)	(.0025)
Avg Size $\cdot\Delta\ln(e)$	$-.0093$	$-.0256$	$-.0252^{*}$			$-.0136$	$-.0041$	$-.0298$	$-.0267^{*}$
	(.0107)	(.0171)	(.0144)			(.0100)	(.0028)	(.0203)	(.0136)
Imp Size $\cdot\Delta\ln(e)$				$-.0034$					
				(.0041)					
Exp Size $\cdot\Delta\ln(e)$				$-.0355^{***}$					
				(.0094)					
Trans Val $\cdot\Delta\ln(e)$					$-.0255^{***}$				
					(.0088)				
$\ln(\text{Cum Value})\cdot\Delta\ln(e)\cdot d^{GDP}_{\text{med}}$						.1056			
						(.0918)			
$\ln(\text{Cum Value})\cdot\Delta\ln(e)\cdot d^{GDP}_{\text{high}}$						.0773			
						(.1335)			
λ		.0206***							
		(.0047)							
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Rel-product FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
GDP/Law FE $\cdot\Delta\ln(e)$	–	–	–	–	–	Y	–	–	–
Country FE $\cdot\Delta\ln(e)$	–	–	–	–	–	–	Y	–	–
Observations	9,061,000	53,550,000	6,326,000	27,120,000	27,120,000	27,120,000	27,120,000	13,530,000	11,150,000

Notes: 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. λ denotes the selection term in a Heckman model. 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 Appendix D. 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. Column (8) and (9) re-run the regression on the sample of positive (including zero) and negative exchange rate changes, respectively.

Table C.4: 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
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta\ln(e)$	.2395	.3420*	.4450**	.7186***	.4023***	$-.3017$	.0993***	.4965*	.3796**
	(.1580)	(.2026)	(.1864)	(.1813)	(.1180)	(.2770)	(.0342)	(.2537)	(.1712)
$PLength \cdot \Delta\ln(e)$	.0013**	.0014***	.0133***	.0019***	.0015***	.0011***	.0007***	.0010**	.0008***
	(.0005)	(.0004)	(.0041)	(.0003)	(.0002)	(.0002)	(.0001)	(.0004)	(.0003)
Time Gap $\cdot \Delta\ln(e)$		.0150***	.0883***	.0056***	.0055***	.0061***	.0040***	.0107**	.0034
		(.0044)	(.0150)	(.0018)	(.0017)	(.0016)	(.0010)	(.0045)	(.0023)
Avg Size $\cdot \Delta\ln(e)$	$-.0101$	$-.0249$	$-.0260^{*}$			$-.0126$	$-.0036$	$-.0308$	$-.0243^{*}$
	(.0128)	(.0169)	(.0144)			(.0097)	(.0029)	(.0210)	(.0137)
Imp Size $\cdot \Delta\ln(e)$				$-.0027$					
				(.0042)					
Exp Size $\cdot \Delta\ln(e)$				$-.0348^{***}$					
				(.0094)					
Trans Val $\cdot \Delta\ln(e)$					$-.0262^{***}$				
					(.0091)				
$PLength \cdot \Delta\ln(e) \cdot d^{GDP}_{\text{med}}$						.1064			
						(.0910)			
$PLength \cdot \Delta\ln(e) \cdot d^{GDP}_{\text{high}}$						.0759			
						(.1334)			
λ		.0195***							
		(.0028)							
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Rel-product FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
GDP/Law FE $\cdot\Delta\ln(e)$	–	–	–	–	–	Y	–	–	–
Country FE $\cdot\Delta\ln(e)$	–	–	–	–	–	–	Y	–	–
Observations	9,061,000	53,500,000	6,326,000	27,120,000	27,120,000	27,120,000	27,120,000	13,530,000	11,150,000

Notes: 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. λ denotes the selection term in a Heckman model. 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 Appendix D. 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. Column (8) and (9) re-run the regression on the sample of positive (including zero) and negative exchange rate changes, respectively.

Table C.5: 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)
$\Delta \ln(e)$	.2345	$.5715^{***}$	$.3044^{*}$	$.4901^{**}$	.3758	$.5078^{***}$
	(.1683)	(.1834)	(.1518)	(.1963)	(.2754)	(.1556)
$\text{Length} \cdot \Delta \ln(e)$	$.0010^{***}$	$.0017^{***}$	$.0012^{***}$	$.0020^{***}$	$.0014^{**}$	$.0015^{***}$
	(.0003)	(.0002)	(.0002)	(.0003)	(.0006)	(.0002)
$\text{Time Gap} \cdot \Delta \ln(e)$	$.0226^{***}$	$.0041^{**}$	$.0040^{**}$	$.0096^{***}$	$.0074^{***}$	$.0052^{***}$
	(.0057)	(.0016)	(.0016)	(.0026)	(.0027)	(.0015)
$\text{Avg Size} \cdot \Delta \ln(e)$	$-.0151$	$-.0390^{**}$	$-.0164$	$-.0345^{*}$	$-.0223$	$-.0337^{***}$
	(.0137)	(.0150)	(.0121)	(.0183)	(.0246)	(.0121)
Time FE	Y	Y	Y	Y	Y	Y
Rel-product FE	Y	Y	Y	Y	Y	Y
R-Squared	.0937	.1130	.0930	.1205	.1310	.0990
Observations	13,700,000	13,420,000	18,140,000	8,984,000	5,848,000	21,270,000

Notes: 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 C.6: 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)
$\Delta\ln(e_{c,t-1,t})$	.4375**	.4076*	.4215*	.2470	.2501	.2496
	(.2014)	(.2055)	(.2089)	(.1575)	(.1561)	(.1557)
$\Delta\ln(e_{c,t-2,t-1})$	.0543***	.0532***	.0551***	.0439***	.0443***	.0472***
	(.0131)	(.0143)	(.0148)	(.0111)	(.0114)	(.0117)
$\Delta\ln(e_{c,t-3,t-2})$		.0010	.0136		.0113	.0114
		(.0136)	(.0160)		(.0140)	(.0136)
$\Delta\ln(e_{c,t-4,t-3})$			.0035			.0159
			(.0143)			(.0107)
$\Delta\ln(e_{c,t-1,t})\cdot Length$	.0014***	.0015***	.0012***	.0009**	.0009**	.0009**
	(.0002)	(.0002)	(.0002)	(.0004)	(.0004)	(.0004)
$\Delta\ln(e_{c,t-2,t-1})\cdot Length$	.0002	.0002	.0003*	.0001	.0000	.0000
	(.0002)	(.0002)	(.0002)	(.0002)	(.0003)	(.0003)
$\Delta\ln(e_{c,t-3,t-2})\cdot Length$		.0002	.0000		.0002	.0001
		(.0002)	(.0002)		(.0003)	(.0003)
$\Delta\ln(e_{c,t-4,t-3})\cdot Length$			.0001			.0002
			(.0001)			(.0002)
Time FE	Y	Y	Y	Y	Y	Y
Rel-product FE	Y	Y	Y	Y	Y	Y
R-Squared	.0831	.0727	.0656	.1381	.1381	.1381
Observations	$20,250,000$	$15,940,000$	$12,950,000$	$9,061,000$	$9,061,000$	$9,061,000$

Notes: 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 (15) 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 $\text{TimeGap}_{mx,t-k,t-(k-1)}$, as well as on the interaction terms $\text{TimeGap}_{mx,t-k,t-(k-1)}\cdot\Delta\ln(e_{c,t-k,t-(k-1)})$ and $\text{AvgSize}_{mx}\cdot\Delta\ln(e_{c,t,t-1})$ are not shown for brevity.

Table C.7: Pass-Through - Country Groups

$\Delta \ln(p_{mxht})$	GDP			OECD		Country Groups	
	Low	Medium	High	Non-Member	Member	Europe	Asia
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta \ln(e)$	.0614	.6676***	.3320	.0136	.4746**	.8412***	.1301
	(.0578)	(.1783)	(.3378)	(.0654)	(.2115)	(.0924)	(.1031)
Length $\cdot \Delta \ln(e)$	.0004**	.0014***	.0015***	.0004**	.0016***	.0014***	.0010***
	(.0002)	(.0003)	(.0002)	(.0002)	(.0001)	(.0003)	(.0003)
Time Gap $\cdot \Delta \ln(e)$	.0057**	.0086*	.0050	.0056*	.0081***	.0057**	.0081**
	(.0027)	(.0050)	(.0038)	(.0030)	(.0026)	(.0023)	(.0038)
Avg Size $\cdot \Delta \ln(e)$	−.0020	−.0436***	−.0088	−.0021	−.0284	−.0532***	−.0077
	(.0056)	(.0120)	(.0282)	(.0068)	(.0176)	(.0077)	(.0090)
Time FE	Y	Y	Y	Y	Y	Y	Y
Rel-product FE	Y	Y	Y	Y	Y	Y	Y
R-Squared	.1066	.1016	.1078	.1033	.1076	.1081	.1036
Observations	14,330,000	6,717,000	6,077,000	15,620,000	11,510,000	6,335,000	16,440,000

Notes: Number of observations has been rounded to the nearest 1,000 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)-(7) show the results for different geographical regions.

Table C.8: 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)
$\Delta \ln(e)$	.1029***	.0957*	.3711***	.4722*	.2488***	.7543**	.1832***	.4590**	.2073***	.2686*
	(.0217)	(.0554)	(.0639)	(.2787)	(.0536)	(.2879)	(.0465)	(.1739)	(.0511)	(.1561)
Length $\cdot \Delta \ln(e)$		.0007***		.0014***		.0015***		.0014***		.0013***
		(.0002)		(.0002)		(.0002)		(.0003)		(.0003)
Time Gap $\cdot \Delta \ln(e)$		.0052**		.0073**		.0023		.0075***		.0051*
		(.0021)		(.0033)		(.0018)		(.0021)		(.0027)
Avg Size $\cdot \Delta \ln(e)$		−.0040		−.0197		−.0489**		−.0328**		−.0136
		(.0053)		(.0219)		(.0234)		(.0142)		(.0123)
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
R-Squared	.0006	.1048	.0011	.1066	.0014	.0999	.0007	.1023	.0004	.1126
Observations	18,240,000	18,240,000	8,886,000	8,886,000	5,911,000	5,911,000	14,220,000	14,220,000	6,991,000	6,991,000

Notes: 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 C.9: Pass-Through Regressions with Shortened MID

	Length			Intensity		
				Trans	Cum value	Prod months
$\Delta \ln(p)$	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln(e)$	0.2114***	0.1433***	0.4844**	0.4991**	0.4551**	0.4736**
	(0.0481)	(0.0434)	(0.1906)	(0.1930)	(0.1894)	(0.1899)
Length $\cdot \Delta \ln(e)$		0.0010***	0.0012***			
		(0.0002)	(0.0002)			
Time Gap $\cdot \Delta \ln(e)$		0.0064***	0.0053***	0.0061***	0.0064***	0.0055***
		(0.0014)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Avg Size $\cdot \Delta \ln(e)$			−0.0310**	−0.0318**	−0.0313**	−0.0296*
			(0.0153)	(0.0155)	(0.0153)	(0.0154)
Intensity $\cdot \Delta \ln(e)$				0.0031***	0.0320***	0.0013***
				(0.0007)	(0.0077)	(0.0002)
Time FE	Y	Y	Y	Y	Y	Y
Rel-product FE (γ)	N	Y	Y	Y	Y	Y
R-Squared	.0007	.0975	.0975	.0975	.0975	.0975
Observations	25,960,000	25,960,000	25,960,000	25,960,000	25,960,000	25,960,000

Notes: Table shows coefficients from specification (1), using the MID where city and address component have been omitted. 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 transactions 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 three alternative measures of relationship intensity described in the text.

Table C.10: Pass-Through Robustness - Relationship Length in Months with Shortened MID ($Length_{mxt}$)

$\Delta\ln(p)$	Every qtr	Selection	Annual	Size	Trans Val	GDP/Law	Full FE	Pos	Neg
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta\ln(e)$	.2167	.3619*	.3817*	.7007***	.4190***	−.2561	.0959***	.5420**	.3509**
	(.1598)	(.2067)	(.1896)	(.1869)	(.1201)	(.2718)	(.0348)	(.2403)	(.1718)
$Length \cdot \Delta\ln(e)$	.0006**	.0010***	.0092**	.0013***	.0009***	.0008***	.0004***	.0008**	.0009***
	(.0003)	(.0003)	(.0035)	(.0002)	(.0002)	(.0002)	(.0001)	(.0003)	(.0003)
Time Gap $\cdot \Delta\ln(e)$		.0135***	.0782***	.0053***	.0051***	.0055***	.0036***	.0071**	.0037
		(.0035)	(.0148)	(.0012)	(.0011)	(.0012)	(.0008)	(.0003)	(.0025)
Avg Size $\cdot \Delta\ln(e)$	−.0076	−.0256	−.0201			−.0125	−.0026	−.0327	−.0227
	(.0128)	(.0167)	(.0148)			(.0095)	(.0029)	(.0201)	(.0141)
Imp Size $\cdot \Delta\ln(e)$				−.0038					
				(.0052)					
Exp Size $\cdot \Delta\ln(e)$				−.0300***					
				(.0073)					
Trans Val $\cdot \Delta\ln(e)$					−.0269***				
					(.0087)				
$Length \cdot \Delta\ln(e) \cdot d^{GDP}_{\text{med}}$						.1131			
						(.0869)			
$Length \cdot \Delta\ln(e) \cdot d^{GDP}_{\text{high}}$						.0889			
						(.1322)			
λ		.0171***							
		(.0032)							
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Rel-product FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
GDP/Law FE $\cdot\Delta\ln(e)$	–	–	–	–	–	Y	–	–	–
Country FE $\cdot\Delta\ln(e)$	–	–	–	–	–	–	Y	–	–
Observations	7,660,000	50,690,000	6,558,000	25,960,000	25,690,000	25,960,000	25,960,000	13,040,000	10,790,000

Notes: Table shows robustness checks for specification (1), using the MID where city and address component have been omitted to define relationships. 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. 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 Appendix D. 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.

Table C.11: Pass-Through Regressions with Concorded MID

	Length			Intensity		
				Trans	Cum value	Prod months
$\Delta\ln(p)$	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\ln(e)$	0.1963***	0.1623***	0.4722**	0.4978**	0.4256**	0.4552**
	(0.0450)	(0.0440)	(0.1843)	(0.1873)	(0.1813)	(0.1849)
Length $\cdot\,\Delta\ln(e)$		0.0012***	0.0013***			
		(0.0002)	(0.0002)			
Time Gap $\cdot\,\Delta\ln(e)$		−.0004	−.0005	−.0001	0.0003	−.0004
		(0.0016)	(0.0014)	(0.0015)	(0.0015)	(0.0015)
Avg Size $\cdot\,\Delta\ln(e)$			−0.0284*	−0.0302*	−0.0292*	−0.0257*
			(0.0149)	(0.0151)	(0.0147)	(0.0150)
Intensity $\cdot\,\Delta\ln(e)$				0.0039***	0.0467***	0.0015***
				(0.0006)	(0.0078)	(0.0002)
Time FE	Y	Y	Y	Y	Y	Y
Rel-product FE (γ)	N	Y	Y	Y	Y	Y
R-Squared	.0006	.0926	.0926	.0926	.0926	.0926
Observations	20,120,000	20,120,000	20,120,000	20,120,000	20,120,000	20,120,000

Notes: Table shows coefficients from specification (1), using the concorded MID described in Appendix A.2 to define relationships. 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 transactions 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 three alternative measures of relationship intensity described in the text.

Table C.12: Pass-Through Robustness - Relationship Length in Months with Concorded MID ($Length_{mxt}$)

$\Delta \ln(p)$	Every qtr	Selection	Annual	Size	Trans Val	GDP/Law	Full FE	Pos	Neg
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta \ln(e)$	.2108	.3410*	.4189**	.4517**	.4260***	−.2784	.1060***	.4594*	.3267*
	(.1587)	(.2044)	(.1717)	(.1730)	(.1161)	(.2684)	(.0349)	(.2490)	(.1619)
Length $\cdot \Delta \ln(e)$	.0008**	.0012***	.0146***	.0014***	.0011***	.0011***	.0006***	.0011***	.0012***
	(.0003)	(.0002)	(.0030)	(.0002)	(.0002)	(.0002)	(.0001)	(.0002)	(.0003)
Time Gap $\cdot \Delta \ln(e)$		.0083***	−.0025	−.0000	−.0007	−.0001	−.0002	.0066***	−.0019**
		(.0032)	(.0198)	(.0015)	(.0014)	(.0012)	(.0008)	(.0023)	(.0009)
Avg Size $\cdot \Delta \ln(e)$	−.0084	−.0236	−.0207			−.0112	−.0031	−.0274	−.0187
	(.0126)	(.0161)	(.0139)			(.0089)	(.0029)	(.0211)	(.0134)
Imp Size $\cdot \Delta \ln(e)$				−.0087					
				(.0071)					
Exp Size $\cdot \Delta \ln(e)$				−.0081***					
				(.0029)					
Trans Val $\cdot \Delta \ln(e)$					−.0264***				
					(.0083)				
Length $\cdot \Delta \ln(e) \cdot d^{GDP}_{\text{med}}$						.1098			
						(.0847)			
Length $\cdot \Delta \ln(e) \cdot d^{GDP}_{\text{high}}$						.0595			
						(.1274)			
λ		.0212***							
		(.0035)							
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Rel-product FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
GDP/Law FE $\cdot \Delta \ln(e)$	–	–	–	–	–	Y	–	–	–
Country FE $\cdot \Delta \ln(e)$	–	–	–	–	–	–	Y	–	–
Observations	5,404,000	39,080,000	5,359,000	20,120,000	20,120,000	20,120,000	20,120,000	9,969,000	8,578,000

Notes: Table shows robustness checks for specification (1), using the concorded MID described in Appendix A.2. 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. 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 Appendix D. 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.

Table C.13: Pass-Through - Control for Total Length

$\Delta \ln(p_{mcxht})$	$Length_{mxt}$	$Trans_{mxt}$	$\ln(CumValue_{mxt})$	$PLength_{mxt}$
	(1)	(2)	(3)	(4)
$\Delta \ln(e)$	$.4772^{**}$	$.4798^{**}$	$.4718^{**}$	$.4714^{**}$
	(.1850)	(.1846)	(.1872)	(.1840)
Length $\cdot \Delta \ln(e)$	$.0008^{***}$			
	(.0002)			
Time Gap $\cdot \Delta \ln(e)$	$.0058^{***}$	$.0063^{***}$	$.0063^{***}$	$.0058^{***}$
	(.0016)	(.0016)	(.0016)	(.0016)
Avg Size $\cdot \Delta \ln(e)$	$-.0328^{**}$	$-.0332^{**}$	$-.0332^{**}$	$-.0327^{**}$
	(.0152)	(.0152)	(.0151)	(.0152)
Tot Length $\cdot \Delta \ln(e)$	$.0076^{***}$	$.0103^{***}$	$.0111^{***}$	$.0090^{***}$
	(.0022)	(.0029)	(.0026)	(.0020)
Intensity $\cdot \Delta \ln(e)$		.0009	.0055	$.0008^{***}$
		(.0009)	(.0083)	(.0003)
Time FE	Y	Y	Y	Y
Rel-product FE	Y	Y	Y	Y
R-Squared	.1055	.1054	.1055	.1055
Observations	27,120,000	27,120,000	27,120,000	27,120,000

Notes: 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) shows the baseline regression with an additional control for the total length of the relationship in months, $\ln(TotLength_{mx})$, interacted with the exchange rate. Columns (2)-(4) repeat this regression using the intensity variable indicated in the header. 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. Trans is the number of transactions completed by the relationship. CumValue is the cumulative value traded up to the current year relative to the average trade value of the relationship. PLength is the number of months since the relationship's first transaction of the given product.

Table C.14: Pass-Through - Network of the Firms

$\Delta \ln(p_{mcxht})$	Types of Relationships							
	One Supplier	2-5 Suppliers	6+ Suppliers	One Customer	2-5 Customers	6+ Customers	One-to-One	Not One-to-One
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \ln(e)$	.0949	.1390	.5845***	.6957***	.6146***	.1516	.7979***	.4800**
	(.1900)	(.1948)	(.1835)	(.1682)	(.1642)	(.2053)	(.2427)	(.1864)
Length $\cdot \Delta \ln(e)$	.0012***	.0011**	.0015***	.0015***	.0014***	.0014***	.0015*	.0015***
	(.0004)	(.0005)	(.0002)	(.0002)	(.0003)	(.0004)	(.0008)	(.0002)
Time Gap $\cdot \Delta \ln(e)$	.0031	.0041	.0060***	.0041	.0096***	.0031	$-.0010$	.0056***
	(.0051)	(.0034)	(.0016)	(.0032)	(.0022)	(.0021)	(.0118)	(.0016)
Avg Size $\cdot \Delta \ln(e)$	.0011	$-.0013$	$-.0400^{***}$	$-.0455^{***}$	$-.0436^{***}$	$-.0065$	$-.0539^{**}$	$-.0314^{**}$
	(.0176)	(.0173)	(.0143)	(.0123)	(.0124)	(.0186)	(.0213)	(.0151)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Rel-product FE	Y	Y	Y	Y	Y	Y	Y	Y
R-Squared	.1259	.1256	.1081	.1233	.1250	.1065	.1367	.1060
Observations	1,197,000	3,514,000	22,130,000	8,477,000	9,080,000	8,941,000	330,000	26,750,000

Notes: 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 relationships where the buyer only has one foreign supplier. Column (2) presents the results for relationships where the buyer has 2-5 foreign suppliers, and column (3) shows the results for relationships when the buyer has six or more foreign suppliers. Column (4) presents the results for suppliers that have only one U.S. customer, column (5) shows the regression results for suppliers that have 2-5 U.S. customers, and column (6) shows the results for suppliers that have six or more U.S. customers. Column (7) presents the baseline regression for the set of relationships where the buyer has only one supplier, and this supplier only has the buyer as its customer. Column (8) presents the complement of this set. 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.

Table C.15: Pass-Through - Exporter-Product Fixed Effects

$\Delta\ln(p_{mcxht})$	$Length_{mxt}$	$Trans_{mxt}$	$\ln(CumValue_{mxt})$	$PLength_{mxt}$
	(1)	(2)	(3)	(4)
$\Delta\ln(e)$	$.4768^{**}$	$.4897^{**}$	$.4480^{**}$	$.4679^{**}$
	$(.1956)$	$(.1986)$	$(.1938)$	$(.1946)$
$\text{Length}\cdot\Delta\ln(e)$	$.0014^{***}$			
	$(.0002)$			
$\text{Time Gap}\cdot\Delta\ln(e)$	$.0052^{***}$	$.0059^{***}$	$.0063^{***}$	$.0054^{***}$
	$(.0015)$	$(.0016)$	$(.0016)$	$(.0015)$
$\text{Avg Size}\cdot\Delta\ln(e)$	$-.0304^{*}$	$-.0312^{*}$	$-.0305^{*}$	$-.0291^{*}$
	$(.0160)$	$(.0162)$	$(.0160)$	$(.0160)$
$\text{Intensity}\cdot\Delta\ln(e)$		$.0037^{***}$	$.0324^{***}$	$.0015^{***}$
		$(.0007)$	$(.0069)$	$(.0003)$
Time FE	Y	Y	Y	Y
Exp-product FE	Y	Y	Y	Y
R-Squared	.0673	.0673	.0673	.0673
Observations	$27,120,000$	$27,120,000$	$27,120,000$	$27,120,000$

Notes: 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)-(4) show the baseline regression with exporter-HS10 fixed effects, instead of relationship-HS10 fixed effects, for each of the four variables of relationship growth indicated in the header. 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. Trans is the number of transactions completed by the relationship. CumValue is the cumulative value traded up to the current year relative to the average trade value of the relationship. PLength is the number of months since the relationship's first transaction of the given product.

Table C.16: Im-Paseran-Shin Test for Unit Roots

	e_{mxht}	p_{mxht}
	(1)	(2)
$\bar{\bar{Z}}$	72.66	-280.7
p-value	1.0000	0.0000
Relationship-Product Triplets	$28,000$	$28,000$
Observations	$837,000$	$837,000$

Notes: Only relationship-product triplets with at least 20 observations are used. The test is conducted on 100 random samples of 20% of the observations, and the average test statistic across these samples is reported. $\bar{\bar{Z}}$ 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. Number of relationship-product triplets denotes the average number of triplets in each random sample. Observations denotes the average number of observations in each random sample.

Table C.17: 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)
$\Delta \ln(e)$	$.1304^{***}$	$.4739^{**}$	$.2395$	$.7422^{***}$	$-.2874$	$.1070^{***}$
	$(.0402)$	$(.1883)$	$(.1473)$	$(.1872)$	$(.2695)$	$(.0342)$
Length $\cdot \Delta \ln(e)$	$.0010^{***}$	$.0011^{***}$	$.0007^{*}$	$.0014^{***}$	$.0008^{***}$	$.0004^{***}$
	$(.0001)$	$(.0001)$	$(.0004)$	$(.0002)$	$(.0001)$	$(.0001)$
Time Gap $\cdot \Delta \ln(e)$	$.0069^{***}$	$.0059^{***}$		$.0056^{***}$	$.0061^{***}$	$.0041^{***}$
	$(.0021)$	$(.0016)$		$(.0017)$	$(.0017)$	$(.0010)$
Avg Size $\cdot \Delta \ln(e)$		$-.0308^{**}$	$-.0087$		$-.0132$	$-.0041$
		$(.0152)$	$(.0117)$		$(.0098)$	$(.0028)$
Imp Size $\cdot \Delta \ln(e)$				$-.0036$		
				$(.0041)$		
Exp Size $\cdot \Delta \ln(e)$				$-.0359^{***}$		
				$(.0095)$		
GDPpc $\cdot \Delta \ln(e)$					$.0555^{*}$	
					$(.0328)$	
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
R-Squared	.0971	.0971	.1377	.0971	.0971	.0973
Observations	27,120,000	27,120,000	6,095,000	27,120,000	27,120,000	27,120,000

Notes: 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.

D Correcting the Pass-Through Regressions for Selection

I re-write regression specification (1) as

$$\Delta \ln(p_{mxht}) = z^1_{mxht}\beta + \gamma_{mxh} + \omega_t + \tilde{\varepsilon}_{mxht}, \tag{16}$$

where z^1_{mxht} is a 1xK vector of regressors used in the pass-through regression and includes unity, β is a Kx1 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

$$s_{mxht} = 1\left[z_{mxht}\delta + \xi_{mxh} + \rho_t + \tilde{a}_{mxht} > 0\right], \tag{17}$$

where s_{mxht} is a selection indicator, $z_{mxht} = [z^1_{mxht} \quad z^2_{mxht}]$ is a vector of regressors, and ξ_{mxh} is relationship-product specific unobserved heterogeneity. Moreover, 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 (16) 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

$$\omega_t = GDP_t\varphi_1 + e_1 \tag{18}$$

and

$$\rho_t = GDP_t\varphi_2 + e_2. \tag{19}$$

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

$$\Delta \ln(p_{mxht}) = z^1_{mxht}\beta + GDP_t\varphi_1 + \gamma_{mxh} + \varepsilon_{mxht}, \tag{20}$$

with

$$s_{mxht} = 1\left[z_{mxht}\delta + GDP_t\varphi_2 + \xi_{mxh} + a_{mxht} > 0\right]. \tag{21}$$

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

Based on this assumption, the selection equation (21) can be written as

$$s_{mxht} = 1\left[\psi_0 + z_{mxh1}\psi_1 + ... + z_{mxhT}\psi_T + GDP_t\varphi_2 + v_{mxht} > 0\right], \tag{22}$$

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 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,

$$E[\gamma_{mxh}|\mathbf{z}_{mxh}, v_{mxht}] = \pi_0 + z_{mxh1}\pi_1 + ... + z_{mxh1}\pi_T + \phi_t v_{mxht}. \tag{23}$$

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

$$E[\varepsilon_{mxht}|\mathbf{z}_{mxh}, \mathbf{GDP}, v_{mxht}] = E[\varepsilon_{mxht}|v_{mxht}] = \rho v_{mxht}. \tag{24}$$

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

$$\Delta \ln(p_{mxht}) = z^1_{mxht}\beta + \bar{z}_{mxh}\pi + GDP_t\varphi_1 + \mu\lambda[z_{mxht}\rho + \bar{z}_{mxh}\eta + GDP_t\varphi_2] + \varepsilon_{mxht}, \qquad (25)$$

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

$$s_{mxht} = 1[z_{mxht}\rho + \bar{z}_{mxh}\eta + GDP_t\varphi_2 + v_{mxht} > 0]. \qquad (26)$$

While it would be desirable to estimate the equation on a fully squared dataset that records a missing observation in every one of the 92 quarters between 1995 and 2017 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, $\Delta \ln(e_{mxht})$, 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 (25). 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.

E Additional Results for the Dynamics of Relationships

In this section, I provide additional results on the dynamics of relationships.

Life Cycle of Value Traded. Figures E.1a and E.1b present the relationship life cycle analogously to Figure 2a, but using the number of products traded or the number of transactions. Specifically, the gray lines in the figures plot the estimated coefficients on the relationship year dummies from regression (2), using as dependent variable $y_{mx\tau}$ the number of products traded or the number of transactions conducted by relationship mx in relationship year τ. The colored lines present the regression results when I condition on how long the relationship lasts in total. I find that the number of products and the number of transactions follow a similar life cycle as the value traded.

Figure E.2a presents the relationship life cycle analogously to Figure 2a when exporters are defined using the shortened MID that omits the city and address component. Figure E.2b shows the life cycle when exporters are defined using the concorded MID as defined in Section A.2. These life cycles are very similar to the one using the reported MID.

Life Cycle of Prices. Table E.1 presents the coefficients of regression (3) analogously to Table 3 using the shortened MID that omits the city and address component. Table E.2 presents the regression coefficients for the concorded MID as constructed in Appendix A.2. The results are similar to the ones using the reported MID.

Role of Quantity on Prices. I next analyze the role of quantity for the price declines. If buyers in older relationships order more, then the price declines I find with respect to relationship age could be due to quantity discounts. To investigate this possibility, I first re-run regression (3), using the log deviation of quantity ordered from the market average for the product as dependent variable. Table E.3 repeats in column 1 the unconditional price regression from column 1 of Table 3 and shows in column 2 the regression with quantity on the left-hand side. Quantity ordered increases with relationship age, which may increase the price discount the buyer receives. To analyze the relationship between prices and quantity, I need to specify how prices are set. In my theory, I 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.[54] 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 for 6-digit NAICS industries are obtained for the period 1997-2016 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 results from running (3) as an OLS regression with the actually observed transaction quantity are shown in column 3 of Table E.3, and the results from the IV regression with my two instruments are shown in column 4. Since the BEA gross output tables do not contain data for all industries at the 6-digit level, the IV sample is smaller than that for the OLS regression. The IV results show that prices decline both due to a quantity effect and a direct effect. While doubling the quantity traded reduces the price by about 17%, prices decline with relationship age even conditional on quantity. On average, a relationship in year six has prices that are about 8.6% lower than in year one for a given quantity. My first stage is good, as evidenced by an F-statistic of 47.1.

Pricing Heterogeneity. Table E.4 repeats column 1 of Table 3 for different product categories. I list how these categories map to HS chapters in Table E.5. Price declines tend to be strongest for

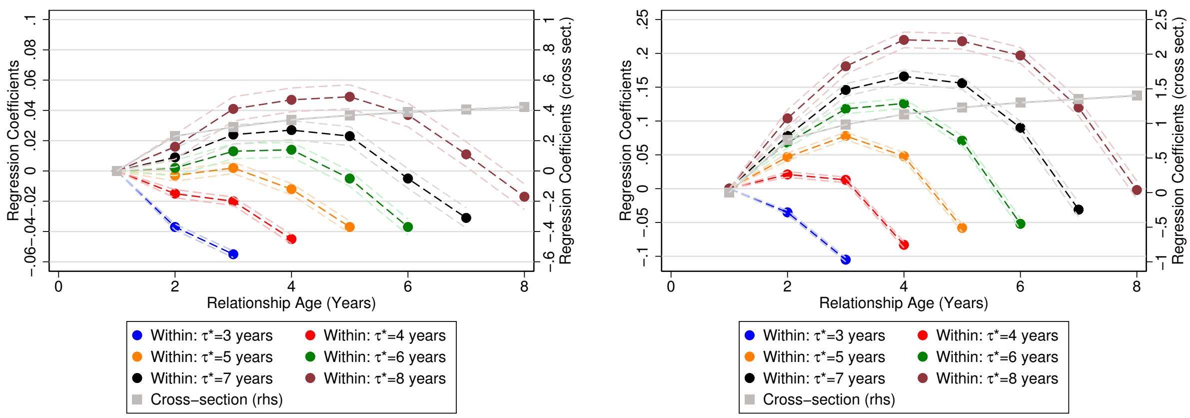
[54] I use the most detailed input-output matrix containing 417 industries.

differentiated products such as chemicals, machinery, and transportation. 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.

Figure E.1: Relationship Life Cycle - Other Variables

(a) Number of Products Traded

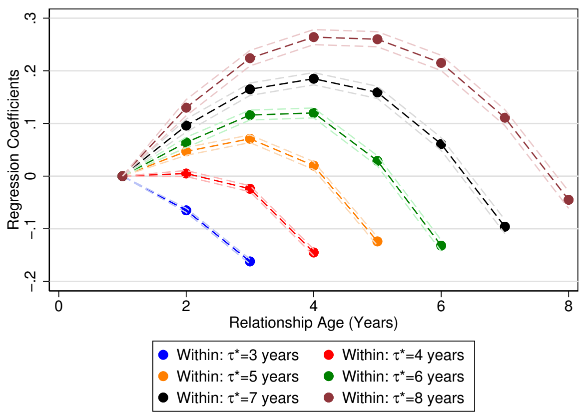
(b) Number of Transactions per Year



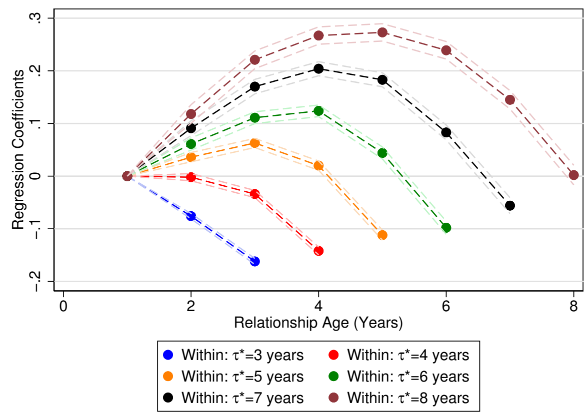
Notes: The figures show the relationship life cycle for the number of products traded and the number of transactions. The gray lines in the figures plot the estimated coefficients on the relationship year dummies from regression (2) against the right-hand side y-axis, using as dependent variable y_{mxt} the number of products traded or the number of transactions conducted by relationship mx in relationship year τ. On the x-axis, relationships are in year one when they are 0-11 months old, relationships are in year two when they are 12-23 months old, and so on. The colored lines present the regression results when I condition on how long the relationship lasts in total and include relationship fixed effects, against the left-hand side y-axis. $\tau^* = 3$ years means that the relationship lasts three full years but fewer than four full years, so 36-47 months. $\tau^* = 4$ years means that the relationship lasts four full years but fewer than five full years, so 48-59 months.

Figure E.2: Life Cycle of Value Traded with Different Exporter Definitions

(a) Shortened MID



(b) Concorded MID



Notes: The figures show the relationship life cycle of value traded. The left panel shows the life cycle using the shortened MID that omits city and address component. The right panel plots the life cycle with the concorded MID using the concordance procedure described in Section A.2. The gray line plots the estimated coefficients on the relationship year dummies from regression (2) against the right-hand side y-axis, using as dependent variable y_{mxt} the value traded by relationship mx in relationship year τ. On the x-axis, relationships are in year one when they are 0-11 months old, relationships are in year two when they are 12-23 months old, and so on. The colored lines present the regression results when I condition on how long the relationship lasts in total and include relationship fixed effects, against the left-hand side y-axis. $\tau^* = 3$ years means that the relationship lasts three full years but fewer than four full years, so 36-47 months. $\tau^* = 4$ years means that the relationship lasts four full years but fewer than five full years, so 48-59 months.

Table E.1: Price-Setting by Relationship Length - Shortened MID

$\ln \tilde{p}_{mxhj}$	3 Years Total	4 Years Total	5 Years Total	6 Years Total	7 Years Total	8 Years total
	(1)	(2)	(3)	(4)	(5)	(6)
2 Years	$-.0127^{***}$	$-.0081^{***}$	$-.0079^{***}$	$-.0110^{***}$	$-.0139^{***}$	$-.0148^{***}$
	(.0011)	(.0009)	(.0010)	(.0018)	(.0022)	(.0020)
3 Years	$-.0207^{***}$	$-.0167^{***}$	-0.0173^{***}	$-.0191^{***}$	$-.0216^{***}$	$-.0272^{***}$
	(.0022)	(.0021)	(.0019)	(.0030)	(.0030)	(.0027)
4 Years		$-.0232^{***}$	$-.0242^{***}$	$-.0246^{***}$	$-.0255^{***}$	$-.0316^{***}$
		(.0024)	(.0054)	(.0047)	(.0056)	(.0035)
5 Years			$-.0317^{***}$	$-.0338^{***}$	$-.0358^{***}$	$-.0389^{***}$
			(.0059)	(.0048)	(.0064)	(.0037)
6 Years				$-.0400^{***}$	$-.0433^{***}$	$-.0485^{***}$
				(.0051)	(.0067)	(.0042)
7 Years					$-.0502^{***}$	$-.0594^{***}$
					(.0075)	(.0048)
8 Years						$-.0679^{***}$
						(.0050)
Rel-product FE	Y	Y	Y	Y	Y	Y
R-Squared	.7973	.7889	.7788	.7735	.7705	.7672
Observations	10,280,000	8,951,000	7,629,000	6,232,000	5,238,000	4,380,000

Notes: 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. Columns 1-6 show the results of running regression (3) for relationships that last in total $\{3,4,5,6,7,8\}$ full years, using the shortened MID that omits city and address component to identify importers and relationships, where relationship-product fixed effects γ_{mxh} have been added. $\tilde{p}_{mxhj}$ is the log transaction price of transaction j of importer-exporter-product triplet mxh minus the log average price of the product and country in that quarter. The coefficients on "2 years",... "8 years" are the coefficients on the dummies d^i_{mxj} that are equal to one if the relationship is i years old at transaction j.

Table E.2: Price-Setting by Relationship Length - Concorded MID

$\ln \tilde{p}_{mxhj}$	3 Years Total	4 Years Total	5 Years Total	6 Years Total	7 Years Total	8 Years total
	(1)	(2)	(3)	(4)	(5)	(6)
2 Years	$-.0128^{***}$	$-.0087^{***}$	$-.0081^{***}$	$-.0125^{***}$	$-.0118^{***}$	$-.0127^{***}$
	(.0014)	(.0011)	(.0015)	(.0033)	(.0042)	(.0029)
3 Years	$-.0227^{***}$	$-.0183^{***}$	-0.0187^{***}	$-.0180^{***}$	$-.0196^{***}$	$-.0274^{***}$
	(.0022)	(.0017)	(.0020)	(.0043)	(.0048)	(.0050)
4 Years		$-.0252^{***}$	$-.0241^{***}$	$-.0230^{***}$	$-.0241^{***}$	$-.0333^{***}$
		(.0026)	(.0043)	(.0060)	(.0067)	(.0049)
5 Years			$-.0307^{***}$	$-.0306^{***}$	$-.0362^{***}$	$-.0378^{***}$
			(.0057)	(.0069)	(.0074)	(.0063)
6 Years				$-.0380^{***}$	$-.0456^{***}$	$-.0454^{***}$
				(.0070)	(.0085)	(.0052)
7 Years					$-.0504^{***}$	$-.0540^{***}$
					(.0097)	(.0060)
8 Years						$-.0615^{***}$
						(.0066)
Rel-product FE	Y	Y	Y	Y	Y	Y
R-Squared	.7878	.7797	.7679	.7646	.7589	.7547
Observations	7,244,000	6,536,000	5,801,000	4,876,000	4,179,000	3,655,000

Notes: 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. Columns 1-6 show the results of running regression (3) for relationships that last in total $\{3,4,5,6,7,8\}$ full years, using the concorded MID to identify importers and relationships, where relationship-product fixed effects γ_{mxh} have been added. $\tilde{p}_{mxhj}$ is the log transaction price of transaction j of importer-exporter-product triplet mxh minus the log average price of the product and country in that quarter. The coefficients on "2 years",... "8 years" are the coefficients on the dummies d^i_{mxj} that are equal to one if the relationship is i years old at transaction j.

Table E.3: Prices and Quantity by Relationship Length

	Price (OLS) $\ln \tilde{p}_{mxhj}$	Quantity (OLS) $\ln \tilde{q}_{mxhj}$	Price (OLS) $\ln \tilde{p}_{mxhj}$	Price (IV) $\ln \tilde{p}_{mxhj}$
	(1)	(2)	(3)	(4)
2 Years	$-.0672^{***}$	$.1829^{***}$	$-.0118^{*}$	$-.0269$
	(.0088)	(.0079)	(.0066)	(.0194)
3 Years	$-.0762^{***}$	$.2137^{***}$	$.-.0126$	$-.0448^{**}$
	(.0111)	(.0081)	(.0084)	(.0223)
4 Years	$-.0832^{***}$	$.2362^{***}$	$-.0143$	$-.0500^{**}$
	(.0127)	(.0083)	(.0097)	(.0234)
5 Years	$-.0862^{***}$	$.2473^{***}$	$-.0146$	$-.0706^{***}$
	(.0147)	(.0084)	(.0109)	(.0224)
6 Years	$-.0918^{***}$	$.2610^{***}$	$-.0195$	$-.0859^{***}$
	(.0173)	(.0100)	(.0127)	(.0221)
7 Years	$-.0943^{***}$	$.2733^{***}$	$-.0175$	$-.0932^{***}$
	(.0170)	(.0103)	(.0111)	(.0246)
8 Years	$-.1066^{***}$	$.2887^{***}$	$-.0285^{**}$	$-.1201^{***}$
	(.0198)	(.0111)	(.0135)	(.0258)
$\ln q_{mxhj}$			$-.1358^{***}$	$-.1741^{***}$
			(.0155)	(.0402)
F-stat				47.1
R-squared	.0012	.0047	.1304	.1831
Observations	150,600,000	150,600,000	150,600,000	23,370,000

Notes: 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. Column 1 presents the regression coefficients of the cross-sectional specification (3). $\tilde{p}_{mxhj}$ is the log price of transaction j of importer-exporter-product triplet mxh minus the log average price of the product and country in that quarter. The coefficients on "2 years",... "8 years" are the coefficients on the dummies d^{i}_{mxj} that are equal to one if the relationship is i years old at transaction j. Column 2 shows the results for the regression that uses transaction quantity $\tilde{q}_{mxhj}$ on the left-hand side, defined as the log quantity of transaction j of importer-exporter-product triplet mxh minus the log average quantity of the product and country in that quarter. Column 3 regresses the relative log price on relationship length dummies and log quantity. Column 4 performs an IV regression where I instrument for quantity using the weighted average gross output of the downstream industries of the imported good (HP filtered) as well as HP filtered U.S. GDP. F-stat indicates the F statistic of the first stage of the IV regression.

Table E.4: Price Regression By Industry

	Animal	Vegetables	Fats	Food	Minerals	Chemicals	Plastics	Leather	Wood
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
3-4 Years	.0047*	.0150	−.0272*	−.0343***	.0028	−.0730***	−.1152***	.0154	−.0442***
	(.0025)	(.0130)	(.0140)	(.0103)	(.0058)	(.0063)	(.0112)	(.0130)	(.0077)
5-6 Years	.0115*	.0212	−.0486***	−.0450***	−.0083*	−.0970***	−.1382***	.0195	−.0514***
	(.0059)	(.0148)	(.0120)	(.0132)	(.0050)	(.0120)	(.0133)	(.0201)	(.0094)
7-8 Years	.0161	.0135	−.0354**	−.0483***	−.0137	−.0936***	−.1965***	.0065	−.0514***
	(.0113)	(.0175)	(.0176)	(.0140)	(.0139)	(.0167)	(.0163)	(.0188)	(.0149)
R-squared	.0001	.0002	.0011	.0009	.0000	.0010	.0022	.0000	.0005
Observations	4,427,000	8,223,000	285,000	6,374,000	871,000	4,406,000	6,763,000	5,035,000	7,431,000
	Textiles	Footwear	Ceramics	Jewelry	Metal Prods	Machinery	Transport	Optics	
3-4 Years	.0046	.0029	−.0396***	.0135	−.0758***	−.2360***	−.1447***	−.1229***	
	(.0066)	(.0065)	(.0108)	(.0239)	(.0062)	(.0243)	(.0343)	(.0305)	
5-6 Years	.0167	.0001	−.0480**	.0001	−.0951***	−.2757***	−.2059***	−.1250***	
	(.0158)	(.0105)	(.0198)	(.0281)	(.0082)	(.0242)	(.0485)	(.0411)	
7-8 Years	.0227	−.0090	−.0415*	.0244	−.1187***	−.2869***	−.2376***	−.1593***	
	(.0255)	(.0089)	(.0238)	(.0220)	(.0121)	(.0203)	(.0783)	(.0601)	
R-squared	.0001	.0000	.0003	.0000	.0015	.0035	.0031	.0020	
Observations	39,300,000	6,893,000	5,156,000	1,111,000	13,220,000	20,480,000	6,215,000	4,586,000	

Notes: 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. Each column presents the regression coefficients of the cross-sectional specification (3) for the broad HS10 product category indicated in the column header. $\tilde{p}_{mxhj}$ is the log price of transaction j of importer-exporter-product triplet mxh minus the log average price of the product and country in that quarter. The coefficients on "3-4 years", "5-6 years", and "7-8 years" are the coefficients on dummies d^i_{mxj} that are equal to one if the relationship is i years old at transaction j.

Table E.5: 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		

F Micro Foundations of the Relationship Capital Process

F.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:

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

subject to

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

Under similar conditions as discussed in Section G.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

$$a' = a + q(p) \tag{27}$$

$$c(0) = c_0. \tag{28}$$

The learning-by-doing setup mirrors the setup introduced in the main text. The process for relationship capital, equation (5), is a generalization of the process presented in equation (27), 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 (27), the model in Dasgupta and Stiglitz (1988) becomes identical to my baseline model without limited commitment.

F.2 Customer Capital

I show that the relationship capital accumulation process (5) 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

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

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).

G Proofs

G.1 Existence of Recursive Representation and an Optimal Policy

Consider first the seller's pricing problem without relationship break-ups. The seller's problem in sequence form is

$$J(a_0, e_0) = \max_{\{p_t\}_{t=0}^{\infty}} E \sum_{t=0}^{\infty} \beta^t \left[(p_t - c(a_t, e_t)) \, q(p_t) \right]. \tag{29}$$

Denote by $A \in \mathbb{R}$ the set of values that a can take, and let $e \in [\underline{e}, \infty)$ and $\underline{e} > 0$. 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 (29) 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 $e_t \in [\underline{e}, \infty)$, any solution to the sequence problem (29) 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 seller's profit function $\Pi_s(a_t, e_t; \tilde{a}_{t+1})$ is continuous in a_t and $\tilde{a}_{t+1}$. Moreover, $\lim_{n\to\infty} \sum_{t=0}^{n} \beta^t \Pi_s(a_t, e_t; \tilde{a}_{t+1})$ exists and is finite.

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

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

Proof. Using equation (7) and the definition of $\tilde{a}_{t+1}$ and re-arranging, the seller's price can be expressed as

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

Therefore, the seller's profits in period t are

$$\Pi_s(a_t, e_t; \tilde{a}_{t+1}) = \left[\left[\frac{\left(\frac{\theta}{\theta-1}\right)^{-\theta}\rho A^{\theta-1}P_t^{\theta}Y_t}{(\tilde{a}_{t+1}-(1-\delta)a_t)}\right]^{1/\theta} - c(e_t, a_t)\right]\frac{1}{\rho}(\tilde{a}_{t+1}-(1-\delta)a_t). \tag{30}$$

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

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

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

$$(\Pi_s)^*(a_{t,}, e_t) = \left(\frac{1}{\theta-1}\right)\left(\frac{\theta}{\theta-1}\right)^{-2\theta} c(a_t, e_t)^{1-\theta}A^{\theta-1}P_t^{\theta}Y_t > 0. \tag{31}$$

□

Lemma 2. *Assume that the marginal cost function is sufficiently convex in a_t, i.e., $c''(a_t, e_t) > (1+\theta)\frac{[c'(a_t,e_t)]^2}{c(a_t,e_t)}$ (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 e_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 twice differentiating equation (31) with respect to a_t I find that the static profit function is strictly concave in relationship capital if and only if

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

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, $p_t^* = \frac{\theta}{\theta-1}c(a_t, e_t)$. From the capital evolution equation (5), at this price the seller in expectation gets additional capital of

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

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

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

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 $e_t \geq \underline{e}$. 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. $\Pi_s(a_t, e_t; \tilde{a}_{t+1})$ is continuous in both a_t and $\tilde{a}_{t+1}$ and $\lim_{n\to\infty} \sum_{t=0}^{n} \beta^t \Pi_s(a_t, e_t; \tilde{a}_{t+1})$ exists and is finite

From the expression in (30), $\Pi_s(a_t, e_t)$ is continuous for all $\tilde{a}_{t+1} > (1-\delta)a_t$. Furthermore, from equation (31), since a^u is finite we have $(\Pi_s)^*(a^u, e) < \infty$ (given $\underline{e} > 0$). Therefore, the maximum profits the seller can obtain in any given state are finite. Hence, $\lim_{n\to\infty} \sum_{t=0}^{n} \beta^t \Pi_s(a_t, e_t; \tilde{a}_{t+1})$ must exist and be finite.

Limited commitment introduces a lower bound for the seller's value $J(a_0, e_0)$. Since this value is finite, the same conditions as before still hold.

G.2 Concavity of the Value Function

Following Acemoglu (2009), Theorem 6.4, the value function $J(a,e)$ is strictly concave in a if the profit function $\Pi_s(a,e)$ 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

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

and therefore

$$\Pi_s(a,e;\tilde{a}') = \left[\left[\frac{\left(\frac{\theta}{\theta-1}\right)^{-\theta} \rho A^{\theta-1} P^{\theta} Y}{(\tilde{a}' - (1-\delta)a)} \right]^{1/\theta} - c(a,e) \right] \frac{1}{\rho} (\tilde{a}' - (1-\delta)a). \tag{32}$$

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

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

and

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

and

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

where $c'(a,e)$ and $c''(a,e)$ are the first and the second derivative of the marginal cost function with respect to a. Since $\tilde{a}' \geq (1-\delta)a$, $c'(a,e) < 0$, and $c''(a,e) > 0$, 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

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

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

$$p > \frac{\theta^2}{\theta-1} \frac{\left[c'(a,e)\right]^2}{c''(a,e)}. \tag{33}$$

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

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

where $p^* = \frac{\theta}{\theta-1} c(a,e)$ is the optimal static price. This condition implies equation (33), 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.

G.3 Slope of the Policy Function

Using (7) and (5) in equation (12) and re-arranging, the first-order condition of the problem becomes

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

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 G.2, the problem is strictly concave, and therefore the SOC is negative. For the numerator we have

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

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

G.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

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

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 $p = \frac{\theta}{\theta-1}c(a,e)$, that

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

and therefore

$$\frac{d(\tilde{a}')^M}{da} = (1-\delta) - \rho\theta\left(\frac{\theta-1}{\theta}\right)^{2\theta} c'(a,e)[c(a,e)]^{-\theta-1}A^{\theta-1}P^{\theta}Y > 1-\delta \tag{34}$$

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

Since $J(a,e)$ is concave in a by G.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 (34) 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.

G.5 Proof of Comparative Statics

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

$$FOC = \left(\frac{\theta-1}{\theta}\right)\left[\frac{\rho\left(\frac{\theta}{\theta-1}\right)^{-\theta}A^{\theta-1}P^{\theta}Y}{(\tilde{a}'-(1-\delta)a)}\right]^{1/\theta} - c(a,e) + \beta\rho EJ_a(a',e') = 0.$$

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 G.2, the problem is strictly concave, and therefore the SOC is negative. For the numerator we have

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

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 $dp/d\delta > 0$.

G.6 Proof of $J_{ae}(a,e) \leq 0$

Denote by $J_e(a,e)$ the derivative of $J(a,e)$ with respect to e. Since an increase in e strictly decreases profits in every period, we have that $J_e(a,e) < 0$ for all a. Fix the level of capital at a, and consider two levels of the exchange rate, e and $e+\varepsilon$, 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 $e+\varepsilon$ than under e. If that were the case then we would have $J(a,e) > J(a,e+\varepsilon)$ but $J(a+\xi,e) \leq J(a+\xi,e+\varepsilon)$, since ε can be chosen arbitrarily small, a contradiction.

Assume for contradiction that $J_{ae}(a,e) > 0$, where $J_{ae}(a,e)$ indicates the cross derivative of $J(a,e)$ with respect to a and with respect to e. Then $J_a(a,e+\varepsilon) > J_a(a,e)$. Choose a $\delta(\varepsilon)$ small enough so that $J_a(a,e+\varepsilon) > J_a(a,e)+\delta(\varepsilon)$, and define $\delta(\varepsilon) \equiv -\frac{\varepsilon}{\xi}J_e(a,e)$, which can be made arbitrarily small for any ε by choosing ξ appropriately since $J_e(a,e)$ is finite and continuous for $e \geq \underline{e} > 0$. Plugging in yields

$$\frac{J_a(a,e+\varepsilon)-J_a(a,e)}{\varepsilon} > -\frac{J_e(a,e)}{\xi}.$$

Re-arranging this expression gives

$$\begin{aligned} J_{ae}(a,e) > -\frac{J_e(a,e)}{\xi} &\Leftrightarrow J_e(a+\xi,e)-J_e(a,e) > -J_e(a,e) \\ &\Leftrightarrow J_e(a+\xi,e) > 0, \end{aligned}$$

which is a contradiction since it must be the case that $J_e(a,e) < 0$ for all a. Therefore, $J_{ae}(a,e) \leq 0$.

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

The FOC of the seller's problem with respect to p is

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

Since a marginal increase in relationship capital only affects the break-up decision for states in which $J(a',e')$ is very close to V, the last term is zero. Re-arranging yields (13).

G.8 Increasing Prices in Constrained Region

I show that prices are increasing in relationship capital when the buyer's participation constraint binds. Using the expression for $W(a,e)$ from (10) and re-arranging when the buyer's participation constraint is binding, $W(a,e)=U$, I get

$$p=\left[\frac{1}{U-\beta E\left[I'W(a',e')+(1-I')U\right]}\left(\frac{1}{\theta-1}\right)\left(\frac{\theta}{\theta-1}\right)^{-\theta}A^{\theta-1}P^{\theta}Y\right]^{1/(\theta-1)}. \tag{35}$$

This expression is increasing in a since $W(a',e')$ is increasing in a'. By G.3, a' and a are positively correlated.

H Alternative Models

H.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

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

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

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

Increases in a lead to higher sales to final consumers, and therefore a higher quantity demanded from the seller. Equation (7) thus becomes

$$q(p) = \frac{y(b)}{Aa^{\gamma}} = (\tfrac{p^f(b)}{P})^{-\theta}\frac{Y}{Aa^{\gamma}} = \left(\frac{\theta}{\theta-1}\right)^{-\theta} a^{\gamma(\theta-1)} P^{\theta} A^{\theta-1} Y p^{-\theta}.$$

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

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

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, $J_a(a',e')$ 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.

H.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

$$q_t(i) = \left(\frac{p_t^f(i)}{P_t} \right)^{-\theta} Q_t, \tag{36}$$

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

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

$$q_t(i) = \left[\sum_{k=1}^{K_1+K_2} (m_t(i,k))^{(\eta-1)/\eta} \right]^{\eta/(\eta-1)}, \tag{37}$$

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

$$m_t(i,k) = \left(\frac{p_t(i,k)}{p_t^f(i)} \right)^{-\eta} q_t(i), \tag{38}$$

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 $\eta < \infty$ 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

$$m_t = a_t x_t, \tag{39}$$

where I assume now, contrary to the main text, that a_t 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_t is subject to marginal input cost w_t, which is equal to a constant ω_l for domestic firms and equal to $w_t = e_t \omega_l^*$ for foreign firms, where e_t is the exchange rate and ω_l^* is the cost of the input in foreign currency. The exchange rate evolves stochastically over time, reflecting exchange rate fluctuations. 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

$$\Pi_s(a_t(i,k), e_t(k)) = \max_{p_t(i,k), m_t(i,k)} \left[p_t(i,k) - w_t(k)/a_t(i,k)\right] m_t(i,k) - F, \tag{40}$$

subject to (37), (38), P_t, and Q_t, where sector quantities are given by (37) and the firm takes all other firms' quantities as given.

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

$$p(i,k) = \frac{\varepsilon(s(i,k))}{\varepsilon(s(i,k)) - 1} \frac{w(k)}{a(i,k)}, \tag{41}$$

where

$$\varepsilon(s(i,k)) = \left[\tfrac{1}{\eta}(1-s) + \tfrac{1}{\theta}s\right]^{-1} \tag{42}$$

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

$$s(i,k) = p(i,k)m(i,k)/(\sum_{k=1}^{K} p(i,k)m(i,k)) = \left(\frac{p(i,k)^{1-\eta}}{\sum_{k=1}^{K} p(i,k)^{1-\eta}} \right). \tag{43}$$

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 e. 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 (41) and using the expression for market shares (43) gives a similar expression as in Atkeson and Burstein (2008):

$$\hat{p}(i,k) = \frac{1}{1+(\eta-1)\Gamma(s(i,k))} \left[\hat{w} - \hat{a}(i,k) + (\eta-1)\Gamma(s(i,k))\hat{p}(i) \right], \tag{44}$$

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 e 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 e, 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 e 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.

H.3 Nash Bargaining Setup

Assume there is a unit mass of buyers indexed by b, and a continuum of foreign sellers indexed by s. Let v denote the mass of unmatched buyers and u denote the mass of unmatched sellers. These firms match according to a CES matching function of the form

$$M(v,u) = (v^{-\iota} + u^{-\iota})^{-\frac{1}{\iota}}, \tag{45}$$

where the probability that an unmatched buyer meets a seller is

$$\pi_b(\vartheta) = M(1,\vartheta) = (1+\vartheta^{\iota})^{-\frac{1}{\iota}}, \tag{46}$$

and the probability that an unmatched seller finds a buyer is

$$\pi_s(\vartheta) = \vartheta(1+\vartheta^{\iota})^{-\frac{1}{\iota}} = \vartheta\pi_b(\vartheta). \tag{47}$$

In a match, sellers produce each unit with marginal cost $c(a,e) = \frac{1}{a^{\gamma}}e\omega_l^*$, where a is relationship capital and evolves according to the same process as in the main text, e is the exchange rate, and ω_l^* is the cost of the foreign input in foreign currency. The seller firms transact with buyers who face the same final consumer demand as in the main text of $y(b) = (\frac{p^f(b)}{P})^{-\theta}Y$, where $p^f(b)$ is the price charged by the buyers to final consumers.

The buyer and seller firms split their surplus in a relationship via bargaining. 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 constant since there is a continuum of countries with stationary and i.i.d. exchange rates, as in the main text. Let $W(a,e)$ be the value of a matched buyer given state (a,e). Similarly, let V and $J(a,e)$ be the value of an unmatched seller and the value of a seller in a relationship, respectively.

Unmatched buyers pay a per-period cost κ to search for matches, and make zero profits when unmatched. The value of an unmatched buyer in state e is then given by:

$$U = -\kappa + \beta \left[\pi_b(\vartheta) EW(a',e') + (1-\pi_b(\vartheta))U\right], \tag{48}$$

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 exchange rates. I impose free entry of buyers so that $U = 0$, which implies that

$$EW(a',e') = \frac{\kappa}{\beta \pi_b(\vartheta)}. \tag{49}$$

An unmatched seller has value function

$$V = \beta[\pi_s(\vartheta) EJ(a',e') + (1-\pi_s(\vartheta))V]. \tag{50}$$

Once the buyer and the seller are in a relationship, from the demand function of final consumers we have

$$y(b) = (\tfrac{p^f(b)}{P})^{-\theta} Y \quad \Rightarrow \quad p^f(b) = (y(b))^{-\frac{1}{\theta}} PY^{\frac{1}{\theta}}$$

and therefore the buyer's revenues are $R(b) = (y(b))^{(\theta-1)/\theta} PY^{1/\theta}$. Using $y(b) = Aq$, the buyer's value function is thus

$$W(a,e) = (Aq)^{\frac{\theta-1}{\theta}} PY^{\frac{1}{\theta}} - T + \beta E\left[\max\left\{W(a',e'),U\right\}\right], \tag{51}$$

where the continuation value depends on the evolution of costs and relationship capital, and the first term in equation (51) represents the revenues of a buyer purchasing quantity q from the seller. The seller's value function is

$$J(a,w) = T - \frac{e\omega_l^*}{a^\gamma} q + \beta E\left[\max\left\{J(a',e'),V\right\}\right]. \tag{52}$$

Given weight ϕ on the buyer, under Nash bargaining the payment satisfies

$$T = \text{argmax}\,(W(a,e) - U)^{\phi}\,(J(a,e) - V)^{1-\phi}. \tag{53}$$

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

$$\phi\,(J(a,e) - V) = (1-\phi)\,(W(a,e) - U). \tag{54}$$

From equations (48)-(52), I have that

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

I can use the fact that condition (54) has to hold at each point in time to simplify and obtain:

$$T=(1-\phi)\left[(Aq)^{\frac{\theta-1}{\theta}}PY^{\frac{1}{\theta}}+\kappa\right]+\phi\frac{e\omega_l^*}{a^\gamma}q+(1-\phi)\beta\pi_b(\vartheta)(\vartheta-1)E\left[W(a',e')-U\right]. \tag{55}$$

Using the free entry condition (49) and re-arranging yields

$$p=\frac{T}{q}=(1-\phi)\left[A^{\frac{\theta-1}{\theta}}PY^{\frac{1}{\theta}}q^{-\frac{1}{\theta}}+\frac{\kappa\vartheta}{q}\right]+\phi\frac{e\omega_l^*}{a^\gamma}. \tag{56}$$

Next, adding up (51) and (52), and deducting (50), I obtain a total match surplus over the outside value of

$$S(a,e)=(Aq)^{\frac{\theta-1}{\theta}}PY^{\frac{1}{\theta}}-\frac{e\omega_l^*}{a^\gamma}q+\beta E\left[\max\{S(a',e'),0\}\right]-\beta\vartheta\pi_b(\vartheta)\frac{1-\phi}{\phi}E\left[W(a',e')-U\right]. \tag{57}$$

Using the free entry condition (49) yields

$$S(a,e)=(Aq)^{\frac{\theta-1}{\theta}}PY^{\frac{1}{\theta}}-\frac{e\omega_l^*}{a^\gamma}q+\beta E\left[\max\{S(a',e'),0\}\right]-\frac{1-\phi}{\phi}\kappa\vartheta. \tag{58}$$

It follows that the surplus $S(a,e)$ 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 e. Therefore, there must exist a threshold level of capital $\underline{a}^{NB}(e)$, which is increasing in e, such that $S(a,e)<0$ whenever $a<\underline{a}^{NB}(e)$, 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 (58) with respect to q, I obtain

$$q=\left(\frac{\theta-1}{\theta}\right)^{\theta}A^{\theta-1}P^{\theta}Y\left[\frac{e\omega_l^*}{a^\gamma}-\beta\rho E\left[I'S_a(a',e')\right]\right]^{-\theta},$$

where $I' = I(a', e')$ is an indicator that is equal to one if the relationship is continued in state (a', e'). Note that the term $E[\frac{dI(a',e')}{dq}(S(a', e') - 0)] = 0$ 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 (56) yields the pricing equation

$$
\begin{aligned}
p = {} & (1-\phi)\left(\frac{\theta}{\theta-1}\right)\left[\frac{e\omega_l^*}{a^\gamma} - \beta\rho E\left[I'S_a(a', e')\right]\right] + \phi\frac{e\omega_l^*}{a^\gamma} \\
& + (1-\phi)\frac{\kappa\vartheta}{A^{\theta-1}P^\theta Y}\left(\frac{\theta}{\theta-1}\right)^\theta\left[\frac{e\omega_l^*}{a^\gamma} - \beta\rho E\left[I'S_a(a', e')\right]\right]^\theta .
\end{aligned} \tag{59}
$$

Pass-through is given by

$$
\begin{aligned}
\frac{d\ln(p)}{d\ln(e)} = {} & \frac{(1-\phi)\left(\frac{\theta}{\theta-1}\right)\left[\frac{e\omega_l^*}{a^\gamma} - \beta\rho\Psi(a', e')\right] + \phi\frac{e\omega_l^*}{a^\gamma}}{p} \\
& + \frac{(1-\phi)\frac{\kappa\vartheta}{A^{\theta-1}P^\theta Y}\left(\frac{\theta}{\theta-1}\right)^\theta \theta\left[\frac{e\omega_l^*}{a^\gamma} - \beta\rho\Psi(a', e')\right]\left[\frac{e\omega_l^*}{a^\gamma} - \beta\rho E\left[I'S_a(a', e')\right]\right]^{\theta-1}}{p},
\end{aligned} \tag{60}
$$

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

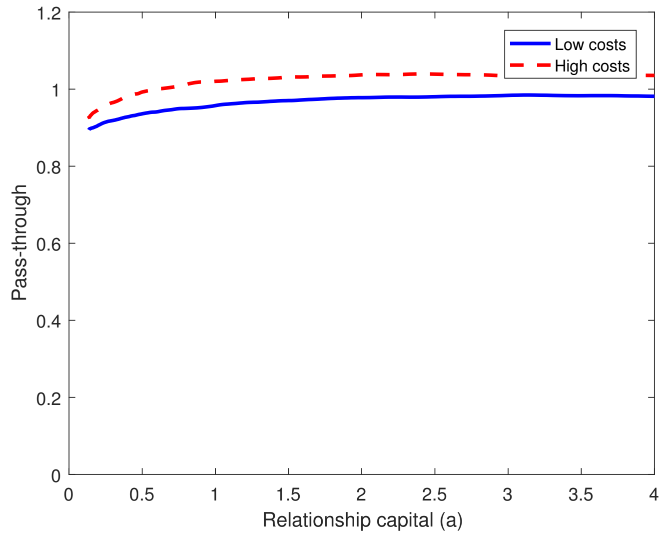
Consider the case of $E\left[I'S_a(a', e')\right]$ and its derivative being approximately zero. Then, pass through is

$$
\frac{d\ln(p)}{d\ln(e)} \approx \frac{(1-\phi)\left(\frac{\theta}{\theta-1}\right)\frac{e\omega_l^*}{a^\gamma} + \phi\frac{e\omega_l^*}{a^\gamma} + (1-\phi)\frac{\vartheta\kappa}{A^{\theta-1}P^\theta Y}\left(\frac{\theta}{\theta-1}\right)^\theta\theta\left(\frac{e\omega_l^*}{a^\gamma}\right)^\theta}{(1-\phi)\left(\frac{\theta}{\theta-1}\right)\frac{e\omega_l^*}{a^\gamma} + \phi\frac{e\omega_l^*}{a^\gamma} + (1-\phi)\frac{\vartheta\kappa}{A^{\theta-1}P^\theta Y}\left(\frac{\theta}{\theta-1}\right)^\theta\left(\frac{e\omega_l^*}{a^\gamma}\right)^\theta} > 1,
$$

since $\theta > 1$. Moreover, if anything pass-through is declining with a.

Figure H.1 presents a quantitative evaluation of pass-through in the fully specified model, where the matching probabilities are calibrated 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.

Figure H.1: Pass-Through under Nash Bargaining



I Value Functions in the Quantitative Model

In this section, I list the value functions of the quantitative model. From the second period of the relationship onward, the value functions are similar to the ones given by equations (8)-(11) in the main text. The seller maximizes

$$J(a,e) = \max_p [p - c(a,e)]\, q(p) + \beta E \left\{ \max \left\{ J(a',e'), V \right\} \right\},$$

where

$$V = \beta[\pi_s(\vartheta) E J^0(a,e) + (1-\pi_s(\vartheta))V],$$

subject to the buyer's participation constraint $W(a,e) \geq U$, where

$$W(a,e) = \left[p^f(a,e) - \tfrac{p(a,e)}{A} \right] y(p^f(a,e)) + \beta E \left[I'(a',e') W(a',e') + (1 - I'(a',e'))U \right],$$

and

$$U = \Pi_b^o + \beta[\pi_b(\vartheta) E W^0(a,e) + (1-\pi_b(\vartheta))U].$$

Here, the only difference to the main text is that new relationships in state (a,e) have a value of $J^0(a,e)$ for the buyer and of $W^0(a,e)$ for the seller, where the superscript 0 indicates functions for the first period. This problem leads to the policy function $p(a,e)$ characterized by equation (13) and the break-up function $I(a,e)$.

The first period value functions are defined by a slightly different system of equations. The seller's maximization problem is

$$J^0(a,e) = \max_p [p - c(a,e)]\, q(p) + \beta E\left\{\max\left\{J(a',e'), V\right\}\right\}$$

subject to the buyer's first-period participation constraint $W^0(a,e) \geq U^0$, where

$$W^0(a,e) = \left[p^{f,0}(a,e) - \tfrac{p^0(a,e)}{A}\right] y(p^{f,0}(a,e)) + \beta E\left[I'(a',e')W(a',e') + (1 - I'(a',e'))U\right]$$

and

$$U^0 = \beta[\pi_b(\vartheta)EW^0(a,e) + (1 - \pi_b(\vartheta))U].$$

While $J^0(a,e)$ and $W^0(a,e)$ are similar to $J(a,e)$ and $W(a,e)$, the lower buyer outside option $U^0 \leq U$ in the first period means that for a given state (a,e) the seller can set a different price $p^0(a,e)$ in her maximization problem, leading to a different price $p^{0,f}(a,e) = \frac{\theta}{\theta-1}\frac{p^0(a,e)}{A}$ for the given state (a,e), and hence both the buyer's and the seller's value in state (a,e) are different in the first period. In practice, the seller can set a relatively high price in the first period when the draw of relationship capital is low since the buyer's outside option has a lower value. This fact generates a substantial average price difference between relationships in their first and in their second year, better aligned with the data. It also means that relationships are more likely to trade even if the relationship capital draw is low, leading to a large number of relationships that trade exactly once, as in the data.

J Parametrization and Estimation

In this section, I provide more details on the calibrated parameters and on the estimation. Section J.1 describes how the calibrated parameters are set. Section J.2 describes how I construct the moments and how they relate to the parameters. Section J.3 provides more details on how the moments identify the parameters. Section J.4 describes the estimation procedure. Section J.5

provides more details on the selection mechanism in the model.

J.1 Calibrated Parameters

I describe how I calibrate the parameters in panel a of Table 4.

Quarterly discount factor (β). I assume a quarterly discount factor of $\beta = 0.992$.

Elasticity of substitution (θ). This parameter is set as $\theta = 4$ as in Nakamura and Steinsson (2008).

Exchange Rate Process (σ_ξ, φ) I discretize the exchange rate process using the methodology by Tauchen (1986) on a five-state Markov chain, and normalize $E[e]$ 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 $\sigma_\xi = .066$, and set $\varphi = 0.99$ to match the persistence of exchange rates.

Productivity and Mean of Relationship Capital (A, μ_a). 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.

Matching Parameters (ϑ, ι). 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.[55] I set π_b using the time U.S. importers spend to find a new supplier following a plausibly exogenous relationship break-up. I define such break-ups as cases where a supplier suddenly stops trading with at least three independent U.S. customers and disappears forever from the LFTTD. Table J.1 provides some statistics for such break-ups, for relationships that have lasted at least 12

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

Table J.1: Break-Up Statistics for Relationships ≥ 12 Months

(1)	Avg. months until new supplier found	14.9
(2)	Avg. months until new supplier for rel ≥ 12 months found	28.2
(3)	Avg. number of suppliers tried before rel ≥ 12 months found	3.0
(4)	Excess gap time between transactions	10.6

Notes: 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 12 months. I define such break-ups as cases where a supplier suddenly stops trading with at least three independent customers and disappears forever. The first row shows the average number of months needed until the importer finds a new supplier. The second row shows the average number of months needed until the importer finds a new supplier with which she forms a relationship that lasts for at least 12 months. The third row documents how many different new suppliers the importer transacts with until she forms a relationship lasting at least 12 months. The fourth row shows the excess gap time, defined as the time an importer needs to find a new supplier after a plausibly exogenous relationship break-up minus the average time gap between the importer's transactions of the supplier's good.

months. After an exogenous break-up of such a relationship, it takes U.S. importers on average 15 months to find a new supplier of the same good (row 1). Finding a new supplier with whom the relationship will last more than 12 months takes even longer, on average 28 months (row 2), and on average importers unsuccessfully try out 3 suppliers before forming that long-term relationship (row 3). The fourth row shows the time needed to find a new supplier minus the average time gap between the importer's transactions of the supplier's good. This statistic shows how much longer it takes to find a new supplier relative to the time interval in which the importer usually buys the good. This excess gap time is on average 11 months. I will use this excess gap time in the estimation, and interpret this time gap as the time needed to search for a new supplier. A time period of 11 months translates into a quarterly probability of finding a new supplier of $\pi_b = 0.26$.

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 16 months. Thus, I set $\pi_s = 0.17$. The probabilities imply $\vartheta = 0.66$ and $\iota = 0.45$. These deep parameters will be used in the counterfactuals.

J.2 Estimated Parameters

I describe how I estimate the parameters in panel b of Table 4. While all parameters are jointly estimated, I discuss how each can be identified from a different set of moments, and provide more details on identification in Section J.3.

Average Pass-Through (α). 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. I do not explicitly target the pass-through gradient with relationship age, which is a key moment to determine the model's success.

Standard Deviation of Shocks to Relationship Capital (σ_ε) and Depreciation (δ). I choose σ_ε to generate the break-up hazard of relationships in their first and second quarter (Figure 2b), and set δ to match the value shares of relationships that are in their first quarter or older than four years, respectively (Figure 1a). A higher value of σ_ε makes large shocks more likely, which raises separations of new relationships. A higher δ pulls relationships towards lower a and therefore reduces survival. 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 $\underline{a}(e)$ 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, decreasing break-ups of very new relationships since it takes time for capital to drift down to the new separation bound.

Effect of Relationship Capital on Costs (γ) and Standard Deviation of New Relationship Capital (σ_a). I set γ to match the steepness of the life cycle profile of value traded (Figure 2a) 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.

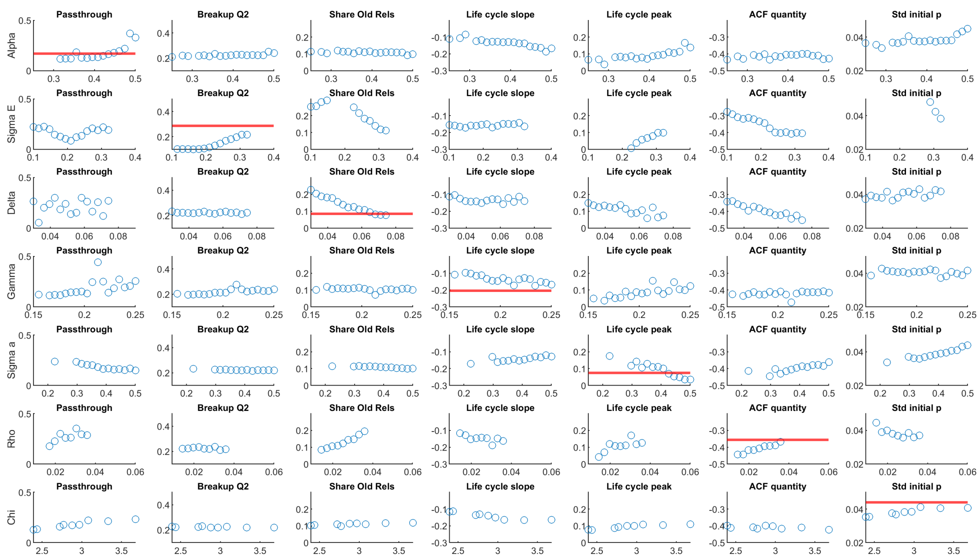
Autocorrelation of Relationship Capital (ρ). I set ρ to match the autocorrelation of a relationship's annual quantity traded and the break-up hazard in quarter eight relative to quarter two. A higher ρ makes the quantity traded more persistent, which increases autocorrelation, and reduces the relative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

Cost of Spot Market Purchases (χ). A higher spot market 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 3c). I set this parameter in the simulation by regressing the price of relationships in their first quarter on their cost draw e, 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. I trim the residual distribution below the 10th and above the 90th percentile to remove outliers.

J.3 Identification

Figure J.1 plots values of each of the seven parameters against values of the seven main moments used to identify them. In each panel, I vary the parameter indicated on the left-hand side along a linear grid while keeping all other parameters fixed at their estimated baseline values. Each panel plots a given parameter (in the row) against a given moment (in the column). The main parameter identifying each moment is along the diagonal, where the red horizontal line indicates the value of the moment in the data. The plot shows that there is generally a monotone relationship between each parameter and its targeted moment. For example, increasing α tends to increase average pass-through, while raising the relationship capital depreciation rate δ reduces the share of old relationships, as described. When the blue circle lies on top of the red line, it means that at this parameter value the moment is perfectly matched.

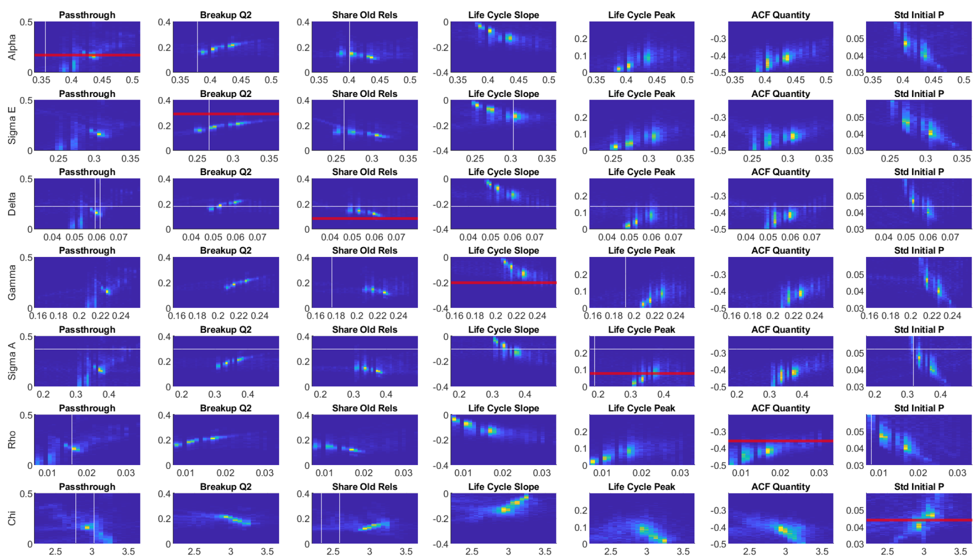
Figure J.1: Identification: Varying One Parameter at a Time



Note: The figure shows scatter plots of each of the seven parameters against each of the seven main moments used. The plot is constructed by fixing all parameters at their estimated baseline values and by varying the row parameter indicated on the left along a linear grid, with values on the x-axis. For each parameter value the estimation is run for 100 parallel chains and then averaged across chains. The resulting average value of the moment for the given parameter value is indicated by the blue circles. Missing circles indicate that the model did not have a (real) solution for the given parameter value. The red line shows the empirical value of the moment listed on the column header. Column 1 plots parameter values 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.

Figure J.2 presents an alternative view on identification. In contrast to the previous figure, I do not hold all parameters fixed at their estimated baseline values. Specifically, 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 as a bin scatter. Lighter areas in the binscatter indicate more frequently observed values in the 100 simulation chains. As before, the parameter-moment combinations of interest are along the diagonal. The plot shows that each of the parameters of interest still varies with its targeted moment as described.

Figure J.2: Identification: Varying All 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. Lighter areas indicate more frequently observed values in the 100 simulation chains. The red line shows the empirical value of the moment listed on the column header. 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.

J.4 Estimation Procedure

I estimate the model via simulated method of moments, following the MCMC procedure by Chernozhukov and Hong (2003). The objective is to find a parameter vector $\hat{\Psi}$ that solves

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

where Ψ is the true parameter vector and $G(\Psi)$ and $G(\hat{\Psi})$ are the data moments and the model moments, respectively. I simulate 400 Markov chains of length 100, starting from 400 different guesses for the parameter vector Ψ. I choose these initial guesses to span a large range of possible parameter values.

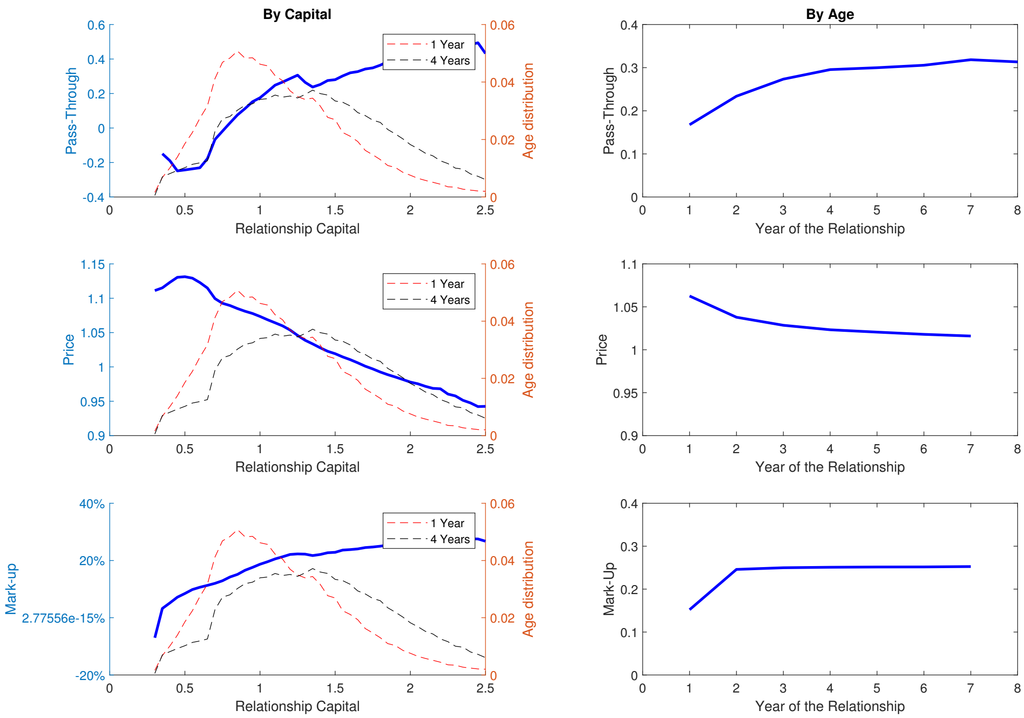
For each proposed parameter vector Ψ in the Markov chains, I solve for the equilibrium of my model using an iterative procedure. First, I guess an aggregate U.S. price level P and solve for the value functions and policies. Given these functions, I simulate a panel of buyer firms and obtain their distribution of intermediate prices p and final goods prices p^f. I then compute the new aggregate price level P given these simulated prices, which I use to update the value functions and policies. I repeat these steps until the model converges to its equilibrium. I compute the criterion function J for each parameter combination.

The final parameter vector with the lowest deviation J from the data is my parameter estimate. I report it in Table 4, together with each parameter's standard deviation across the 20 best Markov chains.

J.5 Intuition for the Selection Mechanism

To gain intuition for the model's selection mechanism, Figure J.3 presents, for the final parameter estimate, the average pass-through, prices, and mark-ups in the simulated panel as a function of relationship capital in the left column (solid blue lines). Pass-through rises, prices fall, and mark-ups increase with relationship capital. The dashed lines plot the distributions of relationship capital for all relationships currently in their first year and in their fourth year, respectively. Older relationships on average have more capital, as illustrated by the rightward shift in the relationship capital distribution. 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 J.3: 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.

K Additional Details on the Cyclical Variation of Imports and Pass-Through

Details on the Decomposition

I provide some additional details on the decomposition in Section 4.2. 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

$$\begin{aligned}\sum_{r\in R_t}\sum_{h\in H_{r,t}} y_{rh,t} - \sum_{r\in R_{t-4}}\sum_{h\in H_{r,t-4}} y_{rh,t-4} = &\left[\sum_{r\in R_t, r\notin R_{t-4}}\sum_{h\in H_{r,t}} y_{rh,t} - \sum_{r\notin R_t, r\in R_{t-4}}\sum_{h\in H_{r,t-4}} y_{rh,t-4}\right] \\ &+\left[\sum_{r\in R_t\cap R_{t-4,t}}\sum_{h\in H_{r,t}, h\notin H_{r,t-4}} y_{rh,t} - \sum_{r\in R_t\cap R_{t-4}}\sum_{h\notin H_{r,t}, h\in H_{r,t-4}} y_{rh,t-4}\right] \\ &+\sum_{r\in R_t\cap R_{t-4}}\sum_{h\in H_{r,t}\cap H_{r,t-4}}\left[\{y_{rh,t}-y_{rh,t-4}\}^{+}+\{y_{rh,t}-y_{rh,t-4}\}^{-}\right]\end{aligned} \tag{61}$$

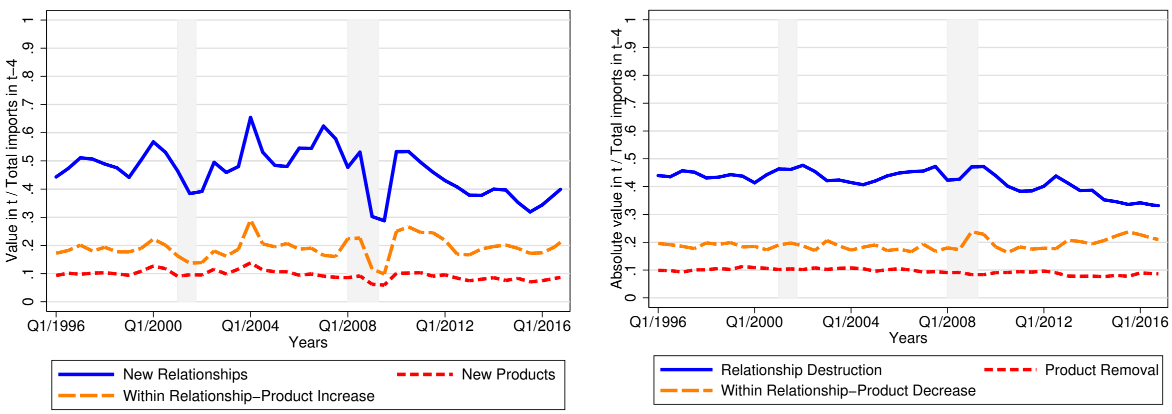
The first bracket represents the value traded by new relationships in t minus the value traded by relationships in $t-4$ that no longer exist in t. The second term is the change in trade due to new product additions minus product removal in continuing relationships. The last term is the intensive margin 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. In Figure 5, I divide each margin by total imports in $t-4$.

Alternative Treatment of Exporters

I conduct a similar decomposition as in the main text, but use the shortened MID or the concorded MID to identify exporters. Using these exporter identifiers to construct relationships, Figure K.1 provides the decomposition using the shortened MID that omits the city and address component to identify exporters, and Figure K.2 shows the decomposition using the concorded MID as constructed in Appendix A.2. The results are similar to the main text.

Figure K.1: Margins of Trade Changes using Shortened MID

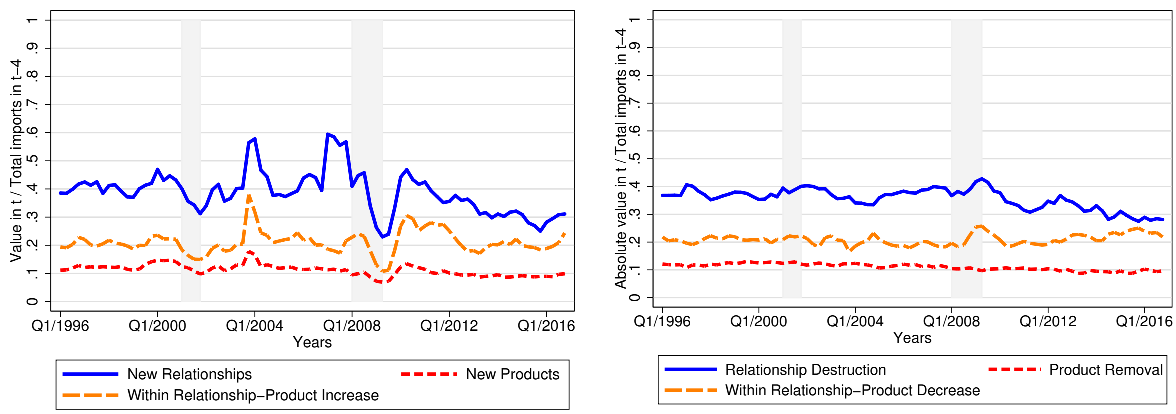
(a) Creation Margins (b) Destruction Margins



Notes: Figure shows the change in U.S. imports between quarters $t-4$ and t decomposed into six margins, using the shortened MID that omits the city and address component to identify exporters. To comply with the Census Bureau's volume of output restrictions, the figure contains data for only Q1 and Q3 of every year, and interpolates across the intermittent quarters Q2 and Q4. The margins are constructed by taking the change in trade between $t-4$ and t for every importer-exporter-product triplet and by assigning this change in trade to one of the six categories based on my definition of whether a relationship or a product is no longer active. "New relationships" is trade by importer-exporter pairs that are new in t compared to $t-4$. "New products" is trade by importer-exporter-product triplets that are new in t compared to $t-4$ where the overall importer-exporter relationship already existed in t. "Within Relationship-Product Increase" is the change in trade for continuing importer-exporter-product triplets that trade more in t than in $t-4$. "Relationship destruction" is the (absolute value) of trade by relationships in $t-4$ that are terminated in t. "Product removal" is the (absolute value) of trade by importer-exporter-product triplets in $t-4$ that are no longer active in t while the overall relationship is still active. "Within Relationship-Product Decrease" is the (absolute value) change in trade for continuing importer-exporter-product triplets that trade less (possibly 0) in t than in $t-4$. The margins add up to the total change in imports.

Figure K.2: Margins of Trade Changes using Concorded MID

(a) Creation Margins (b) Destruction Margins

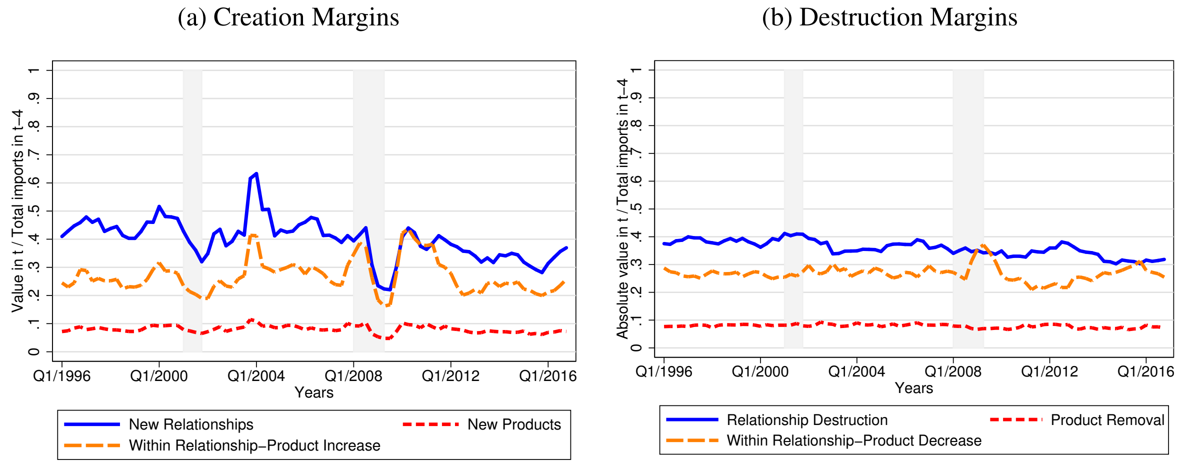


Notes: Figure shows the change in U.S. imports between quarters $t-4$ and t decomposed into six margins, where exporters are identified based on the concorded MID constructed in Appendix A.2. The margins are constructed by taking the change in trade between $t-4$ and t for every importer-exporter-product triplet and by assigning this change in trade to one of the six categories based on my definition of whether a relationship or a product is no longer active. "New relationships" is trade by importer-exporter pairs that are new in t compared to $t-4$. "New products" is trade by importer-exporter-product triplets that are new in t compared to $t-4$ where the overall importer-exporter relationship already existed in t. "Within Relationship-Product Increase" is the change in trade for continuing importer-exporter-product triplets that trade more in t than in $t-4$. "Relationship destruction" is the (absolute value) of trade by relationships in $t-4$ that are terminated in t. "Product removal" is the (absolute value) of trade by importer-exporter-product triplets in $t-4$ that are no longer active in t while the overall relationship is still active. "Within Relationship-Product Decrease" is the (absolute value) change in trade for continuing importer-exporter-product triplets that trade less (possibly 0) in t than in $t-4$. The margins add up to the total change in imports.

Naive Definition of Relationship Length

I perform a robustness check of the decomposition where I use a "naive" definition of relationship length. Specifically, a relationship is created at the first ever transaction of an importer-exporter pair in the data, regardless of time gaps between transactions, and a relationship terminates at the last transaction of the importer-exporter pair in the data. Similarly, a product is new the first time it is traded by an importer-exporter pair, and a product is removed when it is traded for the last time by the relationship in the data. Figure K.3a shows the creation margins and Figure K.3b presents the destruction margins under this definition. While the intensive margin is now more important, relationship creation still accounts for 40% of the drop in trade in 2008/2009.

Figure K.3: Margins of Trade Changes under Naive Relationship Definition



Notes: Figure shows the change in U.S. imports between quarters $t-4$ and t decomposed into six margins, where relationships are defined using a "naive" definition: relationships start when they transact for the first time in the data and end when they transact for the last time. The margins are constructed by taking the change in trade between $t-4$ and t for every importer-exporter-product triplet and by assigning this change in trade to one of the six categories based on my definition of whether a relationship or a product is no longer active. "New relationships" is trade by importer-exporter pairs that are new in t compared to $t-4$. "New products" is trade by importer-exporter-product triplets that are new in t compared to $t-4$ where the overall importer-exporter relationship already existed in t. "Within Relationship-Product Increase" is the change in trade for continuing importer-exporter-product triplets that trade more in t than in $t-4$. "Relationship destruction" is the (absolute value) of trade by relationships in $t-4$ that are terminated in t. "Product removal" is the (absolute value) of trade by importer-exporter-product triplets in $t-4$ that are no longer active in t while the overall relationship is still active. "Within Relationship-Product Decrease" is the (absolute value) change in trade for continuing importer-exporter-product triplets that trade less (possibly 0) in t than in $t-4$. The margins add up to the total change in imports.

Importer Entry and Exit

I perform a final decomposition where instead of focusing on relationships I analyze *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

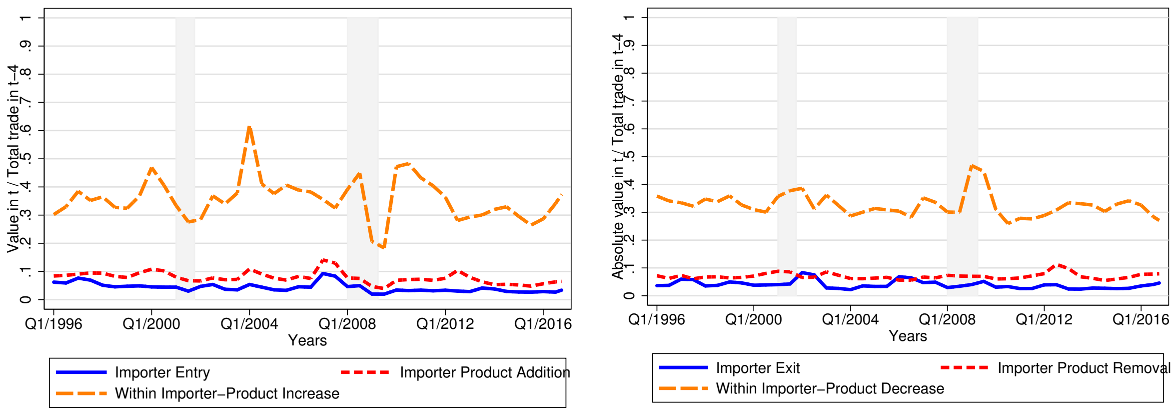
t can be decomposed as

$$\begin{aligned}
\Delta y_{t-4,t} &= \sum_{m\in M_t}\sum_{h\in H_{m,t}} y_{mh,t} - \sum_{m\in M_{t-4}}\sum_{h\in H_{m,t-4}} y_{mh,t-4} \\
&= \left[\sum_{m\in M_t, m\notin M_{t-4}}\sum_{h\in H_{m,t}} y_{mh,t} - \sum_{m\notin M_t, m\in M_{t-4}}\sum_{h\in H_{m,t-4}} y_{mh,t-4}\right] \\
&+ \left[\sum_{m\in M_t\cap M_{t-4,t}}\sum_{h\in H_{m,t}, h\notin H_{m,t-4}} y_{mh,t} - \sum_{m\in M_t\cap M_{t-4}}\sum_{h\notin H_{m,t}, h\in H_{m,t-4}} y_{mh,t-4}\right] \\
&+ \sum_{m\in M_t\cap M_{t-4}}\sum_{h\in H_{m,t}\cap H_{m,t-4}} \left[\left\{y_{mh,t}-y_{mh,t-4}\right\}^{+} + \left\{y_{mh,t}-y_{mh,t-4}\right\}^{-}\right].
\end{aligned} \tag{62}$$

Figure K.4a shows the value of the creation margins from this decomposition, scaled by the total value of imports at $t-4$. 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 K.4b presents the analogous destruction margins. During the Great Recession, the within importer-product margin contributed significantly to the decline in trade, suggesting that importers reduced trade within a given product without dropping the product entirely. Using the findings from the main text, this adjustment occurred mainly by destroying relationships at the usual pace and not forming new ones.

Figure K.4: Margins of Trade Changes for Importers

(a) Creation Margins (b) Destruction Margins



Notes: Figure shows the change in U.S. imports between quarters $t-4$ and t decomposed into six margins. To comply with the Census Bureau's volume of output restrictions, the figure contains data for only Q1 and Q3 of every year, and interpolates across the intermittent quarters Q2 and Q4. The margins are constructed by taking the change in trade between $t-4$ and t for every importer-product pair and by assigning this change in trade to one of the six categories based on my definition of whether a relationship or a product is no longer active. "Importer Entry" is trade by importers that are new in t compared to $t-4$. "Importer-Product Addition" is trade by importer-product pairs that are new in t compared to $t-4$ where the importer already existed in t. "Within Importer-Product Increase" is the change in trade for continuing importer-product pairs that trade more in t than in $t-4$. "Importer Exit" is the (absolute value) of trade by importers in $t-4$ that exit in t. "Importer-Product removal" is the (absolute value) of trade by importer-product pairs in $t-4$ that are no longer active in t while the overall importer is still active. "Within Importer-Product Decrease" is the (absolute value) change in trade for continuing importer-product pairs that trade less (possibly 0) in t than in $t-4$. The margins add up to the total change in imports.

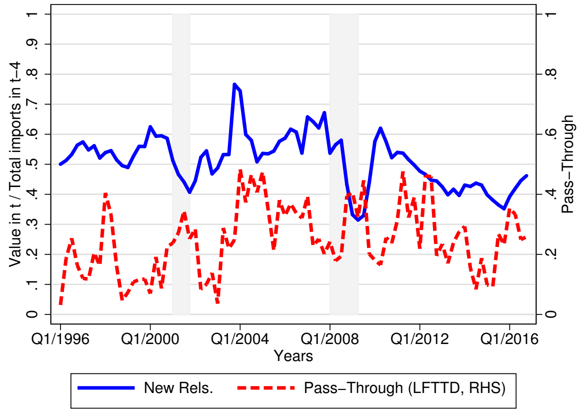
Time Variation in Pass-Through

Figure K.5 presents the coefficients of a regression of price changes on exchange rate changes interacted with quarter dummies in the LFTTD. Specifically, I run:

$$\Delta \ln(p_{mxht}) = \sum_k \beta_k \Delta \ln(e_{mxht}) \cdot \mathbb{I}(t=k) + \omega_t + \varepsilon_{mxht},$$

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, and $\mathbb{I}(t=k)$ is a dummy that is equal to one if the current quarter is k. Moreover, ω_t are time fixed effects that pick up variation in price changes. The regression examines whether the pass-through coefficients β_k differ over time. 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).

Figure K.5: Pass-Through in the LFTTD



Notes: Figure shows the time series of relationship creation from Figure 5a plotted against the coefficients of a pass-through regression that regresses the change in prices of importer-exporter-product triplets on the change in the exchange rate interacted with dummies for each quarter in the sample and time fixed effects.

L Model Validation

I verify four model implications in the trade data to build additional confidence in the model.

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

$$\varsigma_{mxht} = \beta_1 Length_{mxt} + \gamma_{mxh} + \omega_t + \varepsilon_{mxht}, \tag{63}$$

where $Length_{mxt}$ is the length of the relationship in months. Column 1 of Table L.1 shows that the likelihood of negative pass-through declines with a pair's relationship age, as predicted. Column 2 drops outliers with $PT_{mxcht} < -0.3$, 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_{mxt}^{med} to be a dummy that is equal to one if relationship mx trades 10%-30% more in the year associated with quarter t than in year one, and d_{mxt}^{high} a dummy that is one if the relationship trades over 30% 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 in the main text, a better buyer outside option makes it more likely that the buyer trades under a binding participation constraint, which reduces pass-through. I use the buyer's market share in product h in each year t as a proxy for the buyer's outside option. Buyers with a greater market share are more likely to have market power, and may find it easier to find other suppliers. I run

$$\begin{aligned}\Delta \ln(p_{mxht}) = {} & \beta_1 \Delta \ln(e_{mxht}) + \beta_2 \ln(MktShare_{mht}) + \beta_3 \ln(MktShare_{mht}) \cdot \Delta \ln(e_{mxht}) \\ & + \beta_4 Length_{mxt} + \beta_5 Length_{mxt} \cdot \Delta \ln(e_{mxht}) + \beta_6 X_{mxht} + \gamma_{ch} + \omega_t + \varepsilon_{mxcht},\end{aligned} \tag{64}$$

where $MktShare_{mht}$ is the market share of importer m in product h 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-by-product fixed effects, γ_{ch}, rather than relationship-specific fixed effects, since I want to compare pass-through across relationships. Column 4 of Table L.1 shows that pass-through conditional on relationship length and size is indeed lower when the buyer has a greater market share.

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 ($TotLength_{mx}$). I 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,

$$\ln(TotLength_{mx}) = \beta_1 \ln(PT^1_{mxcht}) + \xi_{mh} + \gamma_x + \omega_t + \varepsilon_{mxcht}. \tag{65}$$

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 5 highlights that higher pass-through in the first year implies a longer relationship, consistent with the theory.

A final prediction is that relationships close to separation have a low level of relationship capital. Such relationships should therefore have lower pass-through. I test this implication in column 7 of Table C.1 in Appendix C.1, where I replace *Length* in the pass-through regression with the dummies d^{first}_{mx} and d^{last}_{mx} for whether the relationship is in its first year or in its last year, respectively, for all relationships lasting longer than two years. This table confirms that pass-through is lower in the last year compared to the omitted intermediate years, as predicted.

Table L.1: Model Implication Tests

Dep. var.	Neg Pass-Through Indicator (ς)			$\Delta \ln(p)$		TotLength
	(1)	(2)	(3)	(4)		(5)
Length	$-.0024^{***}$	$-.0045^{***}$			PT Year 1	$.0186^{***}$
	$(.0004)$	$(.0006)$				$(.0059)$
Med. Trade			$-.0005$			
			$(.0006)$			
High Trade			$-.0019^{*}$			
			$(.0009)$			
Share Imp. $\cdot \Delta \ln(e)$				$-.0666^{*}$		
				$(.0368)$		
Time FE	Y	Y	Y	Y		Y
Rel-product FE	Y	Y	Y	–		–
Country-prod FE	–	–	–	Y		–
Imp-prod, Exp FE	–	–	–	–		Y
R-Squared	.2167	.3182	.3181	.0039		.6818
Observations	$27,120,000$	$14,830,000$	$14,830,000$	$27,120,000$		$1,297,000$

Notes: 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. The first column shows the estimated coefficient β_1 in regression (63). The second column shows the same regression but restricted to cases with $PT_{mxcht} \geq 0.3$. The third column replaces $Length_{mxt}$ with two dummies d^{med}_{mxt} and d^{high}_{mxt} indicating whether the relationship trades 10-30% or more than 30% more than in year one. Column 4 shows the estimated coefficient β_3 in regression (64). Column 5 presents the estimated coefficient β_1 in the regression of total relationship length on initial pass-through, specification (65).

Appendix References

Abowd, J. M., F. Kramarz, and D. N. Margolis (1999, March). High wage workers and high wage firms. *Econometrica 67*(2), 251–333.

Acemoglu, D. (2009). *Introduction to Modern Economic Growth*. Princeton University Press.

Amiti, M. and S. Heise (2024). Us market concentration and import competition. *Forthcoming in Review of Economic Studies*.

Artz, K. W. (1999). Buyer-supplier performance: The role of asset specificity, reciprocal investments, and relational exchange. *British Journal of Management 10*(2), 113–126.

Atkeson, A. and A. Burstein (2008). Pricing to market, trade costs and international relative prices. *American Economic Review 98*(5), 1998–2031.

Berger, D. and J. Vavra (2019). Shocks vs responsiveness: What drives time-varying dispersion. *Journal of Political Economy 127*(5), 2104–2142.

Bernard, A. B., J. . B. Jensen, and P. K. Schott (2006). Transfer pricing by u.s.-based multinationals. NBER Working Paper No. 12493.

Cannon, J. P. and W. D. Perreault Jr. (1999). Buyer-seller relationships in business markets. *Journal of Marketing Research 36*(4), 439–460.

Claycomb, C. and G. L. Frankwick (2005). The dynamics of buyers' perceived costs during a relationship development process: An empirical assessment. *Journal of Business Research 58*(12), 1662–1671.

Dasgupta, P. and J. E. Stiglitz (1988). Learning-by-doing, market structure and industrial trade policies. *Oxford Economic Papers 40*(2), 246–268.

Doney, P. M. and J. P. Cannon (1997). An examination of the nature of trust in buyer-seller relationships. *Journal of Marketing 61*(2), 35–51.

Dustmann, C. and M.-E. Rochina-Barrachina (2007). Selection correction in panel data models: An application to the estimation of females' wage equations. *Econometrics Journal 10*(2), 263–293.

Eaton, J., M. Eslava, D. Jinkins, C. J. Krizan, and J. Tybout (2021). A search and learning model of export dynamics. NBER Working Paper No. 29100.

Fort, T. C. and S. D. Klimek (2018). The effects of industry classification changes on us employment composition. CES Working Paper Series No. 18-28.

Ganesan, S. (1994). Determinants of long-term orientation in buyer-seller relationships. *Journal of Marketing 58*(2), 1–19.

Gopinath, G., O. Itskhoki, and R. Rigobon (2010). Currency choice and exchange rate pass-through. *American*

Economic Review 100(1), 304–336.

Gourio, F. and L. Rudanko (2014). Customer capital. *Review of Economic Studies 81*(3), 1102–1136.

Im, K. S., M. H. Pesaran, and Y. Shin (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics 115*(1), 53–74.

Jap, S. D. and E. Anderson (2007). Testing a life-cycle theory of cooperative interorganizational relationships: Movement across stages and performance. *Management Science 53*(2), 260–275.

Kamal, F., C. J. Krizan, and R. Monarch (2015). Identifying foreign suppliers in us merchandise import transactions. *US Census Bureau Center for Economic Studies Paper No. CES-WP-15-11*.

Kamal, F. and R. Monarch (2018). Identifying Foreign Suppliers in U.S. Import Data. *Review of International Economics 26*(1), 117–39.

Kaufmann, D., A. Kraay, and M. Mastruzzi (2010). The worldwide governance indicators: Methodology and analytical issues. Policy Research Working Paper Series 4978, The World Bank 2010.

Kotabe, M., X. Martin, and H. Domoto (2003). Gaining from vertical partnerships: Knowledge transfer, relationship duration, and supplier performance improvement in the u.s. and japanese automotive industries. *Strategic Management Journal 24*(4), 293–316.

Krause, D. R., R. B. Handfield, and B. B. Tyler (2007). The relationships between supplier development, commitment, social capital accumulation and performance improvement. *Journal of Operations Management 25*(2), 528–545.

Monarch, R. (2021). It's not you, it's me: Price, quality, and switching in u.s.-china trade relationships. *The Review of Economics and Statistics*, 1–49.

Monarch, R. and T. Schmidt-Eisenlohr (2023). Longevity and the value of trade relationships. *Journal of International Economics 145*.

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica 46*(1), 69–85.

Nakamura, E. and J. Steinsson (2008). Five facts about prices: A reevaluation of menu cost models. *Quarterly Journal of Economics 123*(4), 1415–1464.

Paciello, L., A. Pozzi, and N. Trachter (2019). Price dynamics with customer markets. *International Economic Review 60*(1), 413–446.

Phelps, E. S. and S. G. Winter (1970). Optimal price policy under atomistic competition. In *Microeconomic Foundations of Employment and Inflation Theory*, pp. 309–337.

Pierce, J. and P. K. Schott (2016). The surprisingly swift decline of u.s. manufacturing employment. *American Economic Review 106*(7), 1632–1662.

Pierce, J. R. and P. K. Schott (2012). Concording u.s. harmonized system categories over time. *Journal of Official*

Statistics 28(1), 53–68.

Tauchen, G. (1986). Finite state markov-chain approximations to univariate and vector autoregressions. *Economics Letters 20*(2), 177–181.

Ulaga, W. (2003). Capturing value creation in business relationships: A customer perspective. *Industrial Marketing Management 32*(8), 677–693.

Wasi, N. and A. Flaaen (2015). Record linkage using stata: Preprocessing, linking, and reviewing utilities. *The Stata Journal 15*(3), 672–697.

Wooldridge, J. M. (1995). Selection corrections for panel data models under conditional mean independence assumptions. *Journal of Econometrics 68*(1), 115–132.