Relationship stickiness, international trade, and economic uncertainty*

Julien Martin[†] Isabelle Mejean[‡] Mathieu Parenti[§]

October 23, 2023

Abstract

We study how stickiness in business relationships influences the trade impact of aggregate uncertainty. To begin, we construct a product-level index of relationship stickiness using firm-to-firm relationship duration data. We then demonstrate how relationship stickiness shapes trade dynamics in response to uncertainty shocks. We find that episodes of uncertainty lead to a decline in the overall establishment of new business relationships, with the impact varying depending on the level of stickiness. In markets characterized by high stickiness, uncertainty shocks primarily impede investments in new firm-to-firm relationships. In contrast, for non-sticky products, the adjustment to uncertainty shocks mainly manifests as the disruption of existing relationships. JEL codes: F12, F14

*We are grateful to F. de Soyres, S. Dhingra, J. di Giovanni, A. Ferrari, S. Garetto, K. Head, S. Heise, A. Levchenko, F. Mayneris, R. Monarch, S. Terry, F. Warzynski and Y. Yotov, as well as participants at numerous seminars and conferences. We thank Alejandra Martinez for terrific research assistance. Mejean gratefully acknowledges support from a public grant overseen by the French National Research Agency as part of the "Investissements d'Avenir" program (Idex Grant Agreement No. ANR-11-IDEX-0003- 02Labex ECODEC No. ANR-11-LABEX-0047 and Equipex reference: ANR-10-EQPX-17 "Centre d'accès sécurisé aux données" CASD) as well as the European Research Council under the European Union's Horizon 2020 research and innovation program (grant agreement No. 714597). Parenti gratefully acknowledges support from the Fund for Scientific Research (FNRS Grant PDR/GTO T.0180.19).

[†]UQAM and CEPR, Email address: martin.julien@uqam.ca.

[‡]Sciences Po and CEPR, Email address: isabelle.mejean@sciencespo.fr.

[§]Paris School of Economics, INRAE, Université Libre de Bruxelles, CESifo, and CEPR, Email address: mathieu.parenti@psemail.eu.

1 Introduction

How do firm-to-firm relationships influence the response of international trade to uncertainty? One distinguishing characteristic of trade relationships is the level of stickiness they exhibit. In certain product categories, particularly intermediate inputs, the presence of search and customizing costs leads to the formation of long-lasting firm-to-firm relationships and the establishment of rigid trade networks (Antràs and Chor, 2013). While extensive research has been conducted on the implications of these rigidities for trade organization, our knowledge regarding their influence on the transmission of uncertainty shocks to trade flows remains limited.

In this paper, we present evidence that products characterized by stickiness exhibit greater persistence in their firm-to-firm networks when faced with uncertainty shocks. Our study makes two primary contributions. Firstly, we introduce a new metric to quantify relationship stickiness across approximately 5,000 product categories, derived from a comprehensive dataset of firm-to-firm trade information. Secondly, we investigate the dynamics of trade adjustment in response to uncertainty shocks, exploring how the magnitude and mechanism of this adjustment differ based on the level of product stickiness.

Our measure of relationship stickiness is based on the idea that the *duration* of firm-to-firm trade relationships provides valuable insights into the degree of specificity associated with products. This measure is developed within a theoretical framework of firm-to-firm input trade. In this model, firms receive offers randomly and decide to switch to a new input supplier only if the offered price is significantly lower than the price charged by their existing partner, allowing to cover the cost associated with establishing a new relationship. Within this model, higher switching costs and search frictions contribute to lengthening existing firm-to-firm relationships, conditional on the quality of a match. Therefore, the duration of relationships is a relevant empirical moment that can be used to derive a product-level measure of stickiness.

To estimate our model, we use firm-to-firm export data from France. This dataset provides a valuable panel dimension, allowing us to track importers over time and calculate the duration of their relationships with French firms. We take advantage of the unique level of disaggregation in the data to account for individual characteristics that influence the quality of a match and contribute to variations in relationship durations within specific product categories. We then leverage the variability in average durations *across* different products to derive a measure of relationship stickiness (RS) for over 5,000 HS6 products. We present a substantial body of evidence supporting the notion that our recovered measure of relationship stickiness effectively captures relational specificity at the product level. The measure correlates with existing proxies for relationship specificity found in the literature and also exhibits additional variation within industries. Furthermore, we delve into the micro-foundations of our relationship stickiness measure. Our results suggest that stickiness is influenced by a combination of technological determinants and characteristics of the market structure.

Equipped with this measure, we delve into the impact of relationship stickiness on the adjustment of trade flows in response to uncertainty shocks. In our stylized model, uncertainty shocks diminish the buyer's propensity to switch to a new match, conditional on the level of stickiness.[1] The effect is particularly pronounced in markets characterized by higher stickiness, where the switching cost is larger. To empirically test the model's prediction, we combine micro-level data on firm-to-firm relationships with macro-level data on uncertainty. Specifically, we leverage quarterly data on country-level uncertainty

[1] In the model, uncertainty episodes are linked to the presence of downside risk. Consequently, the uncertainty shock leads to a reduction in expected future profits, impacting firms' propensity to switch before the risk materializes. We demonstrate that the qualitative findings remain consistent even when subjected to mean-preserving uncertainty shocks, when firm managers exhibit risk-averse behavior.

obtained from Ahir et al. (2019), which we merge with product-level information on the number of new and disrupted relationships involving French firms and their European partners. By integrating measures of aggregate uncertainty shocks and product-level stickiness, we gain insights into the heterogeneity of trade responses at the product level when faced with aggregate uncertainty shocks.

During periods of high uncertainty, there is a consistent decrease in the number of new trade relationships.[2] The quantitative impact exhibits some variation across different specifications, with an estimated contemporaneous effect of approximately -5%. The influence of uncertainty is particularly pronounced in product markets characterized by a high degree of stickiness. As we move from the first to the third quartile of the relationship stickiness distribution (RS), the magnitude of the effect ranges from -1.5% to -10%. Additionally, we provide evidence that separation rates increase during periods of heightened uncertainty, with the impact diminishing as we move along the stickiness distribution and becoming statistically insignificant for the most sticky products. To ensure the robustness of our findings, we conduct an extensive analysis that includes various robustness checks. These tests involve using alternative proxies for relationship stickiness and examining different sub-samples. Our results remain consistent across these robustness analyses.

Lastly, we examine the implications of these findings for trade growth. Consistent with prior research, we estimate a substantial -12 percentage point response of product-level trade growth to episodes of uncertainty. The majority of this effect stems from a decrease in the net creation of firm-to-firm relationships, a trend that is particularly pronounced in sticky markets. Conversely, adjustments at the intensive margin are relatively minor. Interestingly, we can contrast these results with the effects associated

[2] To isolate the role of uncertainty, our regression controls for the state of the economy, as measured by GDP growth, and its interaction with stickiness.

with a shock to the level of growth in the destination market. In instances of low growth, we observe a significant reduction in product-level trade as well. However, approximately 50% of this effect is driven by adjustments at the intensive margin, particularly in sticky-product markets.

Related literature. This paper contributes primarily to two areas of research: the literature on relationship-specific investments in trade and the literature on the transmission of uncertainty shocks into international trade flows. We highlight the significance of stickiness in international contexts, a factor that has been consistently emphasized in models involving relationship-specific investments or search costs in the supplier market, along with market incompleteness (Grossman and Helpman, 2003; Antràs, 2003; Antras and Helpman, 2004; Grossman and Helpman, 2005; Feenstra and Hanson, 2005).[3]

In the existing literature, relationship specificity is typically measured using proxies developed by Rauch (1999) or Nunn (2007).[4] Our contribution to this literature is the development of a novel measure of product relationship specificity, which operates at a detailed level by leveraging information on the duration of firm-to-firm trade relation-

[3]The interaction between relationship specificity and the legal environment plays a crucial role in shaping countries' specialization patterns (Levchenko, 2007; Nunn, 2007), and the resulting welfare gains (Chor and Ma, 2020). The degree of relationship specificity also influences the decision to integrate suppliers domestically or internationally (Acemoglu et al., 2009; Antràs and Chor, 2013). Furthermore, the trade impact, purpose, and optimal design of trade policy are contingent upon the stickiness of business relationships (Antràs and Staiger, 2012; Grossman and Helpman, 2021).

[4]Alternative measures have also been proposed, such as the Herfindahl index of intermediate input use (Levchenko, 2007), the share of wholesalers importing a product (Bernard et al., 2010a), suppliers' R&D expenses and the number of patents they issued (Barrot and Sauvagnat, 2016), or the distance to final demand (Antràs et al., 2012). Chor and Ma (2020) introduce a measure of contractibility inspired by Nunn (2007)'s framework.

ships. In contrast to other measures, our indicator is calculated at a more granular level, and alllows us to capture the influence of a broader range of product-market characteristics that affect churning in product markets. By doing so, our measure provides additional insights and complements the information contained in alternative measures of stickiness.

In doing so, we contribute to the existing literature that explores the relationship between trade frictions and the duration of trade relationships (Besedes and Prusa, 2006; Monarch, 2014; Macchiavello and Morjaria, 2015; Monarch and Schmidt-Eisenlohr, 2015; Heise, 2016).[5] The closest paper to ours is Monarch (2014), who structurally estimates the switching costs across Chinese suppliers for US importers. We employ a less computationally demanding procedure that enables us to obtain a measure of stickiness for a broader range of products.

Additionally, our paper makes a contribution to the literature on the transmission of uncertainty to international trade flows. The literature has established a connection between uncertainty and the volatility of international trade, as demonstrated by Novy and Taylor (2019). Moreover, there is a body of research examining the trade effects of reducing policy uncertainty, such as Portugal's accession to the European Community (Handley and Limao, 2015) and China's entry into the WTO (Handley and Limao, 2017; Pierce and Schott, 2016). The impact of Brexit-induced uncertainty on trade has also

[5]Notably, Monarch and Schmidt-Eisenlohr (2015) and Heise (2016) use similar firm-to-firm data but focus on the heterogeneity in the duration of relationships across firms. Monarch and Schmidt-Eisenlohr (2015) demonstrates that the survival probability of seller-buyer relationships increases with their size and age, using matched US importer-exporter data. Heise (2016) investigates the systematic relationship between exchange-rate pass-through and the duration of firm-to-firm relationships. In contrast, our approach leverages the duration of seller-buyer relationships in international markets to derive a product-level measure of relationship stickiness while controlling for individual characteristics.

been extensively studied, with significant findings of both extensive and intensive trade responses (Graziano et al., 2018; Ahmad et al., 2020; Exton and Rigo, 2020). In comparison to this existing literature, our study provides further evidence that uncertainty affects trade at the extensive margin, specifically at the firm-to-firm level, and that this effect is more pronounced in stickier product markets. These findings align with the work of Carballo (2015) and Carballo et al. (2018), who also highlight the importance of extensive margin adjustments in response to uncertainty.[6]

The remainder of the paper is organized as follows. Section 2 provides a detailed description of the firm-to-firm data that forms the basis of our analysis. In Section 3, we develop a theoretical framework based on a search model to derive our measure of relationship stickiness and discuss its potential impact on the transmission of uncertainty to trade. Section 4 explains the estimation procedure and presents the results of the estimation. Section 5 investigates the transmission of uncertainty shocks into international trade. Finally, Section 6 concludes.

2 Data

This section provides an overview of our dataset and explains the process of constructing the duration of firm-to-firm relationships, which serves as our primary variable of interest. Further details and additional facts about the dataset can be found in the Online

[6] The interaction between uncertainty and the degree of stickiness is also discussed in Heise et al. (2017). They primarily examine the level of trade policy uncertainty and its impact on the stickiness of trade through firms' procurement practices. In contrast, our empirical analysis focuses on temporary uncertainty episodes and their effects on trade dynamics, given the degree of stickiness. Given the temporary nature of uncertainty episodes, we believe that the potential endogeneity of stickiness to uncertainty is not a severe concern in our specific context.

Appendix.

Data sources. Our analysis relies on a panel of firm-to-firm trade data obtained from the French Customs and detailed in Bergounhon et al. (2018). This dataset provides comprehensive information on export transactions between French firms and their individual partners within the European Union. Notably, the data allow us to track and identify both the exporting French firms and their clients over time, using unique tax identifiers. Each transaction in the dataset is associated with a specific product category (at the 8-digit level of the European combined nomenclature), a precise date (month and year), and the corresponding shipment value in euros.

For our baseline analysis, we focus on French exports to the eleven historical members of the European Union during the period of 1996-2010. Our objective is to measure relationship stickiness at the product level. It is important to note that the French customs data do not include information on the specific nature of the product for transactions below a certain value threshold. As a result, our sample may not fully represent the smallest transactions. We further control for changes in the product nomenclature using the harmonization algorithm outlined in Behrens et al. (2018). Details regarding the construction of our sample can be found in the Online Appendix.

Facts on trade relationships. We estimate relationship stickiness using a sample that spans from 1996 to 2006. Within this period, our estimation sample consists of more than 100 million firm-to-firm transactions. These transactions involve 110,000 distinct French exporters and 1.6 million foreign importers. For the purpose of our analysis, we define a relationship as a collection of transactions between a specific pair of firms engaged in trade within a particular product category. Overall, our dataset comprises 19.4 million firm-to-firm relationships, with an average of five transactions per relationship.

The distribution of transactions by buyers exhibits a high degree of skewness. A mere 8% of importers are observed engaging in more than 20 transactions with French firms, yet they contribute to over 85% of total trade. Conversely, 44% of buyers are involved in just one transaction with a French seller throughout the ten-year period. These one-time buyers are associated with remarkably small transactions, accounting for only 1.5% of the total trade value. It is likely that a significant portion of these transactions represents non-market activities, such as exporters sending samples to potential clients. Consequently, we made the decision to exclude these one-shot buyers from our baseline estimation of relationship stickiness. We demonstrate in the online appendix that this choice does not undermine the robustness of our relationship stickiness estimates.

Duration of trade relationships. A crucial component of our measure of relationship stickiness, as discussed in Section 3, is the duration of firm-to-firm relationships. To calculate these durations, we examine the time series of interactions between buyers and French firms. In our baseline estimation, we define the duration as the number of months between the first and last transactions within a continuous relationship involving a specific pair of firms for a given product. A relationship is considered continuous if it comprises a sequence of transactions that is not interrupted by a transaction involving the same importer but a different seller.

The many-to-one matching structure of the firm-to-firm data, where multiple buyers often purchase a particular product from a single French seller, facilitates the definition of continuous relationships. At any given time, over 90% of European buyers purchase a specific product from a single French seller, while French sellers frequently interact with multiple European buyers.[7] This observation allows us to track importers over time in

[7]A similar many-to-one structure has been observed in various contexts. For instance, Monarch (2014) examined U.S. imports from China and found similar patterns, with U.S. importers often sourcing from a single Chinese supplier for a specific product. Additionally, Muûls (2015) documented a similar

their sequential interactions with French firms and define a continuous relationship as a series of consecutive transactions involving the same importer and a specific French firm. However, there are several challenges in operationalizing this measure: i) Some importers interact with multiple exporters within a month for a given product, ii) Durations may be overestimated if the buyer switches to a non-French seller before returning to the previous partner, iii) Transaction frequencies may vary across firms and products, iv) Some relationships are censored, meaning they do not have complete information on the start or end date. We discuss each of these challenges in detail in the Online Appendix and demonstrate the robustness of our relationship stickiness measure when employing alternative duration measures.

In the Online Appendix, we also provide additional insights into the durations of trade relationships. Firstly, we find a substantial heterogeneity in the durations of these relationships. Approximately 40% of the firm-to-firm relationships last only one month, while around 30% persist for over a year. This variation highlights the diverse nature of trade relationships and the differing lengths of time over which buyers and sellers interact. Furthermore, we observe a positive correlation between the duration of trade relationships and the average size of transactions. This correlation holds both across buyers within a specific product and within a buyer across different suppliers encountered throughout their interactions with French firms. These findings suggest that the duration of trade relationships is influenced by the quality of the match between buyers and suppliers. We take into account this aspect of relationship quality in our theoretical model and empirical estimations, recognizing that the nature of the buyer-seller match can impact the duration of trade relationships.

phenomenon among Belgian importers, who also tend to import from a single country for a given product.

3 Theoretical framework

In Section 2, we discussed the panel structure of the firm-to-firm data, which allows us to examine the duration of relationships. Building on this, we now present a stylized theoretical framework that serves two main purposes. First, the theory aims to establish a relationship between the expected duration of relationships and relationship stickiness. This mapping will provide us with a theoretical foundation for our empirical analysis. Second, the theory will shed light on the differential impact of uncertainty shocks across products with varying degrees of stickiness. By incorporating the notion of stickiness into our theoretical framework, we can gain insights into the heterogeneous effects of uncertainty on trade.

3.1 Relationship duration and stickiness in a search model

Our analysis is based on a simple search model that captures the interaction between sellers and buyers of a particular product. Within this model, we recognize that different products exhibit varying levels of relationship stickiness due to heterogeneous search frictions or costs associated with switching between suppliers. To simplify the notation, we omit explicit product-specific subscripts, but it should be noted that all parameters we introduce in the following discussion may vary across products. This is true in particular of the parameters at the root of stickiness which we will define now, namely λ and γ.

Let's consider a buyer who purchases a product from a supplier at a quality-adjusted price of p. The buyer's objective is to maximize the net present value of the stream of future profits, denoted as $V(p)$. We assume that $V(p)$ is decreasing in p, indicating that higher prices reduce the buyer's profitability ($V' < 0$). In each period, the buyer has a probability λ of receiving an offer $\tilde{p}$ from a new input supplier. This offer represents the quality-adjusted price at which the new supplier is willing to sell the product. The specific value of $\tilde{p}$ is determined by a random variable P that follows a cumulative distribution function $H_P(p) = \mathbb{P}(P \leq p)$. Stronger search frictions, characterized by a lower value of λ, result in longer firm-to-firm relationships while offering the current supplier a monopoly position until a better offer is received.

The decision to switch is based on comparing the net present value of future profits under the new offer $V(\tilde{p})$ with the net present value under the current price $V(p)$, taking into account the sunk switching cost $C(\gamma; p)$.[8] The switching cost is assumed to be increasing in a structural parameter $\gamma \geq 1$ ($\frac{\partial C}{\partial \gamma} > 0$). The switching cost may also vary across firms, in which case $\frac{\partial C}{\partial p} \neq 0$. In the case where $\gamma = 1$, indicating no switching costs ($C(1; p) = 0$), the buyer switches suppliers as soon as it receives an offer below the current price. However, when $\gamma > 1$, there is a positive switching cost, and the buyer's reservation price $p^*(\gamma; p)$ is implicitly defined by $V(p^*(\gamma; p)) - V(p) = C(\gamma; p)$. The reservation price $p^*(\gamma; p)$ represents the threshold below which the buyer is willing to switch suppliers. The value function $V(\cdot)$ is defined recursively through a Bellman equation, and its specific form is explained in Appendix A.1. The model captures the decision-making process of the buyer in terms of switching suppliers, considering the trade-off between the potential gains from switching and the associated sunk switching cost.

Under the conditions described, the duration $\mathcal{T}$ of a buyer-seller relationship, conditional on its price, follows a geometric distribution with mean:

$$\mathbb{E}[\mathcal{T}|p] = \sum_{j=1}^{+\infty} j(1 - \lambda H_P(p^*(\gamma; p))^{j-1} \lambda H_P(p^*(\gamma; p)) = \frac{1}{\lambda H_P(p^*(\gamma; p))}. \tag{1}$$

[8]We assume that the price p is determined prior to the arrival of a new offer, and there is no renegotiation between the firm and its supplier when a better offer arrives. Note that relationship duration does not depend per se on buyer-seller surplus division surplus, see, e.g., renegotiations "on-the-match" in Fontaine et al. (2022).

The model can be extended in continuous time, where offers follow a Poisson process. The duration $\mathcal{T}$ of a relationship at price p then follows an exponential distribution $\mathcal{E}$ with parameter $\lambda H_P(p^*(\gamma; p))$.

In this model, the expected duration of a relationship is the reciprocal of the switching probability. It depends on the firm's current deal p, the frequency of offers λ, and the product-specific cost of establishing a new relationship represented by $C(\gamma, p)$, which affects the reservation price $p^*(\gamma; p)$. Holding other factors constant, a firm that encounters a more competitive supplier is more likely to maintain a long-lasting relationship with that supplier. However, conditional on the quality of the match between the supplier and the buyer, higher search frictions and switching costs shift the distribution of durations towards longer and "stickier" relationships. These product characteristics are precisely what our measure of relationship stickiness captures.

Parametrization To prepare for our empirical analysis, we will now concentrate on a specific case that encompasses three parametric assumptions. First, we introduce a parametrization for the switching cost function, which results in a reservation price of $p^*(\gamma; p) = p/\gamma$. This parameter γ now represents the constant price wedge between the current price and the reservation price. Second, we assume that the distribution of quality-adjusted prices follows an inverse-Pareto distribution with a shape parameter of k. Third, we assume an iso-elastic demand curve for the importer, with a price elasticity of demand denoted as $\sigma > 1$.[9] Under the specified assumptions, we can express the distribution of durations conditional on the size r of the transaction, instead of relying

[9] The combination of the second and third assumptions leads to the implication that the distribution of observed transactions between buyers and sellers closely resembles a Pareto distribution for large transaction sizes. This finding is in line with the canonical model of firm heterogeneity under monopolistic competition, as exemplified by Melitz and Redding (2014). Relatedly, assuming a multiplicative friction is also a standard assumption of the trade literature.

on the unobserved price offered by the supplier:

$$\mathcal{T}|\{R = r\} \sim \mathcal{E}\left[\frac{1}{\eta}\left(\frac{r}{r_{min}}\right)^{-\frac{k}{\sigma-1}}\right], \tag{2}$$

where r_{min} is the lower bound of the distribution of transactions and $\eta \equiv \frac{\gamma^k}{\lambda}$. The parameter η acts as an indicator of relationship stickiness specific to each product. It captures various factors that contribute to longer durations in firm-to-firm relationships after a match has been made. These factors include infrequent offers exchanged between the buyer and seller, indicated by a low value of λ, high switching costs faced by the buyer, represented by a high value of γ, or a limited dispersion in the distribution of price offers, reflected in a high value of k. Once we have estimated the value of η, we will delve into analyzing the relative contribution of these different structural forces.

It is worth noting that while equation (2) is derived based on specific parametric assumptions, the underlying insights of the model hold more generally. We discuss this in greater detail in the Online Appendix, where we explore the model's predictions under alternative assumptions such as a fixed switching cost ($C(\gamma; p) = \gamma - 1$) and the use of alternative price distributions. We show that the ranking of products, based on our measure of stickiness, remains consistent even when considering alternative functional forms and assumptions.

3.2 Relationship stickiness and macroeconomic uncertainty

In order to account for macroeconomic uncertainty, we extend the baseline model by introducing a macroeconomic variable, denoted as I, which represents the level of aggregate demand faced by all firms in the market. This variable affects the net present value of a relationship by influencing instantaneous profits. We assume that instantaneous profits are an increasing function of I. The aggregate demand evolves randomly over time according to an autoregressive process of order 1. The law of motion for aggregate demand, denoted as G, is defined by the conditional probability density function $g(I_{t+1}|I_t) = \phi(I_{t+1} - \alpha I_t)$, where ϕ represents the p.d.f of a truncated normal distribution $\mathcal{N}(\mu, \sigma^2)$. We assume the income process to be bounded from above, which means that a shock to the variance σ^2 does not necessarily result in a mean-preserving change. We then simulate the model using increasing values for σ, starting from a high income level. This setup allows us to associate the shock with downside risk, which aligns with the measure of uncertainty used in the subsequent empirical analysis. The chosen measure of uncertainty, taken from Ahir et al. (2019), is also not mean-preserving.[10]

In the extended model, the decision of each buyer to switch is still determined by their reservation price, denoted as $p^*(\{\gamma, G\}; p, I)$, but now it is conditional on the current level of demand I. In Appendix A.1, we derive the value function of a buyer in the presence of economic uncertainty $V(p, I)$. Here, we will outline how uncertainty impacts buyer-seller relationship durations and consequently the definition of relationship stickiness derived in Section 3.1 when there is no uncertainty. Additionally, we will describe how episodes of uncertainty influence buyer-seller trade across the distribution of relationship stickiness.

Ranking buyer-seller relationship durations under uncertainty: In the previous section, we discussed the relationship between product-level stickiness and buyer-seller relationship durations in an economic environment without uncertainty. We demonstrated that a higher degree of stickiness (represented by a higher η value) results in longer buyer-seller relationships, assuming a constant match quality. However, since durations are expected to be influenced by uncertainty, we need to verify that different

[10]In Section O.3.4 of the Online Appendix, we further extend the model to incorporate risk-averse firm managers and mean-preserving uncertainty. We demonstrate that the results discussed in this section remain consistent even under these additional considerations.

Table 1: ***Expected duration of relationships at various points of the price distribution***

	Percentile of price				
	10th	25th	50th	75th	90th
No uncertainty					
No stickiness	35	14	7	5	4
Medium stickiness	60	24	12	8	7
High stickiness	73	29	15	10	8
Low uncertainty					
No stickiness	35	14	7	5	4
Medium stickiness	90	35	17	10	8
High stickiness	256	94	40	21	15
High uncertainty					
No stickiness	35	14	7	5	4
Medium stickiness	121	45	20	11	9
High stickiness	1,315	520	197	72	15

Notes: The table presented displays the simulation results of the model under different levels of uncertainty and product stickiness. The numbers provided represent the expected duration of relationships across the price distribution, measured in months. Specifically, the scenarios include: i) “No stickiness”: This scenario corresponds to a value of $\gamma = 1$, indicating no stickiness effect, ii) “Medium stickiness” and “High stickiness”: These scenarios use stickiness values chosen in the model without uncertainty to match the durations at the median of the price distribution, for the mean product and the product at the third quartile of the distribution in our data (durations of 12 and 15 months, respectively), iii) “No uncertainty”: In this scenario, the aggregate demand is constant, iv) “Low uncertainty” and “High uncertainty”: These scenarios introduce AR(1) aggregate demand shocks with low or high variance, respectively. These simulations allow us to observe the effects of different levels of uncertainty and product stickiness on the expected relationship durations.

levels of uncertainty (σ) do not alter the ranking of products based on the duration of their relationships. To accomplish this, we simulate expected durations for various degrees of stickiness (γ) under different levels of uncertainty (σ).

The results, presented in Table 1, confirm that relationship stickiness can be reliably regarded as an ordinal measure. Product-level buyer-seller relationship durations continue to provide meaningful information about product-level stickiness, even in the presence of uncertainty. Specifically, when we elevate the level of switching costs, the distribution of expected durations is consistently shifted upwards. This observation holds true irrespective of the presence of uncertainty.

Uncertainty shocks and relationship stickiness We use the model to gain insights into how trade adjusts to uncertainty shocks. The simulation involves a population of firms that interact with suppliers drawn from the inverse-Pareto distribution described earlier. These firms make decisions on whether to switch suppliers based on the model dynamics. Initially, the macroeconomic environment exhibits high demand and low uncertainty, with a small variance in the AR(1) process. After reaching a steady state, we introduce an uncertainty shock by increasing the variance of the AR(1) process unexpectedly. Through this simulation, we can observe the adjustment of trade in response to the uncertainty shock. This allows us to understand the dynamics of buyer-seller relationships and switching behavior during periods of increased uncertainty.

Table 2 presents the switching probabilities before and after the uncertainty shock for three different populations of firms operating in markets with varying levels of stickiness for their products. Importantly, the switching probabilities are calculated after the occurrence of the uncertainty shock but before any adjustment in aggregate income, allowing us to capture the pure effect of increased uncertainty about the future. After a shock occurs, the probability of switching trade relationships tends to decrease. The reason is that an increased downward risk reduces the value of all new relationships, thus

Table 2: ***Impact of uncertainty shocks on switching probabilities***

	Stickiness		
	None	Medium	High
Switching probability			
Before	.060	.029	.017
After	.060	.025	.008
Change (%)	-0	-14	-53

Notes: The table shows the switching probability in a population of 2,000 firms before and after an uncertainty shock. The calibration of the model assumes an AR(1) process for aggregate demand shocks that displays a low variance until the economy is hit by an "uncertainty" shock, i.e. an unanticipated shock to the variance of the process. The probability "after" the shock is computed on impact, i.e. when firms realize the variance of the income process has increased but the level of income is still the same as in the "Before" period.

pushing down the reservation price below which firms decide to pay the (sunk) switching cost. The impact of increased uncertainty on switching probabilities is particularly pronounced in markets characterized by higher levels of stickiness. These predictions of the model will be later brought to the data. Specifically, the empirical analysis aims to examine whether the combination of uncertainty and relationship stickiness contributes to the dynamics of establishing new trade relationships.

4 Relationship stickiness: estimation and facts

4.1 Measuring relationship stickiness

In the preceding section, we demonstrated that the ranking of products based on the duration of buyer-seller relationships provides valuable insights into the level of stickiness, irrespective of uncertainty levels. Now, we will explore how we can use the baseline model presented in Section 3.1 to derive an empirical measure of stickiness.

Our dataset consists of a vector of observed durations for all relationships involving a European buyer and a French exporter. To estimate the parameters of equation (2), we leverage the statistical properties of the product-specific empirical distribution of these random variables. Within the model's assumptions, we can express the expected duration of a relationship, given that transactions R fall within the q-th quantile of its product-specific size distribution, as follows:[11]

$$\mathbb{E}\left[\mathcal{T} \mid R \in R_q\right] = \int_{r_{q-1}}^{r_q} \eta \left(\frac{r}{r_{min}}\right)^{\frac{k}{\sigma-1}} H'_R(r)dr = \eta \, \ln\left[\frac{\mathbb{P}(R \geq r_{q-1})}{\mathbb{P}(R \geq r_q)}\right], \tag{3}$$

[11]The first equality follows from the law of iterated expectations, while the second one stems from the properties of the Pareto distribution. If X follows a Pareto distribution with shape parameter κ and locus x_m, then $\frac{q}{Q} = 1 - \left(\frac{X_q}{X_m}\right)^{\kappa}$, where Q represents the number of cut points, and X_q denotes the value for the q-th cut-point. Further details can be found in Appendix A.2.

where R_q denotes the q^{th} quantile of the distribution:

$$R_q := [r_{q-1}, r_q] \equiv \left\{ r \mid \bar{H}_R^{-1}\left(\frac{q-1}{Q}\right) \leq r \leq \bar{H}_R^{-1}\left(\frac{q}{Q}\right) \right\}$$

and $H_R(r) \equiv 1 - \bar{H}_R(r) = \mathbb{P}(R \leq r)$. The log-linear relationship of equation (3) with respect to η allows us to use a fixed effect model to estimate the product-specific index of relationship stickiness, up to a constant term. The implementation details can be found in Appendix A.2, which outlines a straightforward process. The quantity $\left[\frac{\mathbb{P}(R \geq r_{q-1})}{\mathbb{P}(R \geq r_q)}\right]$ measures the mass of transactions within the quantile of interest and is scaled by the position of the quantile in the distribution. The expected duration within a quintile can be calculated directly from the available data.[12]

4.2 Stylized facts on relationship-specific indicators

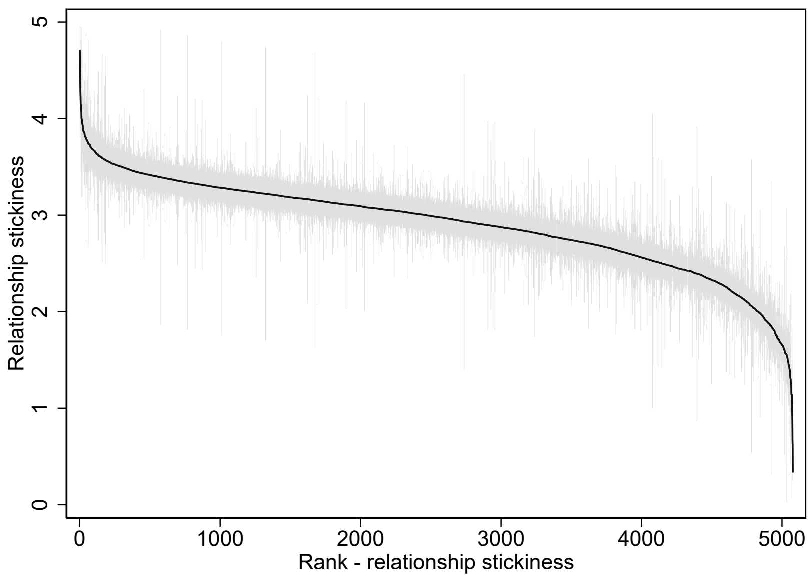
Using the approach described in Section 4.1, we successfully estimate the relative level of stickiness for a total of 5,186 HS6 products.

The analysis reveals substantial variations in the level of relationship stickiness across HS6 products, with a mean at 2.90, a median at 2.98, and an interquartile range of 0.59 (Figure 1). Interpreting the point estimates as the logarithm of the η parameter, an interquartile range of 0.59 suggests that the expected duration of trade flows is approximately 1.8 times longer at the 75th percentile of the product distribution compared to the 25th percentile.[13]

[12] It is worth noting that our objective is not to derive a product×country-specific measure of stickiness. In our model, stickiness is considered a product attribute. Exploring the country dimension of stickiness could be an interesting avenue for future research, although it would require working with a more diverse set of destinations beyond the EU area.

[13] Among the most relationship-specific products are several industrial chemical, pharmaceutical, and mineral products. These findings may appear surprising. Chemicals, for instance, are commonly per-

Figure 1: ***Distribution of RS estimates***



Notes: The figure shows the distribution of estimated relationship stickiness indicators (solid line) and their 10% confidence interval (grey area). The distribution covers 5,077 HS6 products.

It is important to note that the precision of our estimates varies across different products. Empirically, we observe that products with a larger number of firm-to-firm relationships tend to have narrower confidence intervals, with the two variables being correlated at -40%. This pattern is expected since our empirical approach relies on the law of large numbers to smooth the impact of duration heterogeneity within product-specific subsamples. As the number of relationships increases, the approximation improves. Importantly however, the number of observations does not affect the point estimates themselves. To account for estimation errors, our empirical analysis relies on a parametric bootstrap.

Table 3 presents the correlations between our measure of relationship stickiness (RS) and other product-specific attributes commonly used in the literature. The first column shows the pairwise correlation coefficients, while column (2) reports the coefficients from a regression of our RS measure on all other characteristics. Our measure of product stickiness is positively correlated with alternative measures of product specificity such as Rauch (1999) and Nunn (2007). Consistent with Heise et al. (2017), differentiated products tend to exhibit higher levels of relationship stickiness, as shown by the positive correlation with the dummy for differentiated products recovered from Rauch (1999) and the negative correlation with elasticities of substitution estimated in Imbs

ceived as homogeneous products. But the chemical industry comprises both commodity chemicals and specialty chemicals. The latter category involves chemicals that are tailored to the unique requirements of each client, thus contributing to the establishment of enduring relationships. At the other end of the distribution, we find a range of final goods that are typically produced in large quantities and sold in anonymous markets (e.g., men's suits). Additionally, certain non-differentiated primary goods (such as ferro-alloys or raw silk) and various capital goods, including machines used in the textile industry, are also represented. These products are characterized by infrequent purchase patterns and are not subject to the same degree of relationship stickiness.

Table 3: ***Correlation with other measures***

Measure	Corr(η,.) (1)	OLS η (2)
$\mathbf{1}_{differentiated}$ (Rauch)	$.03^{**}$	$-.02$
Share of not homogen. products (Nunn)	$.06^{**}$	.08
Upstreamness (Antras et al.)	$.17^{***}$	$.15^{***}$
Elasticity of subs. (Imbs & Mejean)	$-.16^{***}$	$-.29^{***}$
Product complexity (Haussman & Hidalgo)	$.26^{***}$	$.11^{***}$
Observations		3,805
R^2	-	.12

Notes: This table reports the pairwise correlation coefficients (column (1)) and the multivariate correlations (column (2)) bewteen estimated RS indices and various characteristics of these products. Robust standard errors in (). Significance levels: * 10%, ** 5%, *** 10%.

and Mejean (2015). Similarly, more complex goods, as captured by the measures used in Nunn (2007) and Hausmann and Hidalgo (2014), are also positively correlated with our stickiness measure. The positive correlation between the level of upstreamness and stickiness suggests that products further from final demand involve more buyer-specific investment, elaborate contracts, or customization, in line with the perspective of Antràs and Chor (2013) on global value chains and locked-in effects.[14]

Despite the expected positive correlations, the linear combination of existing indicators can only account for 12% of the heterogeneity observed in our estimation (column (2)). This limited explanatory power arises from the fact that the relationship stickiness (RS) indicator varies within specific industries, while many of the alternative variables are measured at a more aggregated level. For example, while Nunn's index may suggest a high level of input specificity for the car industry, our measure reveals that specific components within the industry exhibit a higher degree of stickiness while the cars are less sticky.

In addition to the main results presented, we provide a comprehensive online appendix that includes a systematic sensitivity analysis. This analysis examines the robustness of our findings with respect to various factors, such as the time period, geographic structure of the data, definition of sales quantiles, empirical model, and measurement of durations. Furthermore, we conducted several external validity checks to evaluate the relevance of our relationship stickiness measure.[15]

[14] There are exceptions to this pattern, with certain products that are upstream in value chains but do not display a high level of stickiness. Examples of such products include ethylene, propene, seeds (colza or sunflower), or salt of rosin.

[15] Namely, we demonstrate the consistency of our measure with three key findings from the literature. First, sectors with higher stickiness levels exhibit a higher share of intrafirm trade, as predicted by Antràs and Chor (2013). Second, the interaction between relational stickiness and institutional quality shapes countries' comparative advantages, aligning with the findings of Levchenko (2007) and Nunn (2007).

4.3 Exploration of the sources of stickiness

In our analysis, relationship stickiness is influenced by both technological determinants and market structure characteristics. In what follows, we perform an exploratory analysis linking different proxies for technological determinants and market structures characteristics to relationship stickiness. We employ two proxies for technological determinants of stickiness. Firstly, we calculate a measure of sunk costs using accounting data and the methodology proposed by Sutton (2007).[16] While sunk costs contribute to the persistence of trade relationships, they do not capture the role of buyer-specific customization costs, which can also drive stickiness. To proxy for this input-specificity, we compute the share of exports in the product category that is intermediated by wholesalers, following the approach outlined in Bernard et al. (2010b). If wholesalers are unable to customize products according to each customer's specific needs, a higher share of wholesalers should indicate lower levels of input-specific investments. Thus, we calculate the value share of exports intermediated by wholesalers and the share of wholesalers among exporters in the product category.

We introduce another set of proxies that capture market structure characteristics. The first set reflects trading partners thickness, which we define as the effective number of French and international sellers (McLaren, 2003): "# of exporting countries", "# of French exporters" and "# of firms worldwide".[17] In line with the literature on customer

Lastly, trade of more relationship-specific products is more sensitive to distance, which is in line with the notion that information and monitoring costs associated with distance are amplified by stickiness, as suggested by Rauch (1999); Head and Ries (2008).

[16] Sunk costs are computed as capital to output ratio at the industry level times the median output of firms in an industry. To obtain a measure that varies at the HS6 level, we compute sunk costs at the industry level and take the median across exporters of a given HS6 product.

[17] The number of firms worldwide is proxied by the ratio of the number of French exporters of a product over French world market share.

Table 4: ***Microfoundations of relationship stickiness***

	coef.	s.e.	R^2	Data source
Proxy for market thickness				
# of exporting countries	-0.043	0.015	0.002	[CEPII-BACI]
# of French exporters	-0.012	0.004	0.001	[French Customs]
# of firms worldwide	-0.024	0.004	0.006	[Estimation]
French HHI	0.273	0.023	0.027	[French Customs]
Proxy for search frictions				
Share salesmen	1.465	0.101	0.040	[Patault and Lenoir (2022)]
Wage bill salesmen	1.138	0.092	0.030	[Patault and Lenoir (2022)]
Price dispersion	0.074	0.009	0.016	[French Customs]
All market. det.			**0.121**	
Proxy for technological specificity				
Sunk costs	0.110	0.006	0.079	[Customs + INSEE-FICUS]
Sh. wholesale (value)	-0.347	0.022	0.050	[Customs + INSEE-FICUS]
Sh. wholesale (count)	-0.107	0.035	0.002	[Customs + INSEE-FICUS]
All techno. det.			**0.143**	

Notes: The Table presents the results of univariate regressions, where each proxy for technological and market-specific parameters is regressed against our baseline measure of relationship stickiness. The first column displays the estimated coefficient, the second column shows the estimated standard deviation, the third column presents the R^2 of the regression, the fourth columns displays the data source. The R^2 values in bold indicate the R^2 of the multivariate regressions for each set of correlates, which include multiple proxies simultaneously.

capital (Gourio and Rudanko, 2014; Patault and Lenoir, 2022), we also consider the average share of salesmen in firms' employment ("Share salesmen") or their wage bill ("Wage bill salesmen"), among exporters of a given HS6 product. These proxies capture the importance of sales personnel in firms' operations and their potential role in building and maintaining customer relationships. Last, drawing inspiration from the empirical literature on search and price dispersion (Kaplan and Menzio, 2015), we compute price dispersion as a proxy for search frictions.[18]

The results presented in Table 4 confirm that all proxies are correlated with our measure of relationship stickiness, with the expected sign. Both sets of proxies contribute similarly to explaining the cross-product dispersion in estimated stickiness ($R^2 = 12\%$ and 14% resp.), indicating that both technological and market structure factors play a role in determining the level of stickiness observed. However, it is important to note that despite the inclusion of these proxies, a significant portion of the dispersion in stickiness remains unexplained. This suggests that there are other factors or features of firm-to-firm relationships that our measure captures but are not fully captured by the chosen proxies.

5 Trade and the heterogeneous impact of uncertainty shocks

In this final section we test for a systematic relationship between trade adjustments, uncertainty shocks and relationship stickiness. Insights from the model in Section 3 suggest that the sensitivity of new business relationships to uncertainty should vary

[18] We compute the dispersion of prices across partners of the same exporrter. This choice is motivated by the fact that dispersion across sellers may reflect technological sources of heterogeneity (see Fontaine et al., 2020, for a discussion).

across products based on their level of relationship stickiness. We study such effects in this section.

5.1 Data and empirical strategy

To test the prediction of our model, we employ a Poisson empirical model:

$$E(X_{pct}|Uncert_{ct}, RS_p, FE) = exp\left(\alpha Uncert_{ct} + \beta RS_p + \gamma RS_p \times Uncert_{ct} + FE\right), \quad (4)$$

where X_{pct} represents either the count of new seller-buyer relationships or the count of terminated relationships in a specific market (product $\times$ destination) at a given point in time.[19] In our model, the variables measuring the number of new seller-buyer relationships and the number of terminated relationships represent two sides of the same concept. However, due to the geographical censorship of our data, where we only observe sellers located in France, we consider both outcome variables in our analysis. We use as explanatory variable an external measure of macroeconomic uncertainty $Uncert_{ct}$ and its interaction with relationship stickiness RS_p, together with other controls. Importantly, the regression systematically controls for product or product$\times$period fixed effects so that the identification exploits the variability across destinations and/or over time, within a product. This dimension of heterogeneity has not been exploited when estimating relationship stickiness and is thus useful to separately identify the response of trade to

[19] In our analysis, new relationships are defined as the initial transaction between a specific pair of firms, taking into account data from the pre-sample period to account for left-censoring. Disrupted relationships, on the other hand, include all relationships that we observe for the last time over three consecutive months, utilizing data from the post-sample period to address right censoring. The estimation period we consider is from 1996 to 2010, with the years 1996 to 1999 used to control for left-censoring and the years 2007 to 2010 used to control for right-censoring.

uncertainty shocks, conditional on the level of stickiness.

We measure uncertainty at the country and quarterly levels using the "World Uncertainty Index" (WUI) developed in Ahir et al. (2019). We define uncertainty episodes based on the WUI series for the 12 countries in our sample. Specifically, we identify periods as uncertainty episodes when the uncertainty index exceeds one standard deviation above its average level.[20] We match the corresponding uncertainty series with our firm-to-firm trade data, which we aggregate to a quarterly frequency to align with the WUI data. In the Online Appendix, we present the time-series of these uncertainty shocks for the countries in our study, alongside their GDP growth. Consistent with previous research by Ahir et al. (2019), we observe that high uncertainty episodes often precede periods of economic growth slowdown. Therefore, we include controls for GDP growth and its interaction with relationship stickiness in our analysis. To obtain market-price GDP growth data, we rely on Eurostat's national accounts indicators. We account for the first-stage error associated with the relationship stickiness (RS) indicator using a parametric bootstrap approach.[21]

[20]We have also conducted sensitivity analyses using a threshold of 1.64 standard deviations above the average, and the results remained virtually unchanged. Additionally, in Table 5, we provide results using the direct level of the index to measure uncertainty.

[21]Specifically, we perform 400 draws of RS for each product from a Gaussian distribution calibrated to the mean and estimated standard deviation of the corresponding RS indicator. Subsequently, we run 400 regressions using the relationship stickiness values generated from these draws. The coefficients and their standard errors reported in the estimation tables are obtained by calculating the mean and standard deviation of these estimates.

5.2 Uncertainty, stickiness, and the extensive margin of trade

The results of the estimation of equation (4) are presented in Table 5 and visually summarized in Figure 2. Columns (1)-(4) of Table 5 examine the impact of uncertainty and its interaction with relationship stickiness on the number of new seller-buyer relationships, while columns (5)-(8) analyze the effect on the number of disrupted relationships. In the odd-numbered columns, the coefficients are identified across countries within a product×period. In the even-numbered columns, the identification is within a country×period, controlling for product×quarter fixed effects to account for seasonal variations in trade. The presence of country×period fixed effects prevents the identification of the level impact of uncertainty. Finally, we either use uncertainty shocks or the level of the uncertainty index as explanatory variables. It is important to note that all specifications involve an interaction with the RS indicator, which takes positive values across the entire distribution. Therefore, interpreting the point estimates may not be straightforward. To provide a sense of the magnitudes, panels (a) and (b) of Figure 2 illustrate the impact of uncertainty across deciles of relationship stickiness, based on the results from columns (1) and (5) of Table 5.

Columns (1) and (3) consistently demonstrate that high uncertainty episodes are associated with a significant reduction in the number of new firm-to-firm relationships, aligning with the intuitive notion that uncertainty discourages firms from engaging in new economic activities. The coefficients in column (1) indicate that an uncertainty shock is linked to a 5.6% (=.35-.14*2.9) decrease in new relationships for the average product in terms of stickiness. These columns also reveal a negative coefficient on the interaction between uncertainty and relationship stickiness, suggesting that the decline in new firm-to-firm relationships during periods of high uncertainty is more pronounced in sticky product categories compared to less sticky ones. The amplified adverse effect of uncertainty on sticky products is further confirmed by columns (2) and (4), which

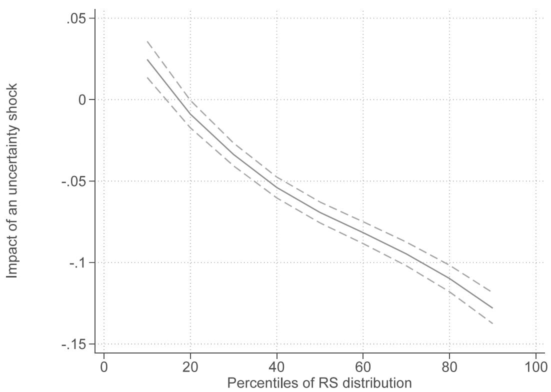
Table 5: ***Uncertainty and relationship stickiness: Baseline results***

	# new relationships				# disrupted relationships			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Uncertainty	.35***		1.15***		.25***		1.04***	
	(.007)		(.022)		(.006)		(.019)	
× RS	-.14***	-.12***	-.47***	-.41***	-.08***	-.05***	-.34***	-.26***
	(.003)	(.002)	(.008)	(.007)	(.002)	(.002)	(.007)	(.006)
Obs	2,880,588				1,953,399			
Uncertainty measure	Shocks		Index		Shocks		Index	
Controls	GDP growth, -×RS				GDP growth, -×RS			
Period	2000-2010				1996-2006			
Fixed effects								
Product time	✓		✓		✓		✓	
Country	✓		✓		✓		✓	
Product quarter		✓		✓		✓		✓
Country time		✓		✓		✓		✓

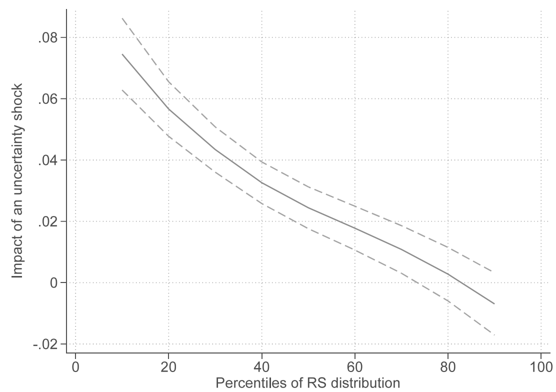
Notes: The estimations were conducted using a Poisson regression framework with high-dimensional fixed effects. Uncertainty shocks are defined as periods when the uncertainty index in the destination country exceeds the average uncertainty plus one standard deviation. The variable *RS* represents our measure of relationship stickiness, which is not centered (Mean: 2.9, P05: 1.8, P95: 3.5). All regressions include controls for the level of GDP growth in the destination country and its interaction with relationship stickiness. The standard errors reported in parentheses are obtained using a bootstrapping procedure. Significance levels: * 10%, ** 5%, *** 1%.

Figure 2: ***Impact of an uncertainty shock along the distribution of RS***

(a) **# of new relationships**



(b) **# of disrupted relationships**



Notes: This figure illustrates the percentage-point impact of an uncertainty shock on the number of new firm-to-firm relationships (panel a) and the number of disrupted firm-to-firm relationships (panel b). The results are obtained from the estimations in Table 5, specifically column (1) for panel (a) and column (5) for panel (b).

use an alternative set of fixed effects. In quantitative terms, specification (1) implies a decrease of approximately 1.5% in the number of new relationships for products in the first quartile of the RS indicator distribution during high uncertainty periods, as depicted in Figure 2. For more sticky products at the third quartile of the RS distribution, the number of new relationships drops by almost 10% during high uncertainty periods.[22] These findings align with the model's predictions that uncertainty hinders the formation of new business relationships, with a more pronounced effect observed for highly sticky products.

In columns (5)-(8), we examine the impact of uncertainty on separation rates using the number of disrupted relationships as a proxy. We find a higher incidence of separations during periods of high uncertainty, but the negative effect diminishes with stickiness. At the higher end of the RS distribution, the effect becomes statistically insignificant. This pattern holds across different specifications using various sets of fixed effects and alternative uncertainty measures. Quantitatively, the specification in column (5), visualized in panel (b) of Figure 2, suggests that during uncertain periods, the number of disrupted relationships increases by 5% for a product in the first quartile of the RS indicator distribution. For a more sticky product in the third quartile of the RS distribution, the number of disrupted relationships increases by less than 1%, and the effect is not statistically significant. Interpreting the impact of uncertainty on exit is more complex within the framework of the model presented in section 3. The model predicts a reduction in switches during uncertain periods, but disrupted trade relationships encompass both switches to non-French suppliers and true exits. The positive association between uncertainty and trade disruption aligns with empirical findings in Carballo

[22]The first quartile is 2.61 and the third quartile is 3.23. Therefore, we compute: $E(X|Uncertainty = 1)/E(X|Uncertainty = 0) - 1 = exp(.35 - 2.61 \times 0.14) - 1$ =-0.015 for the first quartile, and -0.097 for the third quartile using the same formula.

et al. (2018), where they propose a model in which uncertainty lowers the cost cutoff, leading to an increased likelihood of trade disruption. Considering the interaction between uncertainty and relationship stickiness, the results are consistent with the model's prediction that there is relatively less movement among the most sticky products during uncertain times.

The results presented in this section provide evidence supporting the response of trade to uncertainty shocks, specifically in terms of the creation and disruption of firm-to-firm relationships. Notably, our findings highlight the variation in the magnitude of these responses based on the level of product stickiness. We have conducted a series of robustness checks, which are detailed in the Online Appendix O.7. These checks demonstrate that our results hold when excluding durables from the analysis, excluding intrafirm trade, using the ranking of the RS index instead of its level, and utilizing an alternative stickiness index estimated over a different period. Furthermore, in unreported results, we have confirmed that the impact of uncertainty across the distribution of stickiness remains significant even after controlling for the interaction between uncertainty and each of the product market characteristics outlined in Table 3. These robustness checks provide additional support for the validity of our findings.

5.3 Trade adjustments to uncertainty and GDP shocks

The analysis so far has focused on trade adjustments at the extensive (firm-to-firm) margin in response to uncertainty episodes. The model does not explicitly address the dynamics of trade within existing relationships. Novy and Taylor (2019) however highlight the potential impact of uncertainty on trade at the intensive margin, particularly through adjustments in inventories. Comparing the size of adjustments at the intensive and extensive margins is thus useful to confront various adjustment mechanisms.

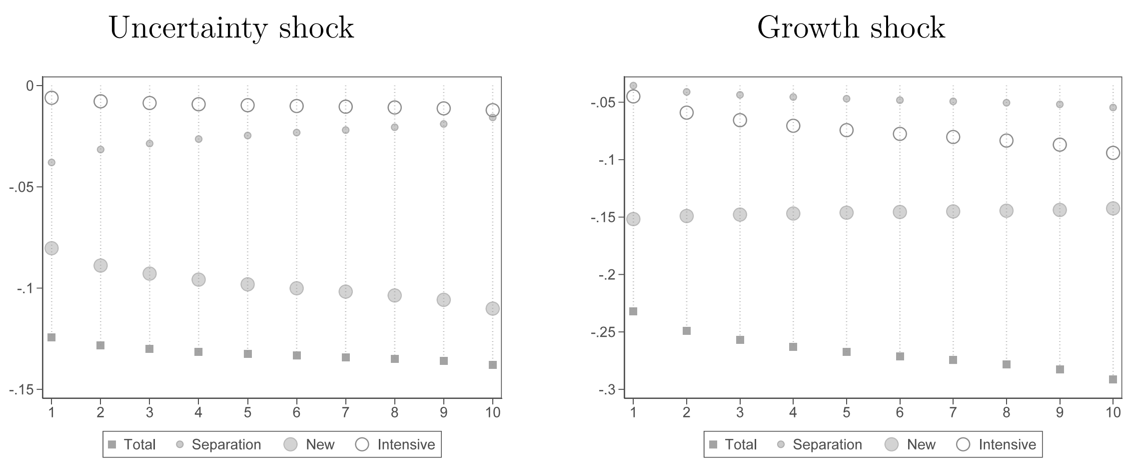
By decomposing the growth in product-level trade of French exports, we can examine the contributions of different components to overall trade dynamics. This decomposition approach is inspired by the work of Bernard et al. (2018). Given the overall (year-on-year) growth of product-level bilateral trade g_{cpt}, we have $g_{cpt} = g_{cpt}^{Intensive} + g_{cpt}^{Start} + g_{cpt}^{End}$ where $g_{cpt}^{Intensive}$ represents the change in the value of trade within existing relationships, whereas g_{cpt}^{Start} and g_{cpt}^{End} stand for the impact of new and disrupted relationships on growth. Growth is measured using mid-point growth rates at the quarterly level. We then regress product-level growth and its components on uncertainty and its interaction with relationship stickiness. Additionally, we control for GDP shocks and their interaction with relationship stickiness. The inclusion of GDP shocks allows us to compare the effects of different types of shocks on trade dynamics. To ensure comparability, we use a binary dummy variable for GDP shocks, indicating when the growth rate in the destination country is one standard deviation below its average over the estimation period. The results remain robust when using the level of GDP growth. The estimated equation reads:

$$Y_{cpt} = \alpha Uncert_{ct} + \gamma RS_p \times Uncert_{ct} + \beta GDP_{ct} + \delta RS_p \times GDP_{ct} + FE + \varepsilon_{pct}$$

where Y_{cpt} is the level of growth or one of its component and the remaining variables are defined as in Section 5.1.

Figure 3 provides a visual representation of the results, and the corresponding point estimates are reported in Table O.11 of the Online Appendix. The left panel focuses on the response of trade growth to an uncertainty shock, while the right panel examines the impact of a growth shock. Several interesting findings emerge from the comparison of these graphs. First, both types of shocks, uncertainty and growth, have a negative effect on trade growth. On average, high uncertainty episodes are associated with a reduction of 0.11 percentage points in trade growth, while a drop in the destination country's growth leads to a larger decrease of 0.15 percentage points. When examining the impact

Figure 3: ***Impact of shocks on trade growth, along the distribution of RS***



Notes: These figures summarize the response of product-level trade to two different shocks: an uncertainty shock (left panel) and a shock to the destination market's growth (right panel). The results are obtained from the estimation of the following equation:

$$Y_{pct} = \alpha Uncert_{ct} + \gamma RS_p \times Uncert_{ct} + \beta GDP_{ct} + \delta RS_p \times GDP_{ct} + FE + \varepsilon_{pct}$$

In this equation, the left-hand side variable (Y_{pct}) represents the mid-point growth rate or one of its components. The variables $Uncert_{ct}$ and GDP_{ct} correspond to uncertainty and GDP shocks, respectively. The term RS_p represents the relationship stickiness variable, and the coefficients α, γ, β, and δ capture the relationships between these variables. The equation also includes fixed effects (FE) at the product$\times$country level to account for any specific characteristics or heterogeneity across products and countries. The error term ε_{pct} captures any unobserved factors or random variation in the data.

across the distribution of RS indices, we observe that the effect of uncertainty shocks remains relatively constant. In contrast, the impact of a GDP shock is 0.5 percentage points larger at the 10th decile compared to the 1st decile of the RS distribution. Another important observation is that the adjustments in trade vary across the different margins. Uncertainty shocks primarily affect the extensive margin, which refers to the net creation of firm-to-firm relationships discussed earlier. This finding is consistent with the results presented in Carballo et al. (2018). The intensive margin, which captures trade within existing relationships, is less elastic to uncertainty shocks. In contrast, the elasticity of trade to GDP shocks primarily arises from the intensive margin. This finding aligns with the evidence presented in Bricongne et al. (2012).

Finally, the intensity of trade adjustments indeed varies along the distribution of stickiness. For uncertainty shocks, the heterogeneity primarily manifests at the extensive margin, consistent with the findings in section 5.2. The results provide strong evidence for subdued extensive adjustments in markets with sticky products, where there are fewer new entries but also fewer separations. On the other hand, when GDP growth shocks occur, the heterogeneity affects adjustments at the intensive margin, while the response of trade at the extensive margin remains relatively constant.[23]

Our findings aligns with the argument presented by Antras (2020), who suggest that severe but temporary shocks, such as the 2008-09 trade collapse or the COVID-19 crisis, do not fundamentally alter firms' sourcing strategies and are often followed by a rapid recovery. The negative effect of such shocks primarily stems from a reduction in the formation of new relationships and, in the case of first-moment shocks, a decline in

[23]In order to validate the robustness of our findings, we examine alternative proxies for first and second moment shocks of uncertainty. Specifically, we use the average stock returns and the average volatility of returns as measures provided by Baker et al. (2020). Results are displayed in Table O.12 of the Online Appendix.

firm-to-firm trade at the intensive margin. However, negative shocks have little to no impact on the disruption of existing sticky firm-to-firm trade relationships. Moreover, our results indicate that the nature of a country's adjustment to shocks is contingent upon the structure of its comparative advantages. The degree to which a country specializes in more or less sticky products is expected to play a role in shaping the various margins of its trade adjustment to macroeconomic uncertainty.[24]

6 Conclusion

This study examines the influence of relationship stickiness on the effects of uncertainty, particularly in international trade. Using detailed firm-to-firm data, we construct a novel measure of relationship stickiness for a wide range of product categories. Our analysis reveals that uncertainty shocks result in a decrease in the creation of business relationships. However, the extent of this impact varies depending on the level of stickiness. Less sticky product categories experience more disruptions in firm-to-firm relationships, while highly sticky categories see a greater slowdown in the formation of new trade relationships. These findings emphasize the significance of considering relationship stickiness when studying the real consequences of uncertainty in trade.

While this paper primarily investigates trade adjustment in response to uncertainty shocks, the concept of relationship stickiness holds relevance for various macroeconomic outcomes, including exchange-rate shocks and trade policy. Additionally, the degree of stickiness in firm-to-firm relationships can influence the international transmission of shocks. We hope that the measure developed in this study will encourage further research exploring these areas and shed light on the broader implications of relationship

[24]It is worth noting that in the case of French exports, the distribution is relatively evenly spread along the RS distribution, implying that averaging the point estimates in Figure 3 provides a reasonable approximation of the response of aggregate exports to uncertainty and GDP growth shocks.

stickiness in macroeconomics.

References

Acemoglu, Daron, Simon Johnson, and Todd Mitton, "Determinants of Vertical Integration: Financial Development and Contracting Costs," *Journal of Finance*, 06 2009, *64* (3), 1251–1290.

Ahir, Hites, Nicholas Bloom, and Davide Furceri, "World Uncertainty Index," 2019.

Ahmad, Saad, Nuno Limão, Sarah Oliver, and Serge Shikher, "Brexit Uncertainty and its (Dis)Service Effects," NBER Working Papers 28053, National Bureau of Economic Research, Inc November 2020.

Antras, Pol, "De-Globalisation? Global Value Chains in the Post-COVID-19 Age," Technical Report, Harvard University November 2020.

Antràs, Pol and Davin Chor, "Organizing the Global Value Chain," *Econometrica*, November 2013, *81* (6), 2127–2204.

Antras, Pol and Elhanan Helpman, "Global Sourcing," *Journal of Political Economy*, 2004, *112* (3), 552–580.

Antràs, Pol and Robert W. Staiger, "Offshoring and the Role of Trade Agreements," *American Economic Review*, December 2012, *102* (7), 3140–3183.

_ , Davin Chor, Thibault Fally, and Russell Hillberry, "Measuring the Upstreamness of Production and Trade Flows," *American Economic Review*, 2012, *102* (3), 412–416.

Antràs, Pol, "Firms, Contracts, and Trade Structure," *The Quarterly Journal of Economics*, 2003, *118* (4), 1375–1418.

Baker, Scott R., Nicholas Bloom, and Stephen J. Terry, "Using Disasters to Estimate the Impact of Uncertainty," NBER Working Papers 27167, National Bureau of Economic Research, Inc May 2020.

Barrot, Jean-Noel and Julien Sauvagnat, "Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks," *The Quarterly Journal of Economics*, 2016, *131* (3), 1543–1592.

Behrens, Kristian, Brahim Boualam, Julien Martin, and Florian Mayneris, "Gentrification and Pioneer Businesses," 2018. Unpublished paper.

Bergounhon, Flora, Clémence Lenoir, and Isabelle Mejean, "A guideline to French firm-level trade data," 2018.

Bernard, Andrew, Andreas Moxnes, and Karen Helene Ulltveit-Moe, "Two-sided Heterogeneity and Trade," *Review of Economics and Statistics*, 2018, *100* (3), 424–439.

Bernard, Andrew B., J. Bradford Jensen, Stephen J. Redding, and Peter K. Schott, "Intrafirm Trade and Product Contractibility," *American Economic Review*, May 2010, *100* (2), 444–448.

— , — , — , and — , "Intrafirm Trade and Product Contractibility," *American Economic Review*, May 2010, *100* (2), 444–48.

Besedes, Tibor and Thomas J. Prusa, "Product differentiation and duration of US import trade," *Journal of International Economics*, 2006, *70* (2), 339–358.

Bricongne, Jean-Charles, Lionel Fontagné, Guillaume Gaulier, Daria Taglioni, and Vincent Vicard, "Firms and the global crisis: French exports in the turmoil," *Journal of International Economics*, 2012, *87* (1), 134–146.

Carballo, Jeronimo, "Global Sourcing and Uncertainty," 2015. Unpublished paper.

— , Kyle Handley, and Nuno Limão, "Economic and Policy Uncertainty: Export Dynamics and the Value of Agreements," NBER Working Papers 24368, National Bureau of Economic Research, Inc March 2018.

Chor, Davin and Lin Ma, "Contracting Frictions in Global Sourcing: Implications for Welfare," Technical Report, Dartmouth November 2020.

Exton, Oliver and Davide Rigo, "The Role of Customer Base in Exporter Dynamics," 2020. Unpublished paper.

Feenstra, Robert C. and Gordon H. Hanson, "Ownership and Control in Outsourcing to China: Estimating the Property-Rights Theory of the Firm," *The Quarterly Journal of Economics*, 2005, *120* (2), 729–761.

Fontaine, François, Julien Martin, and Isabelle Mejean, "Price discrimination within and across EMU markets: Evidence from French exporters," *Journal of International Economics*, 2020, p. 103300.

— , — , and — , "Frictions and adjustments in firm-to-firm trade," CEPR Discussion Papers 18110 2022.

Gourio, François and Leena Rudanko, "Customer Capital," *Review of Economic Studies*, 2014, *81* (3), 1102–1136.

Graziano, Alejandro, Kyle Handley, and Nuno Limao, "Brexit Uncertainty and Trade Disintegration," NBER Working Papers, National Bureau of Economic Research, Inc December 2018.

Grossman, Gene and Elhanan Helpman, "When Tariffs Disrupt Global Supply Chains," 2021. Unpublished paper.

Grossman, Gene M. and Elhanan Helpman, "Outsourcing Versus FDI in Industry Equilibrium," *Journal of the European Economic Association*, 2003, *1* (2-3), 317–327.

— and — , "Outsourcing in a Global Economy," *Review of Economic Studies*, 2005, *72* (1), 135–159.

Handley, Kyle and Nuno Limao, "Trade and Investment under Policy Uncertainty: Theory and Firm Evidence," *American Economic Journal: Economic Policy*, November 2015, *7* (4), 189–222.

— and — , "Policy Uncertainty, Trade, and Welfare: Theory and Evidence for China and the United States," *American Economic Review*, September 2017, *107* (9), 2731–2783.

Hausmann, Ricardo and Cesar Hidalgo, *The Atlas of Economic Complexity: Mapping Paths to Prosperity*, Vol. 1 of MIT Press Books, The MIT Press, January 2014.

Head, Keith and John Ries, "FDI as an outcome of the market for corporate control: Theory and evidence," *Journal of International Economics*, January 2008, *74* (1), 2–20.

Heise, Sebastian, "Firm-to-Firm Relationships and Price Rigidity - Theory and Evidence," CESifo Working Paper Series 6226, CESifo 2016.

_ , Justin Pierce, Georg Schaur, and Peter Schott, "Trade Policy Uncertainty and the Structure of Supply Chains," 2017 Meeting Papers 788, Society for Economic Dynamics 2017.

Imbs, Jean and Isabelle Mejean, "Elasticity Optimism," *American Economic Journal: Macroeconomics*, July 2015, *7* (3), 43–83.

Kaplan, Greg and Guido Menzio, "The Morphology Of Price Dispersion," *International Economic Review*, November 2015, *56* (4), 1165–1206.

Levchenko, Andrei A., "Institutional Quality and International Trade," *Review of Economic Studies*, 2007, *74* (3), 791–819.

Macchiavello, Rocco and Ameet Morjaria, "The Value of Relationships: Evidence from a Supply Shock to Kenyan Rose Exports," *American Economic Review*, 2015, *105* (9), 2911–2945.

McLaren, John, "Trade and Market Thickness: Effects on Organizations," *Journal of the European Economic Association*, 04/05 2003, *1* (2-3), 328–336.

Melitz, Marc J and Stephen J Redding, "Heterogeneous firms and trade," in "Handbook of international economics," Vol. 4, Elsevier, 2014, pp. 1–54.

Monarch, Ryan, ""It's Not You, It's Me": Breakup In U.S.-China Trade Relationships," Working Papers 14-08, Center for Economic Studies, U.S. Census Bureau February 2014.

_ and Tim Schmidt-Eisenlohr, "Learning and the Value of Relationships in International Trade," 2015 Meeting Papers 668, Society for Economic Dynamics 2015.

Muûls, Mirabelle, "Exporters, importers and credit constraints," *Journal of International Economics*, 2015, *95* (2), 333–343.

Novy, Dennis and Alan Taylor, "Trade and Uncertainty," *Review of Economics and Statistics*, Forthcoming 2019.

Nunn, Nathan, "Relationship-Specificity, Incomplete Contracts, and the Pattern of Trade," *The Quarterly Journal of Economics*, 2007, *122* (2), 569–600.

Patault, Berengere and Clemence Lenoir, "Customer capital spillovers: Evidence from sales managers in international markets," mimeo, U. of Amsterdam 2022.

Pierce, Justin R. and Peter K. Schott, "The Surprisingly Swift Decline of US Manufacturing Employment," *American Economic Review*, July 2016, *106* (7), 1632–1662.

Rauch, James E., "Networks versus markets in international trade," *Journal of International Economics*, June 1999, *48* (1), 7–35.

Sutton, John, *Sunk Costs and Market Structure: Price Competition, Advertising, and the Evolution of Concentration*, Vol. 1 of MIT Press Books, The MIT Press, 2007.

A Appendix

A.1 A general formulation of the model

Baseline model without uncertainty: We examine the steady-state value function, denoted as $V(p)$, which arises from the intertemporal optimization problem faced by a buyer when importing inputs at price p, considering a given stickiness parameter γ. In the event of a new match, the firm makes a decision to switch suppliers only if the value of the new offer exceeds the value of its current supplier by an amount that sufficiently compensates for the associated switching cost. This condition implicitly defines an optimal switching policy, denoted as $p^*(\gamma;p)$, which satisfies the equation: $V(p^*(\gamma;p)) - V(p) = C(\gamma;p)$ Here, $V(.)$ represents the value of a match. Note that formally V also depends directly on the parameter γ through $C(\gamma;p)$, we omit this dependence to alleviate notations. The value function is determined by the following Bellman equation:[25]

$$V(p) = \pi(p) + \beta \left[\delta \cdot (V_0 - V(p)) + \lambda \int_0^{p^*(\gamma;p)} \left[V(p') - C(\gamma;p) - V(p)\right] dH_P(p') + V(p) \right] \tag{A.1}$$

Instantaneous profits are represented by $\pi(p)$. The terms enclosed in brackets correspond to the expected future value of the buyer-seller relationship, which is discounted by a factor of β. It is assumed that all firms in all industries face an exogenous probability

[25] For simplicity, the equation is expressed in continuous time. Note that the relationship between duration and the switching probability in continuous time is identical to that obtained in equation (1).

of relationship termination, denoted as δ.[26] When a relationship comes to an end, the buyer's discounted sum of future expected profits is represented by V_0. To ensure that the model allows for a stationary distribution of equilibrium transaction prices, it is necessary to have a strictly positive exogenous separation rate. By differentiating the Bellman equation with respect to γ, and using that the value function is decreasing in γ by construction, we obtain that $V' < 0$: buyers with lower prices are more profitable.

Introducing uncertainty When uncertainty is introduced, the firm's decision to switch suppliers becomes conditional on its expectations regarding the future value of aggregate demand. In this framework, the optimal switching policy, which we denote $p^*(\{\gamma, G\}, p, I)$, depends on the current level of demand and its stochastic process G. The optimal switching policy is implicitly defined by $V(p^*(\{\gamma, G\}; p, I), I) - V(p, I) = C(\gamma, p)$. Here, $V(.)$ solves the following Bellman equation:

$$
\begin{aligned}
V(p, I) \quad = \quad & \pi(p, I) + \beta \int_{\underline{I}}^{\bar{I}} \Big[\delta \cdot (V_0 - V(p, I')) \\
& + \lambda \int_0^{p^*(\{\gamma, G\}; p, I')} (V(p', I') - C(\gamma, p) - V(p, I'))\, dH_P(p') \\
& + V(p, I') \Big]\, dG(I' \mid I)
\end{aligned}
$$

where $\underline{I}$ and $\bar{I}$ are the lower and upper bars of the value of aggregate demand.

A.2 Details on the estimation of relationship stickiness

Equation (1) indicates that the duration of a buyer-seller relationship, given match quality, follows a geometric distribution with mean $\frac{1}{\lambda H_P(p^*(\gamma; p))}$. Under our parametric

[26] We abstract from δ in our baseline model as we measure the duration of buyer-seller relationships between switches. However, it should be noted that while δ impacts the duration of these relationships, it does so in a manner that maintains the ranking of products.

assumptions, P follows an inverse-Pareto distribution with a skewness parameter k, i.e $H_P(p^*) = \left(\frac{p^*}{p_{max}}\right)^k$ where p_{max} represents the upper bound of prices. Substituting the expression for the linear reservation price ($p^* = p/\gamma$) and incorporating the assumption of iso-elastic demand with an elasticity of σ, yields $\left(\frac{p^*}{p_{max}}\right)^{-k} = \gamma^{-k}\left(\frac{r}{r_{min}}\right)^{-\frac{k}{\sigma-1}}$. Finally, by defining $\eta = \gamma^k/\lambda$, we arrive at the expression for the distribution of durations conditional on sales, as provided in equation (2):

$$\mathcal{T}|\{R = r\} \sim \mathcal{E}\left[\frac{1}{\eta}\left(\frac{r}{r_{min}}\right)^{-\frac{k}{\sigma-1}}\right]$$

As described in section 4.1, we can integrate over the range of r values, within a given quantile q to derive a log-linear relationship:

$$\ln \mathbb{E}\left[\mathcal{T} \mid R \in R_q\right] = \ln\left[\int_{r_{q-1}}^{r^q} \mathbb{E}\left[\mathcal{T} \mid R = r\right] dH(r)\right] = \ln\eta + \ln\ln\left[\frac{\mathbb{P}(R \geq r_{q-1})}{\mathbb{P}(R \geq r_q)}\right], \quad \text{(A.2)}$$

The left-hand side of the equation represents the expected duration of a transaction, conditioned on the transaction falling within the qth quantile of the distribution. On the right hand-side the term $\ln\left[\frac{\mathbb{P}(R \geq r_{q-1})}{\mathbb{P}(R \geq r_q)}\right]$ is quantile-specific but does not vary across products and countries, thanks to the joint properties of the Pareto distribution and the Poisson process. In the empirical analysis, we can calculate the logarithm of the mean duration of firm-to-firm relationships within various size quantiles of the product- and country-specific distribution. This quantity is denoted as Dur_{qpc}. It serves as an empirical proxy of conditional expected durations. With this (noisy) measure of conditional expected durations, we can estimate a relative measure of relationship stickiness using a log-linear specification:

$$\log Dur_{qpc} = FE_p + \alpha \ln\ln\left[\frac{\mathbb{P}(R \geq r_{q-1})}{\mathbb{P}(R \geq r_q)}\right] + \epsilon_{qpc}, \quad \text{(A.3)}$$

where FE_p is a product fixed effect, and ϵ_{qpc} is the error term.

To compute the mean duration conditional on a size quantile (Dur_{qpc}), the following steps are taken: (i) The size of a relationship is determined as the average value of transactions involving a specific seller-buyer pair, measured in constant euros;[27] (ii) Each trade relationship is then assigned to a size-decile, which is specific to the corresponding product category; and (iii) Within each decile, the average duration of the relationships is calculated. For the purpose of this calculation, each distribution is divided into 10 quantiles. The first quantile represents transactions falling between the 1st and 10th percentile, the second to ninth quantile correspond to the eight deciles spanning from the 10th to the 90th percentile and the tenth quantile represents transactions between the 90th and 99th percentiles.

[27]To account for inflation, nominal values are deflated using the French PPI constructed by INSEE..