

RELATIONSHIP STICKINESS, INTERNATIONAL TRADE, AND ECONOMIC UNCERTAINTY*

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Abstract

We study how stickiness in business relationships influences the trade impact of aggregate uncertainty. We first develop a product-level index of relationship stickiness estimated from firm-to-firm trade data. The measure is grounded into a search model in which more stickiness implies longer firm-to-firm trade relationships, conditional on match quality. We then show that relationship stickiness shapes the dynamics of trade in response to uncertainty shocks. Episodes of high macroeconomic uncertainty are associated with less trade, mostly driven by a decrease in the net creation of firm-to-firm relationships. Such adjustments are significantly more pronounced among the most sticky product categories.

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1 Introduction

How do firm-to-firm relationships shape the response of international trade to macroeconomic shocks? One defining characteristic of trade relationships is their degree of stickiness. The existence of search and customizing costs to establish new trade relationships in some product categories, prominently intermediate inputs, leads to durable firm-to-firm relationships and rigid trade networks (Antràs and Chor, 2013). Whereas the consequences of these rigidities for the organization of trade have been extensively studied, little is known about how they affect the response of trade to macroeconomic shocks. In this paper, we study trade adjustments to uncertainty shocks, in presence of sticky relationships. Following Dixit and Pindyck (1994), uncertainty indeed affects investment behaviors by creating an option value of waiting. Such transmission of uncertainty shocks to the real economy is likely to be pervasive in the presence of relationship stickiness.

We study this question and make two main contributions. First, we provide a novel measure of relationship stickiness recovered from unique firm-to-firm trade data. Second, we study the transmission of uncertainty shocks to international trade in sticky-product markets. Our measure of relationship stickiness (RS) exploits a rich panel of all firm-to-firm relationships involving French exporters and their European partners over the 2002-2006 period. We use the mean duration of trade relationships to back out a product-level measure of relationship stickiness. Armed with this measure and external time-series of aggregate uncertainty in various destination countries, we then study how trade adjusts to uncertainty shocks and how the size and mechanism of the adjustment varies depending on the degree of product stickiness. Episodes of high macroeconomic uncertainty are shown to be associated with significantly less trade. The response of trade is almost entirely driven by a drop in the net formation of firm-to-firm relationships, which is especially pronounced in sticky product markets. Such adjustments are consistent with wait-and-see behaviors in periods of high uncertainty, magnified by product stickiness. When comparing uncertainty shocks with GDP shocks, we find such behaviors to be specific to uncertainty episodes. Episodes of low GDP growth instead involve large adjustments at the intensive margin, within existing trade relationships.

Our measure of relationship stickiness builds on the idea that the *duration* of firm-to-firm trade relationships conveys information on the relational specificity of products. The measure is grounded into 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 whenever its offer is sufficiently below the price charged by the buyer's existing partner. In this environment, larger switching costs and more search frictions contribute to lengthening existing firm-to-firm relationships, conditional on the quality of a match. The duration of relationships is thus a

relevant moment that can be exploited to recover a product-level measure of stickiness. The measure is built on the ex-post duration of firm-to-firm relationships, and thus encompasses different microeconomic factors at the root of stickiness such as switching costs, relationship-specific sunk investments, information asymmetries, or informational frictions. For estimation, we use French firm-to-firm export data, whose panel dimension allows us to follow importers over time, and compute the duration of each of the importers' relationships with a French firm. The unique level of disaggregation of the data is exploited to control for individual characteristics that affect the quality of a match and contribute to the dispersion in the duration of relationships, within a product category. After controlling for the quality of a match, we can use the variability of average durations *across products* to recover a measure of relationship stickiness (RS) for more than 5,000 HS6 products.

We present a body of evidence supporting the view that the recovered measure of relationship stickiness does capture relational specificity at the product level. First, we show the measure is stable when computed from French exports to different destinations or over different time periods and when estimated from a different dataset of Colombian exports. Second, we find the stickiness measure varies substantially across sectors and across products within a sector. Specialty chemicals or parts and accessories that entail large customization costs are found among the most sticky products, whereas motor vehicles or men's suits are among the least sticky products. Third, we show that our measure correlates with existing proxies for relationship specificity found in the literature. For instance, it correlates with the measure of contractual intensity developed by [Nunn \(2007\)](#), but it displays substantially more variability, notably within the group of manufacturing products. More sticky categories also turn out to be more complex products, products with a smaller elasticity of substitution, and products that are more upstream in the value chain. Fourth, we find that the measure relates to product-level outcomes in a way that is consistent with three theoretical results from the literature: sectors with more sticky products display a higher share of intrafirm trade as predicted by [Antràs and Chor \(2013\)](#); relational stickiness interacts with institutional quality to shape countries' comparative advantages as in [Levchenko \(2007\)](#) and [Nunn \(2007\)](#); and trade of more sticky products is more sensitive to distance, consistent with the view that the information and monitoring costs related to distance are exacerbated by relationship stickiness ([Rauch, 1999](#); [Head and Ries, 2008](#)).

Armed with this novel measure, we study how relationship stickiness affects the adjustment of trade flows to uncertainty shocks. Uncertainty has been shown to be a potential threat to economic growth, because it reduces firms' incentive to invest ([Bloom, 2009](#)). Our analysis focuses on one particular type of investments, namely, investments associated with the firm's

international expansion. Indeed, international trade is associated with substantial sunk costs. For this reason, uncertainty shocks have a large effect on this dimension of firms’ activity (Handley and Limao, 2017a; Novy and Taylor, 2019). We provide evidence consistent with this view using highly disaggregated trade data. We leverage upon the granularity of the data to dig into the mechanism of the adjustment to uncertainty episodes.

We bring together micro data on firm-to-firm relationships and macro data on uncertainty to quantify the trade impact of high-uncertainty episodes. Our analysis uses the “World Uncertainty Index” developed by Ahir et al. (2019) to recover external measures of uncertainty shocks.¹ The database covers 143 countries, including 11 countries in our sample, from 1996 onwards, and measures uncertainty at a quarterly frequency using text-mining techniques applied to the quarterly Economist Intelligence Unit (EIU) country reports. Based on this database, we can construct a panel of “uncertainty shocks” that we merge with product-level information on the number of new (and disrupted) relationships involving French firms and their European partners, at a quarterly frequency. By combining measures of *aggregate* uncertainty shocks and *product-level* stickiness, we are able to dig into the heterogeneity of product-level trade responses to aggregate uncertainty shocks.

Periods of high policy uncertainty systematically display a reduced number of new trade relationships involving French exporters and European importers. Quantitative effects somewhat vary depending on the specification, with a contemporaneous impact estimated between -1% and -9%, and a persistence over at least six months. Interestingly, we show that the impact of uncertainty is especially pronounced in product markets that feature a high degree of stickiness. The impact of uncertainty on the establishment of new firm-to-firm relationships varies between -2% and -11% when moving from the first to the third quartile of the distribution of RS, from the least to the most sticky markets. We also provide evidence of separation rates being affected by uncertainty. Here, the qualitative impact varies along the RS distribution. More uncertainty is associated with a higher probability of trade relationships ending in less sticky markets, whereas the separation rate is muted where relationships are stickier, on average. We run an extensive robustness analysis showing that results are invariant to using various proxies for relationship stickiness and various sub-samples.

Finally, we study the implications of these results for trade growth. Consistent with the previous literature, we estimate a -12 p.p. response of product-level trade growth to uncertainty episodes. The vast majority of this effect is driven by a lower net creation of firm-to-firm relationships, which is especially pronounced in sticky markets, whereas adjustments at

¹In a robustness test, we also check that our results are not specific to this particular measure of uncertainty and also hold using second-moment statistics recovered from stock returns from Baker et al. (2020).

the intensive margin are tiny. Interestingly, we can contrast our results with those associated with a shock to the *level* of growth in the destination. Episodes of low growth are also associated with significantly less product-level trade. But around 50% of the effect is driven by the intensive margin, especially in sticky-product markets.

Overall, the empirical analysis helps refine our understanding of the channels through which uncertainty can impact economic activity. In the vein of [Dixit and Pindyck \(1994\)](#), episodes of uncertainty generate a band of inaction that leads to wait-and-see behavior. The breadth of this inaction band is expected to increase with the structural parameters at the root of the option value of waiting, either sunk costs as in [Fillat and Garetto \(2015\)](#) or search frictions as in [Schaal \(2017\)](#). To the extent that our measure of relationship stickiness indeed captures the ex-post impact of such microeconomic frictions, these models thus predict that the extensive margin response to uncertainty episodes should be larger in sticky product markets, consistent with our findings.

Related literature. The paper contributes primarily to two strands of the literature, namely, the literature on stickiness in trade, and the macroeconomics literature on uncertainty and the business cycle. The importance of stickiness in an international context has been underlined repeatedly in models featuring relationship-specific investments or search costs in the market for suppliers, together with market incompleteness ([Grossman and Helpman, 2003](#); [Antràs, 2003](#); [Antras and Helpman, 2004](#); [Grossman and Helpman, 2005](#); [Feenstra and Hanson, 2005](#)). The interplay of relation specificity with the legal environment shapes the specialization of countries ([Levchenko, 2007](#); [Nunn, 2007](#)), and associated welfare gains ([Chor and Ma, 2020](#)). The degree of relation specificity also governs the decision to integrate suppliers at home or abroad ([Acemoglu et al., 2009](#); [Antràs and Chor, 2013](#)). Last, the trade impact, purpose and optimal design of trade policy depends on the stickiness of business relationships ([Antràs and Staiger, 2012](#); [Grossman and Helpman, 2021](#)).²

In this literature, relationship specificity is usually proxied using either the measure developed by [Rauch \(1999\)](#), or the measure developed by [Nunn \(2007\)](#).³ Our contribution to

²Outside of the trade literature, input specificity has also been shown to be a significant determinant of the propagation of shocks in value chains ([Barrot and Sauvagnat, 2016](#)). [Hémous and Olsen \(2018\)](#) study how stickiness in business relationships can affect innovation incentives and [Boehm and Oberfeld \(2020\)](#) assess the impact of contract enforcement on allocative efficiency when firms rely on relationship-specific intermediate inputs.

³Other related measures have been developed, including the Herfindahl index of intermediate input use ([Levchenko, 2007](#)), the share of wholesalers importing a product ([Bernard et al., 2010](#)), suppliers' R&D expenses and the number of patents that they issued ([Barrot and Sauvagnat, 2016](#)), or the distance to final demand ([Antràs et al., 2012](#)). [Chor and Ma \(2020\)](#) develop a measure of contractibility in the spirit of [Nunn \(2007\)](#).

this literature is a novel measure of product relationship specificity at a disaggregated level recovered from the duration of firm-to-firm trade relationships. The measures developed by [Rauch \(1999\)](#) and [Nunn \(2007\)](#) rely on a characterization of the markets on which products are traded. Rauch’s measure is based on hand classification of product categories across three groups: differentiated products, products traded in organized markets, and products with posted prices. Nunn’s measure uses Rauch’s classification to assess the specificity of inputs entering production processes, a good being called more “specific” when its production is more intensive in differentiated inputs. Whereas such classifications have proved useful, we propose a measure computed at a finer level of disaggregation and that captures the impact of a wider set of product-market characteristics contributing to stickiness. Our results suggest that the information contents of ours and these alternative measures of stickiness are complementary.

In doing so, we contribute to the literature that draws a link between trade frictions and the duration of trade relationships ([Besedes and Prusa, 2006](#); [Monarch, 2014](#); [Macchiavello and Morjaria, 2015](#); [Schmidt-Eisenlohr and Monarch, 2015](#); [Heise, 2016](#)).⁴ Here, the closest paper to ours is [Monarch \(2014\)](#), who structurally estimates the cost of switching across Chinese suppliers for US importers. The author finds that halving switching costs would reduce the US-China import price index by 15%. His analysis focuses on 50 exported products. We develop a less computationally demanding procedure, which allows us to recover a measure of stickiness for a wide range of products.⁵ Furthermore, we work with highly disaggregated seller-buyer relationships observed over various destinations. Doing so allows us to purge our measure from country-specific costs and obtain a measure of relationship stickiness at the fine product level.

Our paper also contributes to the literature on uncertainty and economic growth. Following the seminal contribution by [Dixit and Pindyck \(1994\)](#), a large theoretical and empirical literature has emerged, that studies the consequences of uncertainty in macroeconomics. At the microeconomic level, uncertainty is empirically shown to affect the relationship between

⁴In particular, [Schmidt-Eisenlohr and Monarch \(2015\)](#) and [Heise \(2016\)](#) use very similar data but focus on the across-firm heterogeneity in the duration of relationships. [Schmidt-Eisenlohr and Monarch \(2015\)](#) show the survival probability of seller-buyer relationships increases with their size and age, using matched US importer-exporter data. And [Heise \(2016\)](#) studies the systematic relationship between exchange-rate pass-through and the duration of firm-to-firm relationships. We instead use the duration of seller-buyer relationships in international markets to back out a product-level measure of relationship stickiness, controlling for individual characteristics.

⁵In this procedure, relationship stickiness is evaluated in relative terms along the distribution of products. As a consequence, we cannot directly interpret our estimates in terms of a monetary switching cost, which [Monarch \(2014\)](#) can do. We have checked that, for the 44 products that we can match with his estimates, the correlation between his and our measures is positive.

patenting and firms’ productivity (Bloom and Reenen, 2002), the responsiveness of investment to demand shocks (Bloom et al., 2007), or hiring decisions (Schaal, 2017). In the aggregate, the level of policy uncertainty affects aggregate output and employment (Bloom, 2009). Closer to us is the literature on uncertainty and trade. Novy and Taylor (2019) link uncertainty to the volatility of international trade. A series of papers discuss the reduction in policy uncertainty induced by Portugal’s accession to the European Community (Handley and Limao, 2015), and China’s entry into the WTO (Handley and Limao, 2017b; Pierce and Schott, 2016), and how it explains the boom in exports after entry. Several papers have also explored the impact of Brexit-driven uncertainty on trade. Graziano et al. (2018), Ahmad et al. (2020), and Exton and Rigo (2020) document significant extensive and intensive responses of product-level trade flows to changes in uncertainty tied to the Brexit. In comparison with this literature, we provide further evidence that uncertainty affects trade at the firm-to-firm extensive margin and that the effect is more pronounced in stickier product markets. The role of extensive margin adjustments is consistent with Carballo (2015) and Carballo et al. (2018).⁶

The rest of the paper is organized as follows. Section 2 describes the firm-to-firm data used throughout the paper, and provides stylized facts on the structure and duration of firm-to-firm relationships. Section 3 derives our measure of relationship stickiness from a parsimonious search model, explains how it is estimated, and discusses how it compares with alternative measures used in the related literature. Section 4 is devoted to the empirical investigation of the trade impact of policy uncertainty. Finally, section 5 concludes.

2 Data

2.1 Dataset

Both our measure of relationship stickiness and the empirical analysis based on this measure take advantage of a panel of firm-to-firm trade data provided to us by the French customs and

⁶The interaction between uncertainty and the degree of stickiness is also discussed in Heise et al. (2017). In contrast with us, their focus is on the level of trade policy uncertainty shaping the stickiness of trade through firms’ procurement practices. A reduction in the probability of a trade war, they argue, can foster the adoption of “Japanese”-style procurement practices that entail long-term seller-buyer relationships. Whereas such mechanism could imply that our empirical analysis is threatened by the endogeneity of stickiness to uncertainty, we do not think that this endogeneity is a severe threat in our context. The reason is that we empirically assess the impact of temporary uncertainty episodes, whereas the analysis in Heise et al. (2017) considers a permanent change in the probability of a trade war. Such a long-lasting change in the level of uncertainty is more likely to have feedback consequences on the structure of trade relationships than more temporary episodes.

described in [Bergounhon et al. \(2018\)](#). The dataset covers each export transaction between French firms and their individual partners in the EU. Importantly, the data identify and follow over time both firms involved in the transaction, the exporting French firm and its client. Because the data are collected for tax purposes, both identifiers are recovered from a VAT number that precisely identifies both firms engaged into the transaction.⁷ Each transaction is also characterized by a product category (at the 8-digit level of the European combined nomenclature), a date (month and year), and the value of the shipment (in euros).⁸ The dataset covers the period from 1993 to 2017, but the analysis exploits various sub-periods. The main reason we do not work on the whole panel is that the nomenclature for product categories, which is exploited to characterize product markets by their stickiness, changes over time.⁹ As a consequence, we use the harmonization algorithm described in [Behrens et al. \(2018\)](#) to recover time-invariant product categories. The induced information loss is minimized when the algorithm is applied over shorter horizons. In the baseline specification, relationship stickiness is measured using data from 1996 to 2006. We also check the robustness over time, using the 2011-2017 period as an alternative. The analysis of the impact of uncertainty on the dynamics of firm-to-firm relationships uses data over 2000-2010.

For each product category, we observe all firm-to-firm relationships involving a French exporter and a European buyer, over time.¹⁰ The analysis is restricted to trade with the eleven historical members of the European Union. There are two reasons for excluding the new member states from the analysis. First, we do not observe individual importers prior to their entry into the EU. Second, important trade adjustments following the countries' entry into the European Union are likely to create a lot of churning in firm-to-firm relationships which could bias our estimates of relationship stickiness.

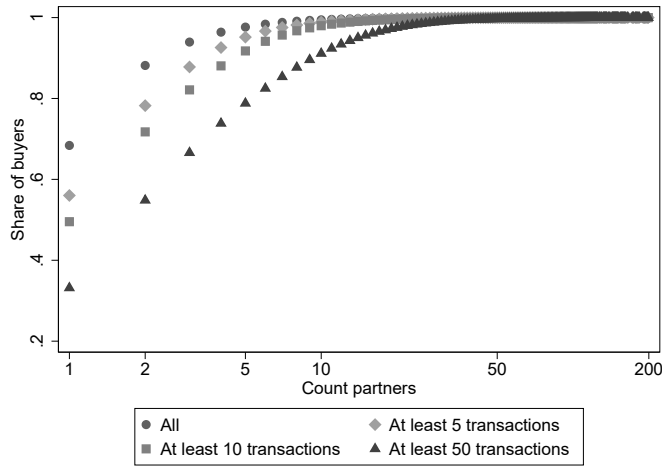
⁷This property of the data helps to allay concerns about the quality of the foreign-buyer identifier that the previous literature has discussed. See for instance the discussion in [Kamal and Monarch \(2018\)](#) regarding the reliability of foreign exporters' identifiers in US LFTTD administrative data and [Krizan et al. \(2020\)](#) on the identifiers for US firms in Colombian data.

⁸Unfortunately, we do not know whether transactions are arm's length or intrafirm. We discuss how intrafirm trade affects our analysis in section 4.2.

⁹Another constraint that we take into account while selecting the sub-periods of analysis is a discontinuity in the data between 2010 and 2011. Since 2011, the export sales threshold above which firms are requested to fill in a detailed customs form that includes the product category of exports has jumped from 150K euros per year to 460K euros. As a consequence, the dataset exploited in our analysis, which makes use of the product dimension, is seriously censored since 2011.

¹⁰Whereas the dataset is exhaustive, exports from the smallest French exporters cannot be exploited, because these firms are allowed to complete a simplified form that does not specify the product category. In 2007, the simplified regime concerned 21,616 exporters (out of 66,131), accounting for 2% of transactions and .5% of the value of French exports.

Figure 1: *Distribution of the number of French partners, per buyer×product*



Notes: Cumulated distribution of the number of partners, per foreign buyer (\times product). A partner is a French exporting firm. The number of partners is calculated over the sub-sample of importers that are involved in at least two transactions ("All") and at least 5, 10 and 50 transactions.

Over 1996-2006, we observe as many as 101 million firm-to-firm transactions. Table A.1 in Appendix provides descriptive statistics on the dimensionality of the data, in the overall EU as well as in each destination. We observe almost 110,000 different French exporters over the period, that interact with 1.6 million foreign importers. In what follows, we define a relationship as a set of transactions involving a particular pair of firms trading over a specific product category. The dataset is composed of 19.4 million firm-to-firm relationships that interact over five transactions, on average.

The distribution of the number of transactions by buyers is highly skewed, as illustrated in Figure B.1. Only 8% of importers are observed over more than 20 transactions with French firms, but they account for more than 85% of trade. The dynamics of their relationships with French firms should thus provide insightful information. At the other end of the spectrum, 44% of buyers are engaged in only one transaction with a French seller over the ten-year period. These buyers make surprisingly tiny transactions: they account for only 1.5% of the value of trade. There are good reasons to believe that a substantial share of these transactions correspond to non-market transactions, such as samples sent by exporters to prospective clients. We thus decided to exclude these one-shot buyers when estimating stickiness. In section 3.2, we argue that this choice is unlikely to bias our estimates.

Figure 1 shows the distribution of the number of French partners with whom individual buyers interact over their entire time in the dataset (after excluding buyers appearing just

once in the data). Overall, 67% of buyers have a single partner in France, whereas less than 7% have three partners or more (see the circles line). Of course, interacting with a single partner in France is more likely to happen for firms that are involved in a small number of transactions. The other three distributions thus display statistics on the number of partners per buyer, for importers that are involved in at least 5, 10, or 50 transactions. Even within the subset of importers that we observe over as many as 50 transactions, we observe a third of “loyal” buyers that repeatedly interact with the same exporter. Such behavior is consistent with the idea that some firm-to-firm relationships in international markets are especially sticky. The question that the empirical analysis addresses is whether this stickiness is systematically related to the specificity of some products or sectors.

2.2 Duration of firm-to-firm relationships

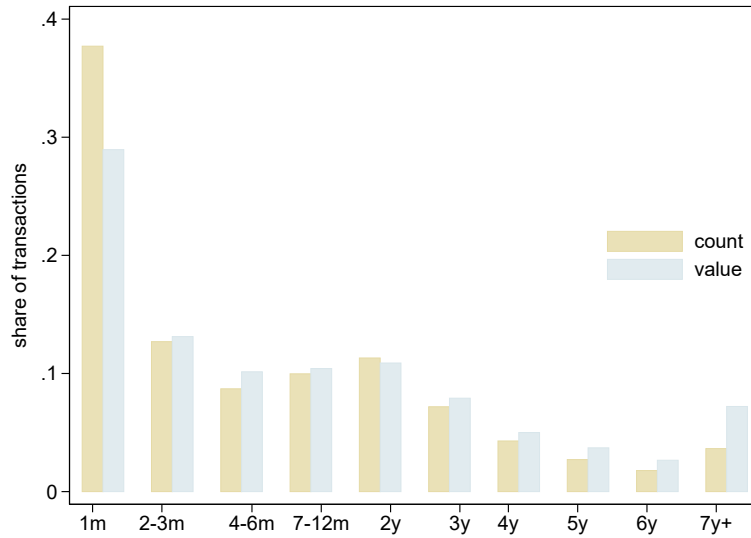
A key statistics for the measure of relationship stickiness described in section 3 is the duration of firm-to-firm relationships. To compute these durations, we use the time series of each buyer’s interactions with French firms. In our baseline estimate, we define duration as the number of months between the first and last transactions in a continuous relationship involving a particular pair of firms for a given product. A relationship is considered continuous if it involves a sequence of transactions which is not interrupted with a transaction involving the same importer but a different seller.

Figure 2 reports the distribution of durations of firm-to-firm (\times product) relationships. The mode is at one month which corresponds to an importer that interacts with a French firm over a single month, before eventually switching to another French or non-French supplier. These very short relationships represent less than 40% of the population, whereas roughly 30% of firm-to-firm relationships last more than a year. Part of this heterogeneity is the consequence of heterogeneous match qualities, an importer being more likely to switch if her current match is not satisfactory.

Results in Table 1 show the duration of trade relationships is positively correlated with the size of the transaction, which we later use as proxy for the quality of the match between the buyer and its supplier. This correlation is true both across buyers within a product and within a buyer, across the different suppliers met throughout its interactions with French firms. This correlation is fully taken into account in our empirical framework, which recovers a measure of the mean duration of trade relationships, *conditional on the quality of a match*.

Before concluding this section, note that the statistics on duration presented in Figure 2 are based on the notion of a *continuous* relationship. To make this notion operational, we have to make different choices that we describe below.

Figure 2: *Distribution of the durations in firm-to-firm relationships*



Notes: Distribution of durations, as a share of total number of relationships (“count”) and as a share of aggregate export value (“value”). Statistics are recovered from the 19.5 million firm-to-firm relationships identified over the 1996-2006 period.

Table 1: *Duration and the size of trade flows*

	(1)	(2)	(3)
	Log of duration		
Log of mean exports	.041*** (.000)	.070*** (.000)	.237*** (.001)
Observations	6,904,758	6,904,585	3,331,224
R ²	0.003	0.151	0.242
Within R ²	0.003	0.007	0.057
Fixed effects		Product	Product × buyer

Notes: This table correlates the duration of a relationship with a measure of the size of this transaction. Statistics are calculated on the dataset covering the 1996-2006 period. Standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

As discussed in Appendix [A.1](#), the network under study displays many-to-one matching, once the product dimension is controlled for: at a point in time (defined by a particular month in a particular year), more than 90% of buyers purchase a particular product from a single seller, whereas sellers simultaneously serve several importers in every destination.¹¹ With a many-to-one structure, we can follow importers over time in their (sequential) interactions with French firms and define a continuous relationship as the set of consecutive transactions involving the importer with a particular French firm. The timespan between the first and last transactions defines the duration of the relationship. In the few cases where an importer interacts with multiple exporters within a month, the notion of a continuous relationship is a bit fuzzy as we can not define the sequence of these transactions. In such cases, we consider the transactions to take place simultaneously. If the importer was already interacting with one of the exporters before, the relationship is considered to continue. If in the next period, the firm is again seen interacting with one or several of these partners, the transaction that was performed simultaneously with others is taken into account. In unreported results, we show our estimates are virtually unchanged if we remove from the estimation sample importers that we eventually see interacting with multiple sellers within a month.

The notion of a continuous relationship is also challenged by the bilateral nature of our data. We do not observe transactions between foreign importers and their non-French suppliers. This censoring does not mechanically affect our measure of duration, which is based on the duration between the first and last transactions involving two firms, whether the relationship terminates because of the importer switching to another French supplier, a non-French partner, or no longer purchasing the product.¹² Still, some durations may be overestimated if the buyer switches to a non-French seller before switching back to her previous partner, in which case we observe two consecutive transactions that we assign to a single continuous relationship. To deal with this issue, we propose an alternative estimate of stickiness in which duration is computed as the number of transactions within a continuous relationship instead of the number of months between any two transactions.

The previous issue is related to the question of the frequency of transactions. Whereas defining continuous relationships would be straightforward with monthly frequencies, using actual transaction data forces us to cope with strongly heterogeneous frequencies. On average,

¹¹The many-to-one structure of firm-to-firm trade relationships at the product level is also documented by [Monarch \(2014\)](#) using data on U.S. imports from China. [Monarch \(2014\)](#) further shows that U.S. importers tend to import from a single country, as do Belgian importers as documented by [Muûls \(2015\)](#).

¹²We discuss in Appendix [A.2](#) how this measure compares with switching probabilities, that instead exploit information on buyers switching from a French supplier to the other and are thus further exposed to a selection bias induced by the impossibility to observe switches to non-French suppliers.

the probability of a transaction occurring in a given month is .33, which corresponds to a transaction every three months. However, 25% of buyers purchase French products more than once every two months, whereas in the first quartile of the distribution, firms purchase products less than once every 10 months (see Table A.2 in appendix). Our baseline definition of durations treats a relationship involving two transactions that take place 6 months apart the same way as a relationship leading to seven monthly transactions. In section 3.2, we test the possibility that heterogeneous frequencies across products may affect our results by reproducing the methodology to estimate stickiness based on an alternative measure of durations that exploits the number of transactions within a particular relationship instead of the number of elapsed months.

Last, working with durations always involves censoring issues. We deal with right censoring throughout the analysis by excluding transactions that start within two years before the end of our estimation sample.

3 Measuring relationship stickiness

Section 2 shows how firm-to-firm trade data can be used to measure and document heterogeneity in the duration of business relationships across firms and products. In this section, we explain how to build and estimate a measure of relationship specificity at the product-level from the duration of firm-to-firm relationships. We then test the robustness to various data treatments, and benchmark our measure against various indicators in the literature to gauge its relevance.

3.1 Empirical strategy

Our measure of stickiness is constructed based on a simple search model between sellers and buyers of a given product. In this model, products systematically vary in terms of their degree of business stickiness because of heterogeneous search frictions and heterogeneous costs associated with switching from one supplier to the other. Such cross-sectional heterogeneity might be explained by the products sold being more or less substitutable, by the size of relationship-specific investments varying across products, or by any other product-specific characteristics. We remain purposely agnostic on the exact micro-foundations at the root of such stickiness. We consider instead these features as given and use the cross-section of products to quantify their relative size across product categories.

Suppose an importer is willing to purchase a certain product. Every period, it receives with probability λ an offer \tilde{p} from a new input supplier and decides whether to stick to its

existing partner or switch and benefit from this offer. Suppose \tilde{p} is the (quality-adjusted) price at which the new input supplier is willing to sell the product. It is the realization of a random variable P drawn into a cumulated distribution function $H_P(p) = \mathbb{P}(P \leq p)$. Conditional on its current deal p , a firm may decide to switch suppliers as soon as it receives an offer that is not only better but also covers its switching cost. That is, the firm decides to switch whenever $\tilde{p} < \frac{p}{\gamma}$, where $\gamma > 1$ is the wedge between the current price and the buyer’s reservation price.¹³ This wedge may stem from switching costs being sunk upon starting a new relationship, but it could also reflect search costs incurred to be able to draw a price offer with probability λ .¹⁴ Our approach representation of these costs is deliberately stylized, which, as we show now, allows us to draw a simple relationship between the model’s parameters and the expected duration of a relationship.

Under these conditions, the duration of a buyer-seller relationship, conditional on its price, follows a geometric law with mean

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

This formula generalizes in continuous time where offers follow a Poisson process and the probability of receiving an offer during an infinitely small period of time dt is λdt . The duration \mathcal{T} of a relationship at price p then follows an exponential law \mathcal{E} with parameter $\lambda H_P(p/\gamma)$ denoted by

$$\mathcal{T}|p \sim \mathcal{E}[\lambda H_P(p/\gamma)].$$

In this model, the expected duration of a relationship is thus the inverse of the probability of switching. It is a function of the firm’s existing deal p , the product-specific degree of business stickiness as measured by γ , and the frequency of offers λ , which reflects the extent of frictions in that market. Everything else equal, a firm that has met a more competitive supplier is

¹³Here, we implicitly assumed p is determined prior to the arrival of a new offer, that is, we do not let the firm and its supplier re-negotiate over the price when a better offer arrives. Alternatively, one may argue that the new offer induces the importer and its existing partner to renegotiate “on-the-match” (see [Postel-Vinay and Robin \(2002\)](#) for an application of this assumption in the context of frictional labor markets). Although such an assumption would suggest firm-to-firm prices tend to decrease with the age of the buyer-seller relationship (consistent with [Fontaine et al. \(2020\)](#)), it would not affect the expected duration of a firm-to-firm relationship, the object of interest in this paper. The reason is that in our model as in this framework, the importer always ends up interacting with the firm with the lowest serving cost, which does not depend on the supplier’s price offer but only its ability to beat potential competitors.

¹⁴In [Appendix A.3](#), we write the Bellman equation stemming from a dynamic model involving search frictions and a sunk cost associated with a switch. Our approach can be seen as a direct parametrization of the wedge obtained in this more general model.

more likely to interact with it over a long relationship. But conditional on a quality-adjusted price, larger switching costs and less frequent offers are also expected to lengthen firm-to-firm relationships. These product characteristics are what we want our measure of relationship stickiness to capture. We now explain how to estimate it using observed durations in the data.

To bring the model to the data, we make two additional parametric assumptions. First, we assume the distribution of quality-adjusted prices is inverse-Pareto with shape parameter k . Second, the importer’s demand curve is assumed to be iso-elastic with $\sigma > 1$ being the price elasticity of demand.¹⁵ Under these assumptions, one can write the distribution of durations conditional on the size r of the transaction, instead of the (unobserved) price offered by the supplier:

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

where r_{min} is the lower bound of the distribution of transactions and $\eta \equiv \frac{\gamma^k}{\lambda}$. Hereafter, we interpret η as a product-specific indicator of relationship stickiness, capturing various forces that tend to lengthen firm-to-firm relationships, conditional on a match. In the context of our model, longer durations conditional on a match can be the outcome of less frequent offers (a low λ), large switching costs (a high γ), or little dispersion in the distribution of price offers (a high k). Although equation (2) relies on parametric assumptions, the model’s insight, namely, that such product-specific characteristics tend to increase durations, conditional on a match, holds more generally (see Appendix A.3 for a non-parametric relationship between sunk costs and the expected average duration).

Our data are a vector of realized durations for all relationships involving a European buyer and a French exporter. To recover the parameters of equation (2), we use the statistical properties of the product-specific empirical distribution of these random variables. Under the model’s assumptions, the expected duration of a relationship conditional on transactions r falling in the quantile of order q of its product-specific distribution can be expressed as

¹⁵Taken together, these two assumptions imply that the distribution of observed transactions between buyers and sellers is approximately Pareto for large transactions. This implication agrees, for instance, with the canonical model of firm heterogeneity under monopolistic competition (Melitz and Redding (2014))

follows:¹⁶

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

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 $H_R(r) \equiv 1 - \bar{H}_R(r) = \mathbb{P}(R \leq r)$. Because equation (3) is log-linear in η and η is specific to product categories but constant across countries and transaction size, it is enough to use a fixed effect model to recover an estimate of the product-specific index of relationship stickiness, up to a constant. See the details of the empirical implementation in Appendix A.4.

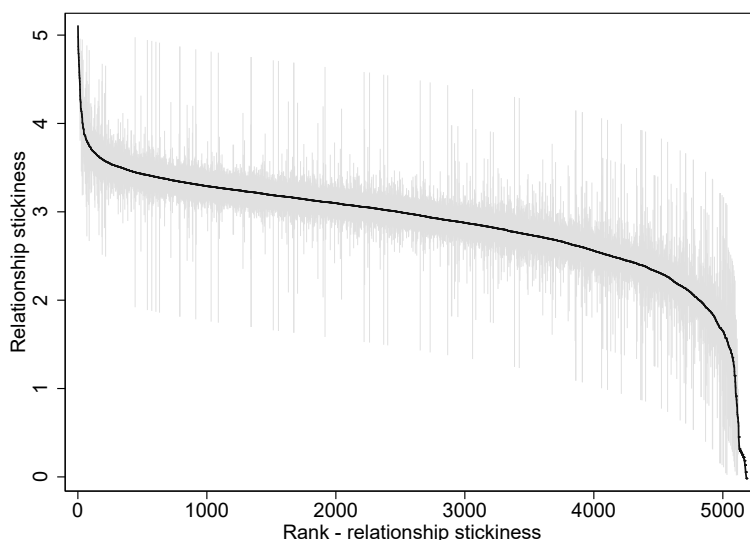
3.2 Stylized facts on relationship-specific indicators

Using the strategy described in section 3.1, we recover the relative level of stickiness for 5,186 HS6 products. Figure 3 shows the distribution of estimates. We see significant differences in the level of relationship stickiness across HS6 products, with a mean at 2.86, a median at 2.97, and an interquartile range of 0.63. Because we estimate the log of the η parameter, an interquartile of .63 means the expected duration of trade flows, conditional on the quality of the match, is 1.88 times larger at the 75th percentile of the product distribution than at the 25th, which is sizable. The precision of estimates however varies across products, as shown by the grey area in Figure 3.¹⁷ Empirically, products for which the number of firm-to-firm relationships is large tend to display tighter confidence intervals, the correlation between these

¹⁶The first line uses the law of iterated expectations, while the second line uses the property of the Pareto distribution. If X is Pareto distributed with shape parameter κ and locus x_m , then $\frac{q}{Q} = 1 - \left(\frac{X_q}{X_m} \right)^\kappa$, where Q is the number of cut points, and X_q is the value for the q^{th} cut-point. See details in Appendix A.4.

¹⁷Given the size of standard errors, listing products found at each tail of the distribution might not be very informative. A glance at the data reveals that among the most relationship-specific products are a number of industrial chemical, pharmaceutical, and mineral products. These goods are highly differentiated, are often customized to the particular needs of the firm's client, and tend to be purchased frequently, thus generating long-lasting relationships between the firm and its client. These facts may seem surprising, because chemicals are often considered as homogenous products. Note the chemical industry is split between commodity and specialty chemicals, the latter being chemicals that are tailored for each client. At the other side of the distribution, one finds a number of final-good products that are usually produced in large quantities and sold in anonymous markets (e.g., men's suits), some non-differentiated primary goods (ferro-alloys or raw sild), and a number of capital goods, such as machines used in the textile industry that are purchased infrequently and are not subject to relationship stickiness as a consequence.

Figure 3: *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 5,186 HS6 products.

two variables being high at 75%. This feature is expected as the empirical strategy relies on the law of large numbers to smooth the impact of heterogeneity in durations within deciles of the product-specific subsamples. The larger the number of relationships, the better the approximation. Importantly, the number of underlying observations does not affect the point estimates, which are orthogonal to the number of observations. We take this margin of error into account in the empirical analysis using a parametric bootstrap procedure.

Table 2 shows how our measure correlates with other product-specific attributes used in the literature. The first column reports the pairwise correlation coefficients, and column (2) reports the coefficients of a regression of our RS measure on all other characteristics. The degree of product stickiness is positively correlated with alternative measures of product specificity used in the literature, most notably, Rauch (1999) and Nunn (2007). Differentiated products tend to be more relationship specific, 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 and Mejean (2015). The correlation confirms the results in Heise et al. (2017) recovered from US data that more differentiated products exhibit longer relationships. More complex goods also involve more stickiness, as shown by the positive correlation of our indicator with both Nunn (2007) and Hausmann and Hidalgo (2014). The correlation with Nunn (2007) indicator is rather small though. The reason is the difference in the level of aggregation. To give a concrete example, in his index, the car

Table 2: *Correlation with other measures*

Measure	Corr(η, \cdot)	OLS η
	(1)	(2)
$\mathbf{1}_{differentiated}$ (Rauch)	.08***	.06**
Share of not homogen. products (Nunn)	.04**	-.02
Upstreamness (Antras et al.)	.14***	.21***
Elasticity of subs. (Imbs & Mejean)	-.6***	-.16***
Product complexity (Hausman & Hidalgo)	.16***	.09***
Observations		3,863
R^2	-	.12

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

industry has a high level of input specificity. Consistent with this measure, we find most parts and accessories in this industry have a high level of stickiness. But final products like cars do not, which lessens the correlation. Finally, we find a positive correlation between the level of upstreamness of a product and its degree of stickiness. This correlation suggests products far from the final demand entail more buyer-specific investment, more elaborated contracts, or more customization than products dedicated to final consumption, which is consistent with [Antràs and Chor \(2013\)](#) view that global value chains entail substantial locked-in effect.

Although these correlations all have the expected sign, the linear combination of existing indicators only explains 12% of the heterogeneity recovered from our estimation (column (2)). The reason is that the RS indicator is extremely heterogeneous, including within particular industries.¹⁸ The high disparity of stickiness is further illustrated in [Figure B.3](#), which compares average RS measures across categories of the broad economic classification (BEC).¹⁹ Final consumption goods like cars or consumer goods display, on average, a low level of stickiness, whereas parts and accessories or food processed for the industry display higher average RS indices. Here as well, however, we see a significant level of dispersion within these categories.

In [Appendix A.5](#), we discuss the robustness of our baseline estimates. We first regress the measure of stickiness against five statistics describing various features of product categories

¹⁸A typical example is the degree of stickiness in the mineral-product industry that encompasses some of the most and the least relationship-specific products.

¹⁹BEC categories corresponding to less than five hs6 products are excluded from the figure.

such as sales concentration, the share of wholesalers, or the number of buyers matched with multiple sellers (see Table B.1). Correlation between these variables and stickiness are meaningful, but the R^2 are low, which shows heterogeneity in terms of relationship stickiness across product categories is not explained by idiosyncracies of French firm-to-firm trade data.

We then conduct an extensive sensitivity analysis, in which the baseline measure of relationship stickiness is compared with fourteen alternative measures of stickiness. These alternative measures are estimated from different empirical specifications, from various country-specific sub-samples, using data for a more recent period, and using similar data on Colombian exports (see Table B.2). The conclusion of this sensitivity analysis is that the distribution of RS indices is extremely stable. Robustness with respect to the empirical specification delivers correlation coefficients above 80% between the baseline and alternative distributions of RS indicators. The correlation with distributions recovered from country-specific samples is around 70% which suggests the stability over space is high as well. Stability over time is a bit smaller, with a correlation coefficient at 56%, in part because the data are not entirely comparable. Finally, indicators recovered from entirely different data, namely firm-to-firm export data for Colombia, still correlate positively with the baseline. The stability is consistent with our interpretation of this measure as capturing deep characteristics of the product markets, that should not vary over space and over time.

3.3 External validity tests

We conclude the description of the measure of relationship stickiness indices by reproducing some results in the literature showing a significant impact of some structural factors at the root of stickiness on various trade outcomes. Whereas the literature is based on alternative measures of relationship specificity, we show the same qualitative results are confirmed using our indicator instead. We think of these exercises as useful sanity checks that the measure we later exploit to assess the impact of uncertainty in sticky-product markets indeed captures what it is meant to. We summarize insights recovered from these exercises in the main text and report the detailed results in Appendix A.6.

Antràs and Chor (2013) argue the locked-in effect induced by relationship-specific investments may have consequences for firms' propensity to vertically integrate. In their property-rights model, downstream firms have an incentive to integrate suppliers because of contractual frictions in the procurement of a customized component later integrated in the production. A corollary of such a framework is that vertical integration should be more pervasive in product markets that display more intense locked-in effects. We confirm this result in Table A.3 using the prevalence of intra-firm trade as a measure of vertical integration. Using US trade

data, we show intra-firm trade as a share of overall trade is significantly larger for products displaying high RS indicators. Alone, RS explains 10% of the cross-product dispersion in the data, and remains significant once we also control for the position of the product in global value chains.

Nunn (2007) and Levchenko (2007) argue high-relationship-specific investment goods require sound institutions, in the form of quality of contract enforcement, property rights, shareholder protection, and so on. As a consequence, institutions can shape the geography of trade as other sources of comparative advantages do. In Table A.4, we replicate the empirical exercise in Nunn (2007) using more disaggregated data and our measure of relationship-stickiness. We further control for the relation-specificity measure developed by Nunn (2007) to identify an effect beyond and above Nunn’s. Both his measure and ours point in the same direction, namely, a specialization of countries with better institutions into the production of goods that display more stickiness, potentially because of larger relationship-specific investments.

Finally, we investigate the impact of relationship stickiness in a gravity context. Namely, Table A.5 interacts distance with our measure of relationship stickiness in an otherwise standard gravity equation for bilateral trade. We find the negative impact of distance on trade flows is stronger for product categories that exhibit a higher degree of relationship stickiness. Although a structural interpretation is not possible in this reduced-form context, several theoretical mechanisms can help rationalize the evidence. First, the increased distance elasticity may be explained by information frictions being large in stickier markets, which on the one hand increases the cost of switching to a new supplier, and on the other hand reinforces the geographic concentration of trade (Rauch, 1999). An alternative interpretation is that stickier relationships are associated with higher monitoring costs, which increase with distance (Head and Ries, 2008).

These sanity checks all point into the same direction. Our indicator of relationship stickiness seems to capture meaningful variability across (disaggregated) product markets, which correlates with external indicators in a way that is consistent with our interpretation.

4 Trade, uncertainty, and stickiness

We now turn to the paper’s core question, namely, how product stickiness shapes the adjustment of trade to economic uncertainty shocks.

4.1 Motivation, data and empirical strategy

In the tradition of [Dixit and Pindyck \(1994\)](#), the transmission of uncertainty shocks to the real economy is interpreted as a consequence of firms' investment decisions, with firms being reluctant to invest in uncertain times. Such transmission has received extensive empirical support. Uncertainty episodes are associated with significantly less patenting and productivity at firm-level ([Bloom and Reenen, 2002](#)), a decline in the response of investment to demand shocks ([Bloom et al., 2007](#)), or postponed hiring decisions ([Schaal, 2017](#)). More recently, uncertainty has been argued to also affect trade dynamics ([Novy and Taylor, 2019](#)) while the decrease in uncertainty associated with binding trade integration arrangements is shown to contribute to their impact on the volume of trade ([Handley and Limao, 2015, 2017b; Pierce and Schott, 2016](#)).

In the international economics literature, the real option of waiting is often explained by the existence of sunk costs to establish a new relationship. In [Handley and Limao \(2017a\)](#), trade-policy driven uncertainty lowers the probability of entry in a destination in presence of a sunk entry cost. In [Fillat and Garetto \(2015\)](#), a higher sunk cost of entry widens the band of inaction: it reduces the probability that a domestic firm enters a foreign market while reducing the exit probability for already exporting firms. Whereas these models consider the decision of a firm to enter a particular destination, the same reasoning obviously applies to a firm's decision to pay a sunk cost to establish a new firm-to-firm relationship, the object of interest in our analysis. Uncertainty may also affect entry and exit decisions in international markets if international trade is subject to search frictions and the search process is costly. The mechanism would thus be similar to [Schaal \(2017\)](#) who shows that in presence of search costs and search frictions in the labor market, uncertainty reduces firms' decision to hire new workers and to fire current ones. Using the same logic, frictions in the market for foreign suppliers should reduce churning in international product markets in periods of high uncertainty.

In this literature, the real option of waiting increases with sunk costs and search frictions, conditional on a level of uncertainty. These parameters are precisely those that drive the dispersion in our measure of relationship stickiness. More specifically, relationship stickiness is higher for products that have high sunk costs and/or are more frictional. Our RS estimates thus offer a nice opportunity to formally test the mechanisms put forward in the literature and dig deeper into the response of trade to uncertainty shocks. This is what we do now, using the firm-to-firm trade data, together with external measures of uncertainty episodes in various destinations of French exports. We conjecture that trade adjustments to uncertainty episodes are driven by a decrease in the net formation of new firm-to-firm relationships, that

we expect to be larger in sticky product markets.

We test this conjecture in an econometric framework in which the dynamics of trade measured at the product and destination level are regressed on an external measure of uncertainty, and its interaction with relationship stickiness. We measure uncertainty episodes at the country and quarterly levels using the “World Uncertainty Index” (WUI) developed in [Ahir et al. \(2019\)](#). Using text analysis of the Economist Intelligence Unit country reports, they construct an uncertainty-index series for 143 countries, at a quarterly frequency from 1996 onwards. The approach to construct the WUI is to count the number of times uncertainty is mentioned in the EIU country reports and scale these numbers by the total number of words in each report. Based on the WUI series for the 11 countries in our sample, we define uncertainty episodes as periods when the uncertainty index is one standard deviation above its average level.²⁰ The corresponding series are matched with the firm-to-firm trade data for 2000-2010, aggregated to the quarterly frequency to fit with the WUI data. [Figure B.5](#) shows a heat map of the corresponding uncertainty series. Although the panel solely covers EU countries, the data display a significant degree of heterogeneity across countries and over time. In some specifications, we also control for GDP growth shocks in the destination to separately identify the impact of uncertainty and other aspects of business cycles. Market-price GDP growth data are taken from Eurostat’s national accounts indicators. The GDP shocks are computed as periods in which GDP growth is lower than the average minus one standard deviation of GDP growth.

Our measure of stickiness is estimated, and we use the standard errors associated with the RS measure to account for this first-stage error. For each product, we make 400 draws of RS in a Gaussian distribution calibrated to the mean and standard deviation of the corresponding estimated standard errors. We then run 400 regressions using the relationship stickiness generated in these draws. The coefficients and their standard errors reported in estimation tables are obtained by taking the mean and standard deviation of these estimates.

4.2 Uncertainty and the extensive margin

We first estimate the impact of uncertainty shocks on the net creation of new firm-to-firm relationships. The estimated Poisson specification takes the following generic form:

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

²⁰We have also tried with uncertainty episodes defined as periods in which the index is 1.64 standard deviations above its average. Results are virtually unchanged. In [Table 3](#), we also present results that directly use the level of the index to measure uncertainty.

where the left-hand-side variable is a measure of trade computed for each country c , product p , and period t and the regressors are a measure of policy uncertainty defined at the level of a destination and a period and its interaction with the relationship stickiness indicator RS_p . 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 uncertainty shocks, conditional on the level of stickiness. In some regressions, we also control for destination country times period fixed effects which de facto absorb all determinants of bilateral trade that do not vary across products, notably gravity variables or changes in the macroeconomic environment. In that case, we can no longer identify the level impact of uncertainty but we can still study its heterogeneity across products.

We first estimate how uncertainty affects the formation of relationships. Namely, we define new relationships as the first transaction involving a particular pair of firms, going back to data from 1993 to avoid left-censoring. Results are presented in Table 3. They consistently show that episodes of high uncertainty are associated with significantly fewer creations of new firm-to-firm relationships, especially in product markets displaying stickier relationships. In column (1), the cross-product heterogeneity in the elasticity of trade to uncertainty is identified with product \times quarter fixed effects to control for seasonality and country \times period fixed effects so that the identification is across products. The negative coefficient on the interaction suggests that the decrease in the rate of creation of firm-to-firm relationships in periods of high uncertainty is significantly more pronounced in sticky than in less sticky markets. The result is confirmed in column (2), where the identification is within a product \times period and across countries that do or do not experience high-uncertainty episodes. In comparison with others, destinations that feature high-uncertainty episodes are characterized by a significantly lower rate of creations of new firm-to-firm relationships, especially in sticky product markets. In quantitative terms, specification (1) implies the number of new relationships for a product in the first quartile of the distribution of the RS indicator drops by about 2% in periods of high uncertainty as shown in Figure 4. For a more sticky product, in the third quartile of the distribution of RS, the number of new relationships drops by 11% in periods of uncertainty.²¹

Columns (3) and (4) use the value of the WUI rather than dummies for high-uncertainty episodes. The finding that the negative effect of uncertainty on new relationships is stronger

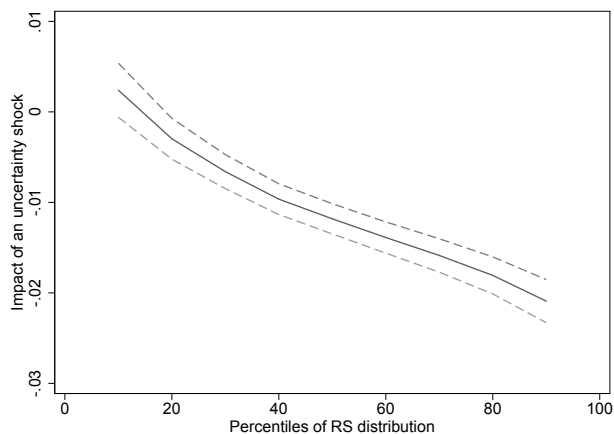
²¹The first quartile is 2.61 and the third quartile is 3.23. For the first quartile, we thus compute: $E(X|Uncertainty = 1)/E(X|Uncertainty = 0) - 1 = \exp(.37 - 2.61 \times 0.15) - 1 = -0.021$. The same formula for the third quartile gives -0.108 .

Table 3: *Uncertainty and the creation of new trade relationships: Baseline results*

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var:	<i># new trade relationships</i>					
Uncertainty episode	0.37*** (0.008)				0.24*** (0.021)	
- × RS index	-0.15*** (0.003)	-0.12*** (0.002)			-0.10*** (0.008)	-0.07*** (0.008)
Uncertainty index			1.27*** (0.023)			
- × RS index			-0.51*** (0.008)	-0.40*** (0.007)		
Observations	3,302,770	3,302,770	3,302,770	3,302,770	3,143,796	3,439,126
Period	2000-2010	2000-2010	2000-2010	2000-2010	2000-2010	2000-2010
RS estimation period	1996-2006	1996-2006	1996-2006	1996-2006	2011-2017	2011-2017
<i>Fixed Effects</i>						
Product × quarter		✓		✓		✓
Product × period	✓		✓		✓	
Country	✓		✓		✓	
Country × period		✓		✓		✓

Notes: Poisson estimations with high-dimensional fixed effects. Uncertainty episode is a dummy equal to 1 in periods when uncertainty in the destination country is above-average uncertainty plus one s.d. of uncertainty. *RS* is our measure of relationship stickiness which is not centered (Mean: 2.9, P05: 1.8, P95: 3.5). In columns (1)-(4), *RS* is estimated using 1996-2006 data whereas we use the out-of-sample dataset recovered from 2011-2017 in columns (5)-(6). Bootstrapped standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Figure 4: *Impact of an uncertainty shock on new relationships, along the distribution of RS*



Notes: This figure is recovered from results in Table 3, column (1). It shows the percentage-point impact of an uncertainty shock, on the number of new firm-to-firm relationships.

for stickier products is robust. Finally, columns (5)-(6) test the robustness of the results using a relationship stickiness indicator estimated from the 2011-2017 period. One may indeed worry that the use of the same data to estimate relationship stickiness in the first step and the response of trade to uncertainty in the second step induces a source of endogeneity. In general, we don't think of it to be an important concern because the source of identification is different in both cases: In the first stage, we estimate RS from the heterogeneity in mean duration *across products* whereas the trade response to uncertainty episodes solely relies on the variability *within* a product. Still, we cannot preclude that unobserved factors simultaneously affect both sources of variability. We check that this is not an important concern by using a measure of RS which is estimated out-of-sample. Results are qualitatively and quantitatively very similar. The impact of an uncertainty episode is estimated to increase from -.02 to -.07 when moving from the first to the third quartiles of the distribution of relationship stickiness, i.e. a range of effects which is only slightly smaller than in the baseline case.

In Table B.3, we dig deeper into the trade effect of uncertainty by looking at its correlation over space and time. In columns (1)-(2), we test for spillover effects of uncertainty shocks, on other destination countries. In theory, an uncertainty shock in country c could have two opposite effects on trade with alternative destinations. Trade could be *diverted* to these destinations, so that the decline in the creation of new trade relationships in the destination hit by the shock would be compensated by an increase in the rate at which French exporters establish new relationships with importers from other countries. But the spillover could

also be negative, with uncertainty in one country reducing firms' incentive to invest in new trade relationships in other destinations as well. We expect this scenario if firms perceive uncertainty to potentially spread to the rest of the EU. To address this question empirically, the specification in column (2) of Table 3 is augmented with a variable summing uncertainty shocks occurring in all alternative EU destinations but the country itself, interacted with the RS indicator. Results suggest the overall spillover effect is negative, that is, shocks in another EU destination induce a significant decline in the creation of new trade relationships in the country under study. As expected, the effect is smaller than the impact of the shock itself and is significantly larger in product markets displaying higher relationship stickiness. The same qualitative results are found in column (2), using identification across products within a destination \times period. In columns (3)-(4) of Table B.3, we finally study the dynamics of the trade impact of uncertainty. To this aim, we augment the benchmark specification with lags of the uncertainty variable, interacted with the RS indicator. The impact of uncertainty is shown to be persistent over time, for at least four quarters.

Up to now, the analysis has focused on the creation of new firm-to-firm relationships as an outcome variable. The reason is that the trade literature has extensively discussed the prevalence of fixed costs as a barrier to the international development of firms. To the extent that some of these costs affect the value of waiting, we also expect to see an impact on separation rates. Firms should indeed be reluctant to end a costly trade relationship when uncertainty is high. We investigate this possibility in Table 4. Here, the left-hand-side variable is the number of disrupted relationships observed over a particular period. The variable is constructed using relationships that we observe for the last time over a particular month. The number of disrupted relationships over a quarter and destination is the number of such relationships cumulated over the last quarter. The assumption is that, if these relationships had not ended, firms would have been active at least once in the next quarter. This assumption is reasonable because transactions take place once every three months, on average (Table A.2).

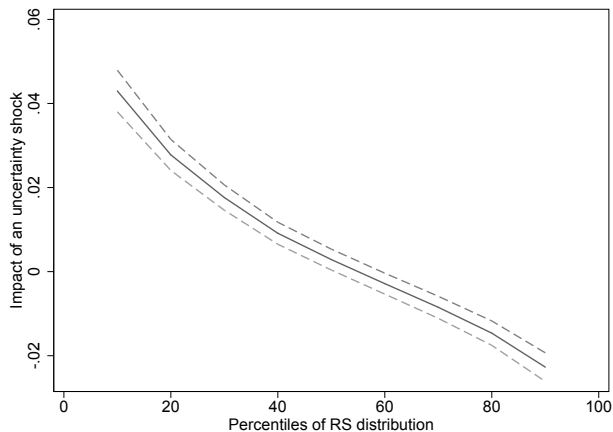
Results in Table 4 suggest the impact of uncertainty shocks on separation rates is indeed significant, although the sign of the relationship varies along the distribution of relationship stickiness. As illustrated in Figure 5, uncertainty periods are associated with significantly more firm-to-firm separations, in product markets displaying little stickiness. In the first quartile of the distribution, the impact is thus positive and significant, at 2%. In the third quartile, the effect is instead negative, at -2%. The fact that stickiness increases the real option of waiting is consistent with standard models of investment choice under uncertainty. However, that uncertainty increases separation rates for the least sticky products suggests instead that our measure of uncertainty also has a negative impact on the level of expected profits. One can

Table 4: *Uncertainty and the disruption of trade relationships*

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var:	<i># disrupted trade relationships</i>					
Uncertainty episode	0.23*** (0.007)				0.25*** (0.025)	
- × RS index	-0.08*** (0.003)	-0.03*** (0.007)			-0.08*** (0.009)	-0.05*** (0.009)
Uncertainty index			1.14*** (0.021)			
- × RS index			-0.38*** (0.008)	-0.24*** (0.007)		
Observations	2,546,156	2,546,156	2,546,156	2,546,156	2,433,146	2,433,146
Period	2000-2010	2000-2010	2000-2010	2000-2010	2000-2010	2000-2010
RS estimates	1996-2006	1996-2006	1996-2006	1996-2006	2011-2017	2011-2017
<i>Fixed Effects</i>						
Product × quarter		✓		✓		✓
Product × period	✓		✓		✓	
Country	✓		✓		✓	
Country × period		✓		✓		✓

Notes: Poisson estimations with high-dimensional fixed effects. Uncertainty shocks is a dummy equal to 1 in periods when uncertainty in the destination country is above-average uncertainty plus one s.d. of uncertainty. *RS* is our measure of relationship stickiness, which is not centered (Mean:2.9, P05: 1.8, P95: 3.5). In columns (1)-(4), RS is estimated using 1996-2006 data whereas we use the out-of-sample dataset recovered from 2011-2017 in columns (5)-(6). Bootstrapped standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Figure 5: *Impact of an uncertainty shock on disrupted relationships, along the distribution of RS*



Notes: This figure is recovered from results in Table 4, column (1). It shows the percentage-point impact of an uncertainty shock, on the number of disrupted firm-to-firm relationships.

rationalize this positive effect through two alternative interpretations. First, our measure of uncertainty may be negatively correlated with expected demand, which would affect expected profits. Second, even if uncertainty shocks were pure second-moment shocks, they could still have a level impact in presence of managers’ risk aversion or non-constant elasticities of profits to demand shocks. Whereas a first-moment negative shock on profits would only reinforce the negative impact of uncertainty on entry, it could act as a countervailing force on exit: wait-and-see behaviors would still dominate for high-enough levels of stickiness, while separation rates could increase for low RS products.

In sum, results presented in this section provide strong evidence for a response of trade to uncertainty shocks, at the extensive margin. Such adjustments are consistent with episodes of high uncertainty generating significant wait-and-see behaviors from firms that need to invest money in their international development. Importantly, we provide strong evidence that the magnitude of these wait-and-see behaviors is significantly more pronounced in sticky markets.

4.3 Robustness checks

In Tables B.4 and B.5 in the Appendix, we provide an extensive robustness analysis of the results discussed in Section 4.2. Both tables are organized the same way, with Table B.4 testing the robustness of results regarding the impact of uncertainty on entries when Table B.5 investigates the robustness of exit patterns. Columns (1) and (2) correspond to the baseline already shown in columns (1) and (2) of Tables 3 and 4. In columns (3) to (6), we

test the robustness of results to the measure of relationship stickiness. In columns (7) to (10), we investigate how our results vary in various sub-samples.

Relationship stickiness: level vs. rank. Columns (3)-(4) use the ranking of products in the distribution of stickiness indicators displayed in Figure 4, instead of the level of the indicator. One may indeed argue that the level of RS is potentially contaminated by uncertainty. However, the *ranking* of products should be immune from this source of endogeneity as long as uncertainty is common across products. Results are robust to using this measure of stickiness and actually imply a stronger heterogeneity in adjustments to uncertainty than in the baseline specifications.

Alternative RS estimates from Colombian data. In columns (5)-(6), we restrict the analysis to the subset of products that we can match with the measure of RS recovered from the Colombian data. The number of observations in the estimation sample is halved as a consequence. Qualitative results however remain unchanged in Table B.4, regarding the consequences of uncertainty episodes for the creation of firm-to-firm relationships. When we study separation rates in this reduced sample, results are slightly different, however. The negative relationship between the response to uncertainty episodes and the degree of stickiness is confirmed but the level of the elasticity is now positive at the third quartile of the distribution of RS indicators. One possible reason is that the subset of products which is exported by both French and Colombian firms is biased towards relatively low stickiness products, for which more uncertainty is associated with significantly more separations. Whereas such composition effects can have consequences for the overall qualitative effects, we see these sets of robustness as generally reassuring regarding the possible endogeneity of the RS indicator in the baseline specification of section 4.2.

Non-durable goods. In columns (7)-(8), we run the same regressions on a sub-sample that excludes durable products. In [Novy and Taylor \(2019\)](#), durable goods feature the largest degree of magnification in response to uncertainty shocks. According to their model, firms can delay orders of such products in periods of high uncertainty by relying on their inventories. How such behaviors would affect our results is not entirely clear as these behaviors prominently affect adjustments at the intensive margin but firms may still delay the search of new partners if they can count on their inventories. Again, we find our results to be robust to excluding these products, although the focus on non-durable products also shifts elasticities of separations to uncertainty episodes towards more positive values.

Excluding intra-firm trade. Finally, columns (9)-(10) present results of an attempt to control for the possible impact of intra-firm trade on our estimates. As explained in section 2, the data at hand do not permit to distinguish arm’s length and intra-firm transactions. However, one may worry that the response of both types of trade flows to uncertainty episodes entirely drives the heterogeneity that we attribute to stickiness in Section 4.2. To build the sub-sample used in columns (9)-(10), we leverage upon external data from the INSEE-LiFi survey to identify French exporters that belong to multinational firms. We then remove from the analysis all their exports to countries with which they have multinational linkages, either because they have an affiliate there or because their headquarter is located in the country. By doing so, we remove from the estimation sample all intra-firm trade flows. Note that we most probably also remove transactions that do not take place intrafirm as exporters with affiliates in a country may also export to non-affiliated partners. Here as well, results are qualitatively and quantitatively unchanged when it comes to the response of entries to uncertainty episodes. But elasticities at the exit margin are again shifted towards slightly more positive values as neglecting intra-firm transactions amounts to over-representing less sticky products since stickiness is correlated with the prevalence of intra-firm trade (Table A.3).

All in all, results presented in this section confirm the results in Section 4.2 regarding the sensitivity of trade to uncertainty episodes, the role of extensive margin adjustments, and the magnified impact in more sticky product markets.

4.4 Trade adjustments to uncertainty and GDP shocks

Until now, the analysis has focused on trade adjustments at the extensive (firm-to-firm) margin in response to uncertainty episodes. However, as argued by [Novy and Taylor \(2019\)](#), uncertainty can also affect trade at the intensive margin, if firms hold inventories of intermediaries and order shipments infrequently. In response to an uncertainty episode, firms will optimally adjust their inventory, which can cause a decline of trade within existing relationships. Comparing the size of adjustments at the intensive and extensive margins is thus useful to confront various adjustment mechanisms.

To this aim, we first decompose the mid-point growth in product-level trade of French exports into an intensive-margin component, the growth of trade within continuing relationships, and two extensive margin components, the start of new relationships and the ending of existing relationships.²² Trade growth is computed using year-on-year growth for each

²²In doing so, we follow [Bricongne et al. \(2012\)](#) and [Carballo et al. \(2018\)](#). Unlike these papers, we can run the analysis at the seller-buyer level. The entry term is thus the start of a new relationship between a French

quarter to remove seasonality. We then regress product-level growth and its components on uncertainty and its interaction with relationship stickiness. Here, we further control for GDP shocks and its interaction with RS. By doing so, we can compare trade adjustments to two types of shocks that are likely to generate qualitatively different responses. For comparability purposes, the GDP shock variable is a dummy that takes the value of one when the growth in the destination is one standard deviation below its average over the period of estimation. Results are robust if we use the growth level instead.

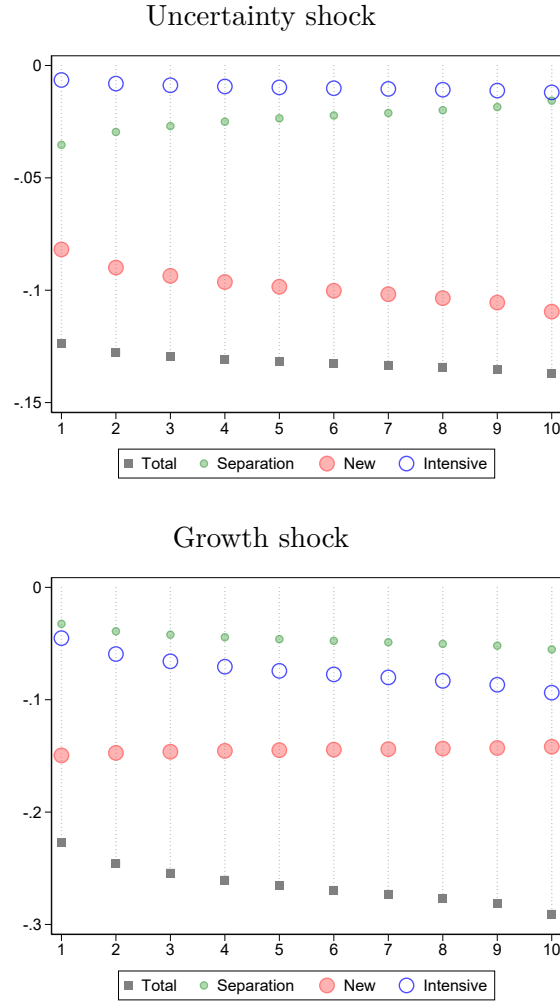
We report the point estimates in Table 5, and plot the implied response of the different margins to uncertainty and GDP shocks in Figure 6. The top panel summarizes the response of trade growth to an uncertainty shock, and the bottom panel concerns a growth shock. Several interesting results emerge from the comparison of these graphs. First, both shocks are associated with significantly less trade growth. In comparison with normal times, episodes of high uncertainty are associated with .12 percentage points less growth, on average. The impact of a drop in the destination country’s growth is larger, at -.25 percentage points. For uncertainty shocks, the impact is roughly constant over the distribution of RS indices. Instead, the impact of a GDP shock is .6 percentage points larger at the 10th than at the 1st decile of the distribution. Second, the margins of adjustments to both shocks are significantly different. The response of trade to uncertainty shocks is mostly driven by the extensive margin, namely, the wait-and-see behaviors documented earlier. This result is in line with Carballo et al. (2018). Instead, the intensive margin does not adjust much to uncertainty episodes.

The mechanisms of the adjustment are markedly different in case of a GDP shock. Here, the intensive margin is a significant driver of the response of trade. This finding is consistent with evidence in Bricongne et al. (2012) who show the trade collapse in 2008 was largely driven by the intensive margin. In the panel under study, the intensive margin contributes to one fifth to one third of the overall adjustment, depending on the degree of stickiness in the product market.

Finally, the intensity of trade adjustments does vary along the distribution of stickiness. For uncertainty shocks, the heterogeneity mostly kicks in at the extensive margin. Consistent with those in section 4.2, results show strong evidence for muted extensive adjustments in sticky-product markets, with fewer entries somewhat compensated by fewer separations. When the shock hits GDP growth, the heterogeneity instead affects adjustments at the intensive margin, whereas the response of trade at the extensive margin is roughly constant. Intensive adjustments amount to .09 percentage points at the 10th decile of the RS distri-

seller and a foreign buyer for a given product, irrespective of the status of the seller in the market during the previous period.

Figure 6: *Impact of shocks on trade growth, along the distribution of RS*



Notes: These figures summarized the response of product-level trade to an uncertainty shock (top panel) and a shock to the destination market’s growth (bottom panel). Results are recovered from the estimation of the following equation:

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

where the LHS variable is the mid-point growth rate or one of its components, $Uncert_{ct}$ and GDP_{ct} respectively denote an uncertainty and GDP shocks, and FE denotes fixed effects at the product×country level.

Table 5: *Uncertainty and trade growth: margin decomposition*

	(1)	(2)	(3)	(4)
Dep. var:	Growth	=Start	+ End	+ Intensive
RS index	-0.07*** (0.002)	-0.21*** (0.002)	0.13*** (0.001)	0.01*** (0.001)
Uncertainty shock	-0.11*** (0.004)	-0.05*** (0.002)	-0.06*** (0.002)	0.001 (0.001)
- × RS index	-0.01*** (0.001)	-0.02*** (0.001)	0.01*** (0.001)	-0.003*** (0.0004)
GDP shock	-0.14*** (0.007)	-0.16*** (0.004)	-0.002 (0.003)	0.02 (0.003)
- × RS index	-0.04*** (0.002)	0.01*** (0.001)	-0.01*** (0.001)	-0.03*** (0.001)
Observations	3,538,965	3,538,965	3,538,965	3,538,965
Period	1996-2010	1996-2010	1996-2010	1996-2010
RS estimation period	1996-2006	1996-2006	1996-2006	1996-2006

Notes: OLS estimation. Bootstrapped standard errors are in parentheses. Growth is the 12-month growth of product-level French exports to a destination. Start, end, and intensive are the different growth margins, namely the number of new seller-buyer relationships, the number of disrupted relationships, and the evolution of seller-buyer sales along the intensive margin. Uncertainty shocks is a dummy equal to one in periods when uncertainty in the destination country is above average uncertainty plus one s.d. of uncertainty. GDP shock is a dummy equal to one in periods when GDP growth is below average GDP growth minus one s.d. of GDP growth. *RS* is our measure of relationship stickiness, which is not centered (Mean: 2.9, P05: 1.8, P95: 3.5). Significance levels: * 10%, ** 5%, *** 1%.

bution, against only .04 p.p. at the 1th decile. The strong impact of growth shocks at the intensive margin in sticky product markets is consistent with models of production networks in which demand shocks transmit upstream along the supply chain (Acemoglu et al., 2016). The heterogeneity along the RS distribution confirms evidence in Barrot and Sauvagnat (2016).

We checked the robustness of these results by using two alternative proxies for first and second moment shocks. More specifically, we use the average stock returns and the average volatility of returns computed by Baker et al. (2020).²³ The results, presented in Table B.6, show an increase in the volatility of returns is associated to a decrease in entry – magnified for the most sticky products, and a increase in the disruption of trade relationships – dampened for the most sticky products. These findings are consistent with the wait-and-see behavior of

²³We use the macro measures computed by Baker et al. (2020), because they have a better country coverage.

sticky products when uncertainty increases.^{24,25}

Antras (2020) argues severe but temporary shocks such as the 2008-09 trade collapse or the COVID-crisis do not fundamentally change firms' sourcing strategies and are likely followed by a fast recovery. Our findings are consistent with this view. The adverse effect of negative shocks is mainly driven by a reduction in the creation of new relationships and, for first-moment shocks, a drop in firm-to-firm trade along the intensive margin. By contrast, negative shocks have little impact, if any, on the disruption of sticky firm-to-firm trade relationships. Firms are thus likely to expand quickly in the aftermath of a negative shock by building on their existing relationships.

5 Conclusion

In this paper, we discuss the extent to which stickiness in firm-to-firm relationships can amplify the real impact of uncertainty with a particular emphasis on international trade. This question is a topical one for at least two reasons. On the one hand, uncertainty is prevalent in the current international context. Firms engaged in international markets have to cope with the uncertainty induced by negotiations over Brexit, the trade war involving the US and most of its partners, and now the consequences of the COVID-19 pandemic. On the other hand, sticky trade relationships are prevalent within global value chains. The fragmentation of production processes generates locked-in effects as a consequence of relationship-specific investments (Antràs and Chor, 2013). Firms engaged in global value chains often need to customize product, or adjust their logistics chain to the particular needs of the firm located downstream. This need generates a substantial degree of persistence in firm-to-firm relationships.

We study the interaction between these two phenomena from an empirical standpoint. We exploit highly detailed firm-to-firm data involving French firms and their partners in the EU, covering a period of more than 10 years. Using these data, we first construct an indicator of relationship stickiness at the product level. The empirical strategy consists of comparing the average duration of firm-to-firm relationships conditional on a match quality and derive from this comparison an ex-post measure of stickiness. Armed with the RS indicator, we

²⁴An increase in the level of returns (a positive shock to the first moment) leads to higher export growth, in particular for the most sticky products, which is largely driven by the intensive margin.

²⁵We also ran a set of specifications in which the uncertainty and GDP shocks are further interacted with Nunn's measure of product specificity. Results, presented in Table B.7, show that the heterogeneity in trade adjustments to uncertainty and GDP shocks across products with different levels of stickiness holds with these additional controls. Furthermore, interaction terms between uncertainty and GDP shocks and Nunn's measure of product specificity are often non significant.

estimate the propagation of uncertainty shocks to the real economy. We estimate a significant impact of uncertainty on the extensive margin of trade. Episodes of high uncertainty are characterized by significantly fewer new firm-to-firm relationships, the impact being stronger in product markets displaying stickier trade partnerships. This finding is consistent with sticky relationships generating high sunk costs, which firms are reluctant to pay in periods of high uncertainty. The propagation of policy uncertainty to the real economy is thus intimately linked to the type of relationship in which sellers and buyers are engaged. The modern organization of production into fragmented processes increases the sensitivity of the economy to uncertainty shocks.

Finally, note we have focused here on trade adjustment to uncertainty shocks, but stickiness may be important for a range of macroeconomic outcomes. The responses of trade to exchange-rate shocks or trade policy might differ across products with different levels of stickiness (Heise, 2016). The degree of stickiness also affects the international transmission of shocks, with implications for the level and the comovement of economic fluctuations. We hope the measure developed in this paper will stimulate research along these questions.

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.
- , Ufuk Akcigit, and William Kerr, “Networks and the Macroeconomy: An Empirical Exploration,” *NBER Macroeconomics Annual*, 2016, *30* (1), 273–335.
- 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.
- Besedes, Tibor and Thomas J. Prusa, “Product differentiation and duration of US import trade,” *Journal of International Economics*, 2006, 70 (2), 339–358.
- Bloom, Nicholas, “The Impact of Uncertainty Shocks,” *Econometrica*, May 2009, 77 (3), 623–685.
- and John Van Reenen, “Patents, Real Options and Firm Performance,” *Economic Journal*, March 2002, 112 (478), 97–116.
- Bloom, Nick, Stephen Bond, and John Van Reenen, “Uncertainty and Investment Dynamics,” *Review of Economic Studies*, 2007, 74 (2), 391–415.
- Blum, Bernardo S., Sebastian Claro, Kunal Dasgupta, and Ignatius J. Horstmann, “Inventory Management, Product Quality, and Cross-Country Income Differences,” *American Economic Journal: Macroeconomics*, January 2019, 11 (1), 338–388.
- Boehm, Johannes and Ezra Oberfield, “Misallocation in the Market for Inputs: Enforcement and the Organization of Production,” *The Quarterly Journal of Economics*, 2020, 135 (4), 2007–2058.
- 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.
- Dixit, Avinash K. and Robert S. Pindyck, *Investment under Uncertainty* number 5474. In ‘Economics Books.’, Princeton University Press, 1994.
- 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.
- Fillat, José L. and Stefania Garetto, “Risk, Returns, and Multinational Production,” *The Quarterly Journal of Economics*, 2015, *130* (4), 2027–2073.
- 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.
- Gaulier, Guillaume and Soledad Zignago, “BACI: International Trade Database at the Product-Level. The 1994-2007 Version,” Working Papers 2010-23, CEPII research center October 2010.
- 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*, 2017, *107* (9), 2731–2783.
- 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.
- , Thierry Mayer, and Mathias Thoenig, “Welfare and Trade without Pareto,” *American Economic Review*, 2014, *104* (5), 310–316.
- 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.
- Hémous, David and Morten Olsen, “Long-term Relationships: Static Gains and Dynamic Inefficiencies,” *Journal of the European Economic Association*, 2018, *16* (2), 383–435.
- Hornok, Cecília and Miklós Koren, “Administrative barriers to trade,” *Journal of International Economics*, 2015, *96* (S1), 110–122.
- Imbs, Jean and Isabelle Mejean, “Elasticity Optimism,” *American Economic Journal: Macroeconomics*, July 2015, *7* (3), 43–83.

- Kamal, Fariha and Ryan Monarch, “Identifying Foreign Suppliers in U.S. Import Data,” *Review of International Economics*, 2018, 26 (1), 117–139.
- Kaufmann, Daniel, Aart Kraay, and Massimo Mastruzzi, “The worldwide governance indicators : methodology and analytical issues,” Policy Research Working Paper Series 5430, The World Bank September 2010.
- Krizan, C., James Tybout, Zi Wang, and Yingyan Zhao, “Are Customs Records Consistent Across Countries?,” Technical Report CES-WP-20-11, US Census Bureau Center for Economic Studies 2020.
- 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.
- Mayer, Thierry and Soledad Zignago, “Notes on CEPII’s distances measures: The GeoDist database,” Working Papers 2011-25, CEPII research center December 2011.
- 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.
- 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.
- Pierce, Justin R. and Peter K. Schott, “A concordance between ten-digit U.S. Harmonized System codes and SIC/NAICS product classes and industries,” Finance and Economics Discussion Series 2012-15, Board of Governors of the Federal Reserve System (US) 2012.
- and –, “The Surprisingly Swift Decline of US Manufacturing Employment,” *American Economic Review*, July 2016, 106 (7), 1632–1662.
- Postel-Vinay, Fabien and Jean Marc Robin, “Equilibrium Wage Dispersion with Worker and Employer Heterogeneity,” *Econometrica*, 2002, 70 (6), 2295–350.
- Rauch, James E., “Networks versus markets in international trade,” *Journal of International Economics*, June 1999, 48 (1), 7–35.
- Schaal, Edouard, “Uncertainty and Unemployment,” *Econometrica*, November 2017, 85 (6), 1675–1721.
- Schmidt-Eisenlohr, Tim and Ryan Monarch, “Learning and the Value of Relationships in International Trade,” 2015 Meeting Papers 668, Society for Economic Dynamics 2015.

Table A.1: *Summary statistics on the structure of the dataset*

	# transac.	# sellers	# buyers	# sellers ×products	# buyers ×products	# buyer×seller ×products
	(1)	(2)	(3)	(4)	(5)	(6)
EU12	101,379,585	109,522	1,583,220	1,340,346	14,195,710	19,383,546
Belgium	19,872,676	74,924	185,596	637,007	2,488,213	3,596,690
Denmark	1,938,872	23,057	26,962	126,801	249,992	352,214
Germany	19,426,804	61,159	349,803	495,009	2,621,373	3,537,033
Greece	2,003,763	20,238	31,828	139,837	302,191	419,877
Ireland	1,293,531	16,414	15,925	88,334	182,032	270,832
Italy	12,662,419	51,963	280,641	381,644	2,144,174	2,792,808
Luxemburg	3,086,374	31,580	19,028	199,820	402,186	560,297
Netherlands	6,158,922	44,031	90,507	267,196	772,004	1,099,336
Portugal	4,833,183	33,528	67,248	238,463	762,041	1,024,489
Spain	12,581,119	53,471	237,767	419,964	1,928,424	2,490,565
UK	10,487,916	49,325	151,545	360,504	1,321,563	1,923,611

Notes: This table is based on French customs firm-to-firm data for 1996-2006. The first line corresponds to all countries, and the rest of the table gives statistics for individual countries. Column (1) reports the number of transactions, a transaction being defined as a trade flow in a given month and year, involving a particular seller-buyer pair, for a given product. Column (2) is the number of exporters observed over the period. Column (3) is the number of importers. Column (4) is the number of seller-product pairs. Column (5) is the number of buyer-product pairs. Column (6) is the number of seller-buyer-product triplets observed over time, also called “relationships” in the rest of the paper.

A Appendix

A.1 Details on the data

Table A.1 provides detailed statistics about the dimensionality of the data in the sub-sample used to compute the baseline measure of relationship stickiness. This dataset covers the period 1996-2006 and the eleven historical members of the European Union. The unit of observation is a transaction, which is identified by a seller, a buyer, a product and a particular month. Columns (1)-(3) provide statistics on the number of transactions and the number of firms involved into these transactions, for each bilateral trade flow. In the analysis, all statistics are defined at the fine (harmonized nc8) product level. Columns (4)-(6) further provide statistics about the dimension of the graph, once we treat multi-product importers and exporters as independent units.

In the cross-section, the dataset has the structure of a bipartite graph linking individual seller×product pairs to individual importers. The structure of this graph is largely consistent with many-to-one matching. At a point in time (defined by a particular month in a particular year), we observe most buyers purchasing a particular product from a single seller, whereas sellers simultaneously serve several importers (even within a country). This finding is illustrated in Figure A.1, which shows the distribution in the number of sellers interacting with a given importer during a particular month (top panel) and the distribution in the number of partners from the same country a French exporter is interacting with (bottom panel). More than 90% of importers have only one French supplier for a given product within a given month. Even when we concentrate on importers that we observe over many (i.e., at least 50) transactions, this proportion is high, above 80%. Instead, 26% of French exporters sell the same product within the same month to several partners located in the same country, the

proportion increasing to 55% when we pool partners located in different countries.²⁶ Given this data structure, the model in section 3 assumes many-to-one matching with importers interacting with a single supplier at a point in time. When the same importer is seen interacting with two different exporters within a month, we consider the two transactions to take place simultaneously.

A.2 Measuring the duration of a trade relationship

In the model, the duration of a relationship is written as a function of the probability of a switch, that is, of an importer leaving its current partner to start interacting with a new one. In the data, the two objects do not map exactly, because of the heterogeneity in the frequency of transactions. This difference is illustrated in Table A.2, which compares statistics on (i) the mean duration of a buyer’s relationships with French suppliers, (ii) the inverse of the probability of this buyer’s switching to a new supplier, and (iii) the inverse of the probability of switching, conditional on trade. If buyers purchased French products at regular intervals, for example every month, the three statistics would deliver the same information. As shown in the fourth line of Table A.2, the frequency of transactions is neither close to 1, nor homogenous across buyers. On average, the probability of a transaction occurring in a given month is equal to .332, which corresponds to a transaction every three months. Twenty-five percent of buyers, however, purchase French products more than once every two months, whereas in the first quartile of the distribution, firms purchase products less than once every 10 months. Because of heterogeneous frequencies, the three available measures of duration are not equivalent. In general, one can show that the mean duration is between the two switching probabilities. In the data, the three statistics are correlated at more than 50%, meaning heterogeneity in the frequency of transactions does not completely distort the distribution of trade durations, across buyers and products.

Finally, note that our definition of a relationship implies that the same firms interacting over two continuous periods, interrupted by another relationship involving the same importer but a different French exporter, are considered two different relationships, i.e. we do not keep the whole history of an importer’s partners in memory. Abstracting from the whole history of the buyer’s interactions with French sellers greatly simplifies the analysis. Moreover, the probability of a “recall”, that is, of a buyer switching back to a supplier it knows from before, is very small in the data (see the last line in Table A.2).

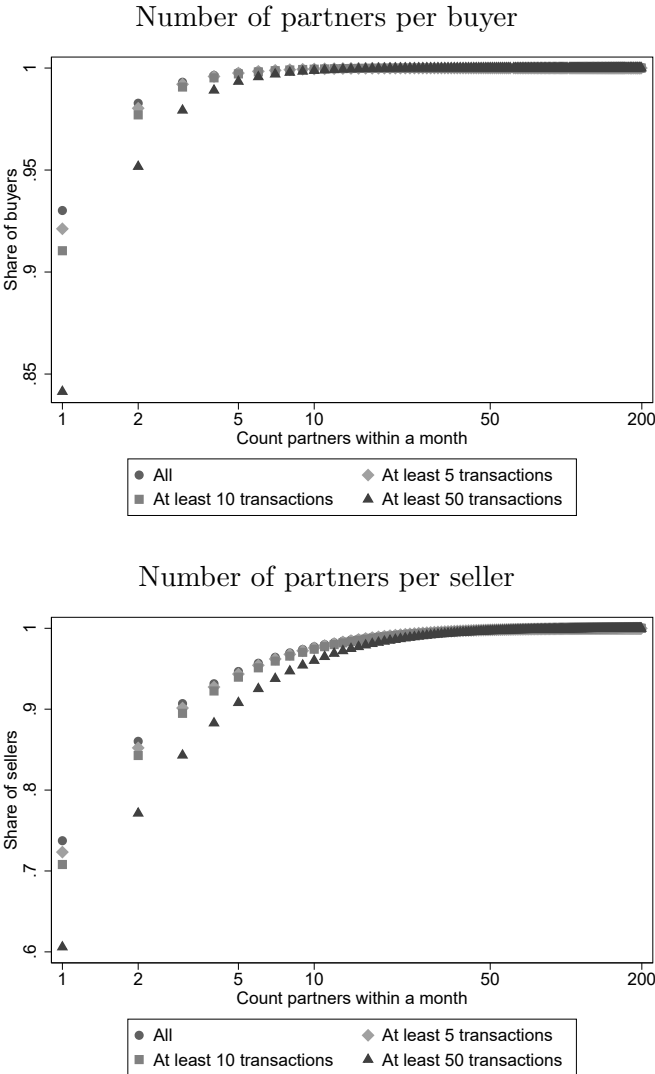
A.3 A variant of the model with a fixed sunk cost

We consider here the steady-state value function $V(p)$ which results from the intertemporal optimization problem of a buyer importing its input at price p . Instantaneous profits are denoted by $\pi(p)$, r denotes the real instantaneous rate of interest, and a relationship may break with exogenous probability δ , in which case a buyer’s discounted sum of future expected profits becomes V^0 . At a stationary state, we have

$$rV(p) = \pi(p) + \delta \left(V^0 - V(p) \right) + \lambda \int_0^{p^*(p)} [V(\tilde{p}) - F - V(p)] dH_P(\tilde{p})$$

²⁶This is in contrast with Bernard et al. (2018) who use qualitatively similar data and find that the matching between exporters and importers display many-to-many relationships. Beyond their data covering a different country, a possible reason for such discrepancy is that they do not condition on a particular product while we do. Indeed, we do see in our data that buyers often interact with several French exporters in a given month, although to purchase different products (see Figure B.2 and the comparison with Figure A.1, the later counting the number of partners within a product while the former cumulates partners across products within a firm). Once we condition on a given product, purchasing from multiple French exporters becomes very rare.

Figure A.1: *Distribution of the number of partners, per buyer/seller and date (month×year)*



Notes: Cumulated distributions of the number of partners a French exporter interacts with in a given country (bottom panel) and the number of partners a foreign buyer (\times product) interacts with within a particular month (top panel). The number of partners is calculated over the sub-sample of importers (resp. exporters) that are involved in at least two transactions over the period of analysis ("All") and at least 5, 10, and 50 transactions.

Table A.2: *Descriptive statistics on alternative measures of the duration of firm-to-firm relationships*

	Mean	Median	P25	P75
Mean duration	18	10	3	25
$1/\mathbb{P}(\text{switch})$	9	20	9	41
$1/\mathbb{P}(\text{switch} \text{Trade})$	2	3	2	6
Frequency of transactions	0.332	0.222	0.095	0.500
Proba Recall	0.013	0.000	0.000	0.000

Notes: This table provides statistics on alternative measures of durations. The first line is based on our benchmark measure, and is defined as the mean number of months between the first and the last transactions involving a particular pair of firms over a continuous relationship (“Mean duration”). “ $1/\mathbb{P}(\text{switch})$ ” is the inverse of the switching probability recovered as the number of switching episodes divided by the total number of months a particular buyer is present in the data. “ $1/\mathbb{P}(\text{switch}|\text{Trade})$ ” is the inverse of the switching probability conditional on a transaction, computed as the number of switching episodes over the total number of transactions. The “Frequency of transactions” is computed as the number of transactions divided by the overall timespan over which the importer is observed in the data and thus measures the monthly probability of a transaction. “Proba Recall” measures the probability that, during a switching episode, the buyer starts interacting with an exporter already known from a past relationship. Statistics are calculated for each importer before averaging across buyers, using the dataset covering 1996-2006.

where $H_P(\tilde{p})$ is the cumulated distribution of quality-adjusted prices and $F > 0$ denotes the fixed sunk cost associated with switching sellers. In equilibrium, the fixed cost is paid only when the price offer \tilde{p} falls below the buyer's reservation price $p^*(p)$, reflecting again that the price wedge must offset switching costs.

Differentiating with respect to p the above equation implies that buyers with lower import prices are more profitable $V'(p) < 0$. The average duration of a buyer-seller relationship is the inverse of the switching probability

$$\mathbb{E}[\mathcal{T} | p] := \frac{1}{\lambda H(p^*(p))}$$

This model implies a one-to-one mapping between the sunk costs F and the wedge $p^*(p)$ given p . Our baseline model can be seen as the result of a direct parametrization of the wedge $p^*(p) = p/\gamma$.

A.4 Detailed on the estimation of relationship stickiness

As explained in section 3.1, relationship stickiness is estimated by exploiting the following prediction of a search model with switching costs:

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

where $\mathbb{E}[\mathcal{T} | R \in R_q]$ is the expected duration of a transaction, conditional on the transaction falling in the q th quantile of the distribution, $\eta \equiv \frac{\gamma^k}{\lambda}$ is the product-specific index of business stickiness, and $\ln \left[\frac{\mathbb{P}(R \geq r_{q-1})}{\mathbb{P}(R \geq r_q)} \right]$ solely depends on the definition of quantiles.

The empirical counterpart of the left-hand side of this equation is the log of the mean duration of firm-to-firm relationships, in various size quantiles of the product- and country-specific distribution:

$$Dur_{qpc} \equiv \frac{1}{N_{qpc}} \sum_{sb \in R_{qpc}} Dur_{sb(c)p},$$

where $Dur_{sb(c)p}$ is the duration of the relationship involving buyer $b(c)$ located in country c , French exporter s , and product p , and N_{qpc} is the number of such relationships in the quantile under study (R_{qpc}). Dur_{qpc} is the empirical counterpart of the expectation term in (3).

Based on this (noisy) measure of conditional expected durations, recovering a relative measure of relationship stickiness using the following log-linear specification is thus possible:

$$\log Dur_{qpc} = FE_p + \alpha \ln \ln \left[\frac{\mathbb{P}(R \geq r_{q-1})}{\mathbb{P}(R \geq r_q)} \right] + \epsilon_{qpc}, \quad (\text{A.2})$$

where FE_p is a product fixed effect, and ϵ_{qpc} is the error term. The product fixed effect recovered from equation (A.2) can be interpreted as a measure of the relative stickiness of relationships in product market p .

To compute the mean duration conditional on a size quantile (Dur_{qpc}), we proceed as follows: (i) We compute the size of a relationship as the average value of transactions involving a given seller-buyer pair, in constant euros,²⁷; (ii) we assign all the trade relationships to a size-decile (specific to a product category); and (iii) we take the average duration within each bin. Each distribution is cut into 10 quantiles, the eight deciles in between the 10th and the 90th percentiles of the distribution plus a quantile defined by transactions between the 1st and the 10th percentile, and the quantile of transactions between the 90th and the 99th percentiles.

²⁷Nominal values are deflated by the French PPI constructed by INSEE.

A.5 Robustness analysis

In Table B.1, we present the results of a regression of our measure of stickiness on various statistics directly calculated from the firm-to-firm data. Products with a higher share of buyers that appear only once in our data and with a higher share of buyers that interact with several suppliers within a month exhibit lower levels of stickiness. These correlations are consistent with the view that if buyers can afford to enter markets for short periods of time or if they trade with many suppliers, they can more easily switch from one supplier to another.²⁸ We then explore two predictions of our model, namely, that stickiness should be higher in markets with more frictions and where the distribution of sales is more concentrated. As a proxy of sales distribution, we measure the concentration of exports across French firms for each product category. As expected, product categories with a higher level of sales concentration exhibit a higher level of stickiness.²⁹ The explanatory power of sales concentration is low (R^2 of 1%), however, suggesting the distribution of sales is not the main force explaining heterogeneity in stickiness across products. As a rough measure of frictions, we compute the dispersion of unit values recovered from the whole distribution of transaction-level unit values within product categories. The correlation between stickiness and price dispersion is positive and significant (R^2 of 3%), consistent with the view that products with higher levels of frictions are more sticky. Last, we look at the correlation between the activity of wholesalers in a product category and the level of stickiness. We find a negative and significant correlation between stickiness and the share of wholesalers, which is consistent with the view that the least sticky products involve less customization and specificity and are thus more likely to be exported by intermediaries.

Table B.2 summarizes a set of robustness exercises that are meant to test the stability of the estimated RS indicators. A first set of robustness checks uses alternative definitions of sales quantiles in equation (3), namely quintiles instead of deciles, country-specific quantiles or a subset of the top quantiles of the distribution of transactions' size.³⁰ In all three cases, the recovered distribution of RS indices is highly correlated with the baseline, at more than 80%, and displays comparable inter-quartile ranges. We also tried constraining the semi-elasticity of the duration with respect to the size of the quintile to unity, as in the theoretical model. Results are virtually unchanged.³¹ The same is true when we control for country fixed effects.

A second source of potential concern tackles the measurement of durations. As explained

²⁸We also compute stickiness on a sample in which we exclude buyers interacting with several suppliers within a month. Stickiness measured on this sample has a correlation of .87 with our baseline measure.

²⁹An alternative interpretation of this correlation relies on the accuracy of our RS measure when the law of large numbers does not hold. Averaging data on firms within each decile of the distribution of firms' size is meant to reduce the impact of a single firm on the RS indicator. Of course, in markets that display very concentrated trade, the averaging is mechanically less effective. In such cases, the RS indicator is more likely to reflect the duration of relationships between large firms and their foreign partners. The low correlation between sales concentration and RS suggests that this problem is not an important concern though.

³⁰With country- (and product-) specific quintiles, instead of product-specific moments, the support and shape of the distribution of productivities is not constrained to homogeneity across destinations, within a product. Focusing on the top percentiles implies restricting the analysis to the right part of the distribution of firms' size, that fits relatively better with the model's Pareto assumption (Head et al., 2014).

³¹The structural model implies that the semi-elasticity of the duration with respect to the mass of firms in the corresponding quantile of the distribution should be equal to 1 (see equation (3)). In our baseline estimation, we find a semi-elasticity that is significantly lower, at .15. In another robustness exercise, we have also tested imposing a coefficient of one. The correlation with our baseline estimates is almost perfect. The reason is that this component of the estimated equation does not absorb a large share of the heterogeneity. To gauge the importance of controlling for the size of the transaction, we also ran the specification without size control. Estimates from this alternative specification are also almost perfectly correlated with our baseline

in section 2.2, our measure of durations is less precise when transactions take place infrequently. One may worry that artificially long durations may be measured for products that are purchased infrequently, which would push the corresponding products’ stickiness up. To rule out this possibility, we conducted a robustness check that takes an extreme position on this problem. Namely, we reproduced the analysis using a measure of “durations” that is based on the *number* of transactions observed within a continuous relationship instead of the timespan between the first and last transactions. The correlation between the indicator recovered based on this left-hand side variable and the baseline estimate is equal to 75%. The inter-quartile range is also comparable in both distribution (Table B.2). Mis-measurement of durations induced by the heterogeneous frequency of purchases does not seem to be an important concern here.³²

A third set of results tests the stability of the RS estimates across estimation samples. Our argument is indeed that the estimation strategy allows us to capture the ex-post impact of product-specific attributes. If this is the case, we should expect our estimates to be roughly consistent regardless of the time period or the country sample used to estimate relationship stickiness. We therefore estimated a country-specific distribution of RS indicators using the same empirical strategy but estimating RS for each destination.³³ The correlation between the baseline distribution recovered from the pooled sample and the country-specific estimates is high (around 60%). We also checked the stability of our estimates over time, by estimating relationship stickiness using the 2011-2017 period. Here as well, the correlation is significant, at .60, as illustrated in Figure B.4. Note our baseline distribution of RS indices is the one estimated over 1996-2006, because the underlying customs data are of better quality in the earlier years of the sample.³⁴ We also performed the same estimation strategy on completely different data, namely the panel of firm-to-firm trade flows recovered from Colombian exports. As the dataset covers a smaller number of exporting firms and a more concentrated structure of exports, it has not been possible to estimate RS for the exact same set of products, unfortunately. Instead, we estimated equation (3) for 383 hs4 products for which the dataset contains more than 100 transactions, pooling all destination countries together. The correlation of the recovered estimates with the mean value of RS per hs4 product in our baseline estimates is significant and positive, at .4. Overall, the stability analysis implies rather high levels of correlation across RS estimates recovered from various datasets, including a database covering a completely different exporting country. These positive correlations provide empirical support to our interpretation of RS as capturing the consequences of structural factors that give raise

estimates, which is consistent with the fact that the size variable adds little explanatory power (R^2 without the size control drop from .21 to .20).

³²It has to be noted that this robustness tackles a possible concern regarding systematic differences across products in the frequency of purchases. Another concern is a possible heterogeneity within a product, across firms. A large share of this variability is smoothed out when we average out durations across firms within a quintile. But this problem may still be a concern if the measurement error associated with lumpy transactions is systematically correlated with the size of the transaction. Such correlation may well exist if there are fixed cost per shipment as argued by [Hornok and Koren \(2015\)](#) or [Blum et al. \(2019\)](#), among others. Intuitively, fixed costs per shipment are likely to reduce the heterogeneity in the size of transactions within a product, as small transactions will be grouped into a smaller number of infrequent shipments. The stability of results recovered from various definitions of durations and quantiles however suggests that this is not an important concern in practice.

³³Here, we focus on those countries that are important destinations for France exports, namely, Belgium, Germany, Italy, Spain, and the UK, because the empirical strategy requires the observation of a sufficient number of firm-to-firm relationships for each product category.

³⁴As mentioned in section 2, the dataset is censored because the Customs administration does not request that firms declare the product exported, below a certain threshold. Because the threshold tripled in 2011, censoring is significantly larger in the most recent period.

to significantly different mean durations in relationships across various product categories.

A.6 External validity tests

Relationship stickiness and intrafirm trade. In Table A.3, we examine whether the prevalence of intra-firm trade in US product-level trade data is systematically different along the distribution of relationship-stickiness indicators. Namely, we correlate the relationship-specific indicator with the share of intra-firm trade in US exports (columns (1)-(2)) and US imports (columns (3)-(4)). In columns (2) and (4), we further control for additional product-level characteristics that we know are correlated with RS (see Section 3.2). The share of intrafirm trade is computed from data released by the Bureau of Economic Analysis for year 2002. Intrafirm trade is reported by 6-digit NAICS categories that are merged with the HS6 nomenclature (version 2002) using the correspondence developed by [Pierce and Schott \(2012\)](#). We find a positive and significant correlation between the level of relationship stickiness of a product and its share of intrafirm trade. Relationship stickiness explains around 10% of the dispersion in the share of intrafirm trade across product categories.

Relationship stickiness and comparative advantages: [Nunn \(2007\)](#) and [Levchenko \(2007\)](#) provide strong evidence that countries with good contract enforcement specialize in the production of goods for which relationship-specific investments are most important. We use this well-established result to test the validity of our measure. We reproduce the same exercise as [Nunn \(2007\)](#) but working with more disaggregated data recovered from the UN-COMTRADE database at the 6-digit level of the Harmonized Nomenclature which is merged with our own measure of relationship stickiness. The results are reported in Table A.4. In every regression, we further control for the relation-specificity measure developed by [Nunn \(2007\)](#). In the first three columns, we follow Nunn and explain the value of countries' exports at the product level by an interaction term between the quality of the country's institutions, as measured by [Kaufmann et al. \(2010\)](#), and the degree of the relationship-stickiness of the product. In columns (4) and (5), we deviate from [Nunn \(2007\)](#) and consider measures of specialization that allow us to account for product-country pairs with zero trade flows, namely, the Balassa index and a dummy identifying Balassa indices above 1.³⁵ We confirm [Nunn \(2007\)](#) findings that countries with good contract enforcement specialize in the production of more relationship specific goods. In columns (3) and (5), we show both Nunn's and our measures of product stickiness have explanatory power in this regression. When we instead use the Balassa index as a measure of comparative advantage, the interaction with Nunn's measure becomes insignificant while our indicator remains positively associated with more trade from countries with good enforcement laws.

Relationship stickiness and the distance effect: In a final sanity check, we investigate how relationship stickiness interacts with standard determinants of international trade to shape the geography of trade. Namely, we use the gravity equation and interact the distance variable with our measure of relationship stickiness. Results are summarized in Table A.5. Bilateral trade data at the hs6 level are taken from the BACI database for 2005 ([Gaulier and Zignago, 2010](#)). Distance is the weighted distance between countries' main cities from [Mayer and Zignago \(2011\)](#). Finally, we also control for the product upstreamness in value chains and its interaction with distance. Results consistently show the distance effect is magnified in product markets that display more relationship stickiness. This result is true whatever the structure of fixed effects, including in the most demanding specification in column (4). The elasticity of trade to distance also seems to increase for more upstream goods, although the effect is sensitive to the structure of fixed effects. Interpreting the magnified impact of

³⁵The Balassa index is computed using BACI multilateral data and is defined as the value of product-level exports originating from one particular source country over the value of worldwide exports in the same product category.

Table A.3: *Share of intrafirm trade and relationship stickiness*

	(1)	(2)	(3)	(4)
	<i>Share of intra-firm</i>			
	<i>exports</i>		<i>imports</i>	
RS (η)	0.152*** (0.025)	0.092*** (0.034)	0.097*** (0.021)	0.062** (0.026)
Nunn' measure		0.409*** (0.066)		0.202*** (0.049)
Upstreamness		0.067*** (0.016)		0.021* (0.012)
Elasticity (σ)		-0.002 (0.006)		-0.008** (0.003)
Observations	439	378	439	378
R-squared	0.074	0.133	0.055	0.075

Robust standard errors are in parentheses with *, **, *** denoting significance at the 10, 5, and 1% levels.

distance for high-RS products is not possible in such a reduced-form framework. A possible interpretation is that information frictions are more stringent in those markets, which on the one hand increases the cost of switching to a new supplier, and on the other hand induces the geographic concentration of trade (Rauch, 1999). An alternative interpretation is that stickier relationships are associated with higher monitoring costs, which increase with distance (Head and Ries, 2008).

Table A.4: *Institutional comparative advantage*

	(1)	(2)	(3)	(4)	(5)
		log(exports)		Balassa Index	$\mathbf{1}_{Balassa>1}$
Rule of law					
× <i>RS</i>	0.196*** (0.034)		0.224*** (0.030)	0.110** (0.047)	0.010*** (0.003)
× Nunn specif.		0.812*** (0.100)	1.070*** (0.144)	0.367 (0.302)	0.041** (0.020)
× Upstreamness			0.077* (0.045)	0.041 (0.072)	0.008 (0.005)
Fixed effects <i>country(122) and sector(4, 326)</i>					
Observations	296,185	296,185	292,957	527,406	527,406
R-squared	0.604	0.606	0.609	0.012	0.139

Clustered (country) standard errors are in parentheses with *, **, *** denoting significance at the 10, 5, and 1% levels.

B Additional results

Table A.5: *Gravity for trade in goods with sticky relationship*

	(1)	(2)	(3)	(4)
Distance (log)	-0.553*** (0.015)	-0.370*** (0.019)	-0.521*** (0.020)	-0.893*** (0.025)
- × RS		-0.064*** (0.006)	-0.056*** (0.006)	-0.028*** (0.006)
- × Upstreamness		0.002 (0.005)	0.012** (0.005)	-0.021*** (0.007)
RS	-0.198*** (0.007)	0.322*** (0.051)		
Upstreamness	0.044*** (0.005)	0.026 (0.040)		
Fixed effects				
Exporter	✓	✓	✓	
Importer	✓	✓	✓	
Product			✓	
Exporter × Product				✓
Importer × Product				✓
Observations		5,704,026		5,473,532
R-squared	0.164	0.164	0.285	0.578

Clustered (country) standard errors are in parentheses with *, **, *** denoting significance at the 10, 5, and 1% levels.

Table B.1: *Correlation with moments of French data*

Reg. RS on:	β	R^2
Share buyers active a single month	-0.95*** (0.038)	0.068
Share buyers matched with multiple suppliers	-3.78*** (0.111)	0.118
Product-level HHI	0.17*** (0.018)	0.010
Product-level dispersion in unit values	0.10*** (0.006)	0.03
Value share of wholesalers	-0.26*** (0.016)	0.032

Notes: Coefficients obtained from the regression of the measure of relationship stickiness on different statistics computed on French data. *Share buyers active a single month* is the share of buyers within a product category that import only once over the period. *Share of buyers with many suppliers* is the share of buyers within a product category that import a given product from several French suppliers within a given month. *Product-level HHI* is the Herfindahl index computed for each product category using firm-level exports. *Product-level dispersion in unit values* is computed as the interquartile range of unit values with product categories. *Value share of wholesalers* is the share of French exports within a product category that is made up by firms identified as retailers or wholesalers. Standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table B.2: *Alternative estimates of stickiness*

	(1)	(2)	(3)
	corr. w/ baseline	IQR	# of products
Baseline	100%	0.62	5,186
<i>Robustness to the definition of size quintiles:</i>			
Quintiles	91%	0.61	5,017
HS6-iso2 specific quantiles	92%	0.61	5,016
Top quantiles	84%	0.63	4,891
Imposing alpha==1	98%	0.60	5,186
Without size control	99%	0.60	5,186
<i>Robustness to the specification:</i>			
Adding country fixed effects	99%	0.61	5,186
# of transactions rather than months	75%	0.60	4,967
<i>Stability over space and over time:</i>			
Focus on Belgium	63%	0.70	5,113
Focus on Germany	62%	0.71	5,084
Focus on Italy	57%	0.71	5,022
Focus on Spain	53%	0.70	5,057
Focus on UK	56%	0.76	4,952
Sample 2011-2017	55%	0.55	4,921
Using Colombian data (HS4 level)	44%	0.56	383

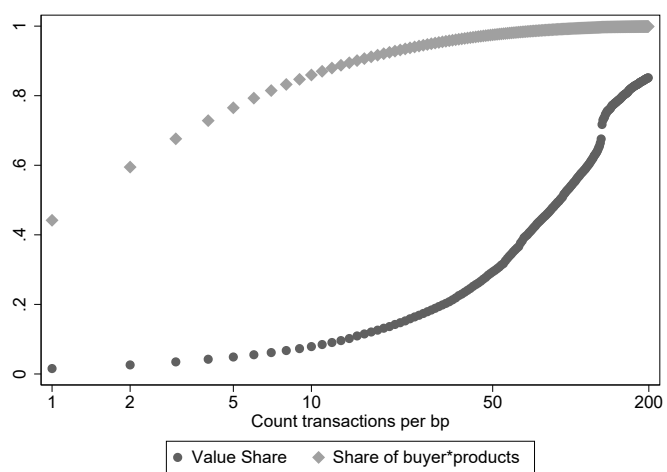
Notes: The table compares the baseline set of RS estimates with a number of robustness sets discussed in the text. Column (1) is the correlation coefficient with the baseline. Column (2) corresponds to the inter-quartile range and Column (3) is the number of estimated coefficients.

Table B.3: *Uncertainty and the creation of new trade relationships: Spillovers and persistence*

	(1)	(2)	(3)	(4)
Dep. var:	<i># new trade relationships</i>			
Uncertainty	0.27*** (0.007)		0.25*** (0.006)	
- × RS index	-0.12*** (0.002)	-0.12*** (0.002)	-0.10*** (0.002)	-0.08*** (0.002)
Uncertainty other countries	-0.01*** (0.002)			
- × RS index	-0.002** (0.001)	-0.003*** (0.001)		
Uncertainty × Lag 1			0.19*** (0.005)	
- × Lag 2			0.25*** (0.005)	
- × Lag 3			0.19*** (0.005)	
- × Lag 4			0.22*** (0.006)	
Uncertainty × RS Index × Lag 1			-0.08*** (0.002)	-0.07*** (0.002)
- × Lag 2			-0.09*** (0.002)	-0.07*** (0.002)
- × Lag 3			-0.08*** (0.002)	-0.06*** (0.002)
- × Lag 4			-0.08*** (0.002)	-0.04*** (0.002)
Observations	3,637,726	3,637,726	3,636,211	3,637,726
<i>Fixed Effects</i>				
Product × period			✓	
Product × quarter	✓	✓		✓
Country	✓		✓	
Country × period		✓		✓

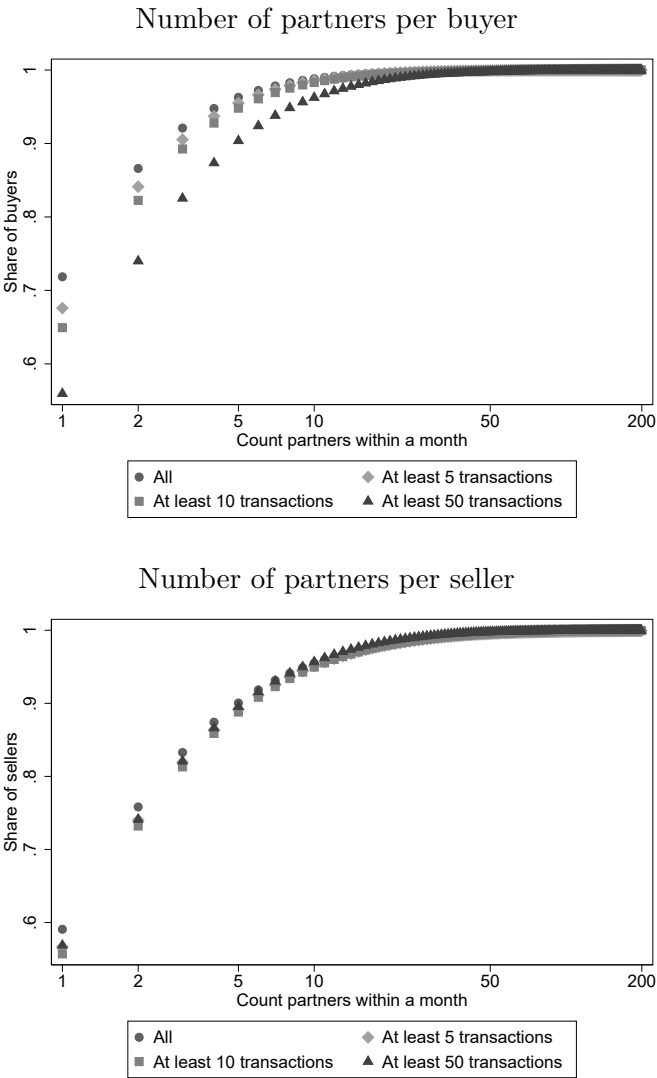
Notes: Poisson estimations with high-dimensional fixed effects. Uncertainty shocks is a dummy equal to one in periods when uncertainty in the destination country is below average uncertainty minus one s.d. of uncertainty. *RS* is our measure of relationship stickiness. Trade diversion examined in columns (1) and (2). Persistence examined is columns (3) and (4). Standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Figure B.1: *Distribution of the number of transactions, per buyer×product*



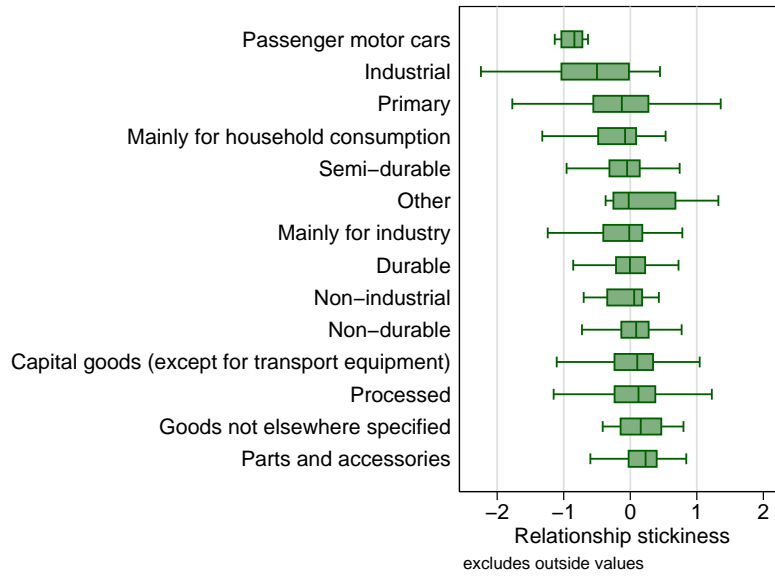
Notes: Cumulated distribution of the number of transactions per foreign buyer (\times product). A transaction is the purchase of a particular good, to a given seller, in a given month. The light grey line corresponds to the share in the population of buyers and the dark line measures what this represents in the overall value of exports.

Figure B.2: *Distribution of the number of partners, per buyer/seller and date (month×year), without conditioning on a particular product*



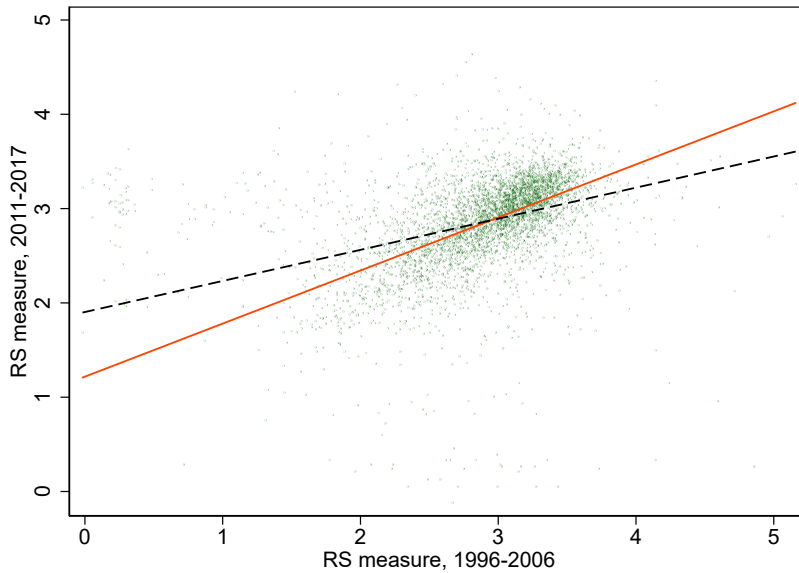
Notes: Cumulated distributions of the number of partners a French exporter interacts with in a given country (bottom panel), and the number of partners a foreign buyer interacts with within a particular month (top panel). Both statistics are calculated across products within a firm. The number of partners is calculated over the sub-sample of importers (resp. exporters) that are involved in at least two transactions over the period of analysis ("All"), and at least 5, 10 and 50 transactions.

Figure B.3: *Relationship stickiness across Broad Economic Categories*



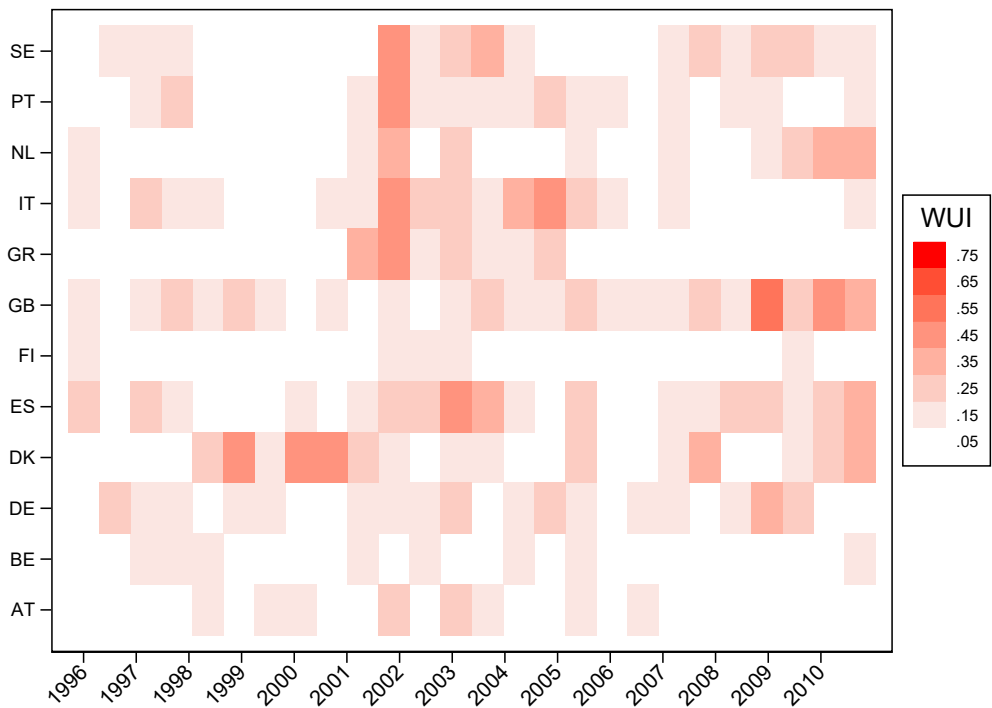
Notes: Boxplot of relationship stickiness across Broad Economic Categories (BEC). Link between the two measures based on the correspondence between 2003 BEC and HS 2002 nomenclature.

Figure B.4: *Comparison of estimated stickiness indicators, across periods*



Notes: Scatter plot of the baseline RS indicator recovered from the 1996-2006 period (x-axis) against the measure estimated from 2011-2017 (y-axis). The red and dotted lines correspond to the fitted lines, recovered from an unweighted linear fit (dotted line) or a linear regression in which products are weighted by the inverse of the estimated standard error recovered in the baseline case (red line).

Figure B.5: *Heat map of the uncertainty series*



Notes: The figure shows a heat map of the World Uncertainty Index, in the panel under study.

Table B.4: *Uncertainty and the creation of new trade relationships: Robustness*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep. var:	# new trade relationships									
Uncertainty episode	0.37*** (0.008)		0.06*** (0.007)		-0.06*** (0.004)		0.38*** (0.024)		0.33*** (0.022)	
- × RS index		-0.15*** (0.003)						-0.15*** (0.009)		-0.10*** (0.008)
- × RS Percentile				-0.003*** (0.000)						
- × RS Colombia					-0.124*** (0.016)	-0.083*** (0.017)				

Specification	Baseline	RS Pctiles	RS Colombia	wo durables	wo MNEs
Observations	3,302,770	3,301,474	1,519,565	2,596,421	2,791,709
<i>Fixed Effects</i>					
Product × quarter	✓	✓	✓	✓	✓
Product × period	✓	✓	✓	✓	✓
Country	✓	✓	✓	✓	✓
Country × period	✓	✓	✓	✓	✓
<i>Effect of uncertainty for products at P25 and P75 of the RS distributions</i>					
P25	-0.02	-0.01	-0.03	-0.02	-0.01
P75	-0.10	-0.15	-0.09	-0.09	-0.08

Notes: Poisson estimations with high-dimensional fixed effects. Uncertainty episode is a dummy equal to 1 in periods when uncertainty in the destination country is above-average uncertainty plus one s.d. of uncertainty. *RS* is our measure of relationship stickiness. Columns (1) and (2) present the baseline estimates. In columns (3) and (4), the percentile of RS are used instead of RS. In columns (5) and (6), RS estimated using Colombian data is used. In columns (7) and (8), durable goods are excluded from the sample. In columns (9) and (10), observations related to bilateral exports of firms having an affiliate or their HQ in a destination are excluded. To make the estimates comparable, we report at the bottom of the table the impact of an uncertainty shocks for products at the P25 and P75 of relationship stickiness. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table B.5: *Uncertainty and the disruption of new trade relationships: Robustness*

Dep. var:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	<i># disrupted trade relationships</i>									
Uncertainty episode	0.23*** (0.007)		0.096*** (0.007)		0.031*** (0.004)		0.271*** (0.025)		0.241*** (0.023)	
- × RS index	-0.08*** (0.003)	-0.117*** (0.010)					-0.087*** (0.009)	-0.031*** (0.009)	-0.075*** (0.008)	-0.033*** (0.008)
- × RS Percentile				-0.002*** (0.000)	-0.001*** (0.000)					
- × RS Colombia						-0.105*** (0.016)	-0.070*** (0.017)			

Specification	Baseline	RS Ptiles	RS Colombia	wo durables	wo MNEs
Obs.	2,546,156	2,546,156	1,273,821	1,931,331	2,212,145
<i>Fixed Effects</i>					
Product × quarter	✓	✓	✓	✓	✓
Product × period	✓	✓	✓	✓	✓
Country	✓	✓	✓	✓	✓
Country × period	✓	✓	✓	✓	✓

<i>Effect of uncertainty for products at P25 and P75 of the RS distributions</i>		
P25	.02	.06
P75	-.03	-.01
	.05	.04
	-.05	0.001

Notes: Poisson estimations with high-dimensional fixed effects. Uncertainty episode is a dummy equal to 1 in periods when uncertainty in the destination country is above-average uncertainty plus one s.d. of uncertainty. *RS* is our measure of relationship stickiness. Columns (1) and (2) present the baseline estimates. In columns (3) and (4), the percentile of RS are used instead of RS. In columns (5) and (6), RS estimated using Colombian data is used. In columns (7) and (8), durable goods are excluded from the sample. In columns (9) and (10), observations related to bilateral exports of firms having an affiliate or their HQ in a destination are excluded. To make the estimates comparable, we report at the bottom of the table the impact of an uncertainty shocks for products at the P25 and P75 of relationship stickiness. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table B.6: *Uncertainty and trade growth: margin decomposition*

	(1)	(2)	(3)	(4)
Dep. var:	Growth	=Start	+ End	+ Intensive
RS index	-0.02 (0.017)	-0.31*** (0.012)	0.27*** (0.008)	0.01 (0.006)
Vol. of returns	-0.18*** (0.006)	-0.09*** (0.004)	-0.08*** (0.003)	-0.01*** (0.002)
- × RS index	0.01*** (0.002)	-0.01*** (0.001)	0.02*** (0.001)	-0.00 (0.001)
Level of returns	-0.01** (0.005)	0.01*** (0.003)	-0.02*** (0.002)	-0.01*** (0.002)
- × RS index	0.01*** (0.002)	-0.01*** (0.001)	0.01*** (0.001)	0.01*** (0.001)
Observations	3,538,965	3,538,965	3,538,965	3,538,965

Notes: OLS estimation. Growth is the 12-month growth of product-level French exports to a destination. Start, end, and intensive are the different growth margins, namely the number of new seller-buyer relationships, the number of disrupted relationships, and the evolution of seller-buyer sales along the intensive margin. The level and volatility of stock returns are from (Baker et al., 2020). RS index is our measure of relationship stickiness, which is not centered (Mean: 2.9, P05: 1.8, P95: 3.5). Significance levels: * 10%, ** 5%, *** 1%.

Table B.7: *Margin decomposition, addind Nunn' measure of specificity*

Dep. var:	(1) Growth	(2) =Start	(3) + End	(4) + Intensive
Uncertainty shock	-0.12*** (0.017)	-0.04*** (0.012)	-0.08*** (0.008)	0.00 (0.006)
RS index	-0.08*** (0.002)	-0.24*** (0.003)	0.14*** (0.001)	0.01*** (0.001)
RS× Uncert.	-0.01 (0.005)	-0.02*** (0.004)	0.02*** (0.003)	-0.00** (0.002)
GDP shock	-0.12*** (0.021)	-0.14*** (0.013)	-0.01 (0.010)	0.03*** (0.008)
RS × GDP	-0.05*** (0.006)	0.00 (0.004)	-0.02*** (0.003)	-0.04*** (0.002)
Nunn specif.	-0.11*** (0.004)	-0.06*** (0.003)	-0.02*** (0.002)	-0.02*** (0.001)
Nunn × Uncert.	0.00 (0.009)	-0.01 (0.006)	0.01** (0.004)	0.00 (0.004)
Nunn × GDP	-0.01 (0.011)	-0.03*** (0.007)	0.02*** (0.005)	0.00 (0.005)
Observations	3,123,125	3,123,125	3,123,125	3,123,125

Notes: OLS estimation. Growth is the 12-month growth of product-level French exports to a destination. Start, end, and intensive are the different growth margins, namely the number of new seller-buyer relationships, the number of disrupted relationships, and the evolution of seller-buyer sales along the intensive margin. RS index is our measure of relationship stickiness, which is not centered (Mean: 2.9, P05: 1.8, P95: 3.5). Nunn specific. is Nunn measure of product specificity ($frac - lib - dif$). (Significance levels: * 10%, ** 5%, *** 1%.)