Trade Relationships During and After a Crisis: Evidence from Road Disruptions in Colombian Flower Exports *

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Abstract

I study the impact of an extreme weather event on international trade relationships. Exploiting variation in Colombian flower exporters' access to cargo terminals during an unprecedented La Niña season in 2010-11 when some roads became impassable, I find that exporter-importer relationships exposed to road disruptions became 7 to 9 percentage points *less* likely to end in the short run. But in the medium to long run, importers who had multiple relationships exposed to the shock were *more* likely to end them. I present a theoretical framework that rationalizes these empirical results based on (1) the relative cost of establishing a new trade relationship, and (2) the proportion of relationships in firms' portfolios that are exposed to the shock. The findings shed light on the dynamics of international buyer-seller relationships in the context of extreme weather events.

Keywords: La Niña, Supply Chains, International Contracts, Weather Shocks
JEL classification: F18, L14, O19, Q54

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1 Introduction

In less-than-perfect product markets, firms must establish buyer-seller relational contracts.[1] As extreme weather events get more frequent and severe, these relationships become more often affected by supply chain disruptions. Firms or relationships can become sensitive to small aggregate shocks when adversely affected, and established networks can be disrupted, preventing firms from building resilient trade relationships.[2] Understanding the consequences of supply chain disruptions on the dynamics of buyer-seller relationships is particularly important in the context of international contracts that have limited enforceability, especially for industries and countries that rely heavily on international trade.

Different factors can influence how buyers and sellers respond to adverse shocks in terms of keeping or severing current relationships. On the one hand, lower trade tariffs or improved market access can facilitate the formation of diversified business portfolios. On the other hand, a lack of effective contract enforcement between buyers and sellers can prevent the formation of new relationships.[3] Given the many factors that influence firms' portfolio choices, empirically estimating how decisions about relationships change in response to shocks can be challenging.

In this paper, I study the effects of weather shocks on the continuation of established relationships between exporters and importers. I focus on Colombian flower exporters and their US importers, and exploit the extreme rain season of La Niña in 2010-11 that disrupted road access to cargo terminals for Colombian flower exporters. I use variation in these disruptions to identify the effect on relational contracts.

The Colombian flower export industry is an example of buyer-seller trade relationships with limited contract enforceability. Given that exporters only access international markets via established direct relationships, this context provides a unique opportunity to understand forces that drive relationship portfolio decisions when the exporter has limited outside options. Also, focusing on the flower export industry, an industry that does not heavily rely on upstream suppliers, i.e., firms that provide inputs, ensures that sellers do not face input shortages from upstream supply disruptions, isolating the shock transmission channel. In the specific context I study, flower production was barely affected by flooding at the production sites, and the disruption to trade came only from road closures.

[1] Relational contracts are defined by Baker, Gibbons, and Murphey (2002) as, "informal agreements sustained by the value of future relationships."

[2] In a recent paper, Elliott, Golub, and Leduc (2022) demonstrate how idiosyncratic shocks can have domino effects at the aggregate level. Di Giovanni, Levchenko, and Mejean (2014) and Magerman, De Bruyne, Dhyne, and Van Hove (2016) demonstrate how firm-level shocks can generate aggregate volatility.

[3] See Bernard, Moxnes, and Saito (2019) for evidence on market access for Japanese companies; Benguria (2022) for evidence on trade agreements and relationship formation in Colombia, and Rauch and Watson (2003) on firms struggling to break into unfamiliar markets.

I construct a novel data set on road disruptions and flower exporters' routes to cargo terminals for all buyer-seller pairs using a firm-to-firm panel of Colombian customs data from 2007 to 2019. I use an event study approach to estimate the effect of exposure to road disruptions on the probability of a relationship ending.[4] In the short run, I find that during the shock period, relationships exposed to road disruptions are actually *less* likely to be terminated – by 7 percentage points – but I see no differential effect in subsequent periods. Then focusing in more detail on the variation across relationships within a firm in a given time period, I compare relationships affected by road disruptions with those not affected. For exporters, I find that this variation is not sufficient to arrive at statistically significant estimates, since most of these firms have either all of their portfolio affected or none. But within the importers' portfolios, I find that the probability of a relationship ending in the short-run is 9.3 percentage points *lower* if it is exposed to the shock. This 9.3 percentage point decrease represents a 54% deviation from the baseline population mean of 0.17 of the share of relationships ending in any given period before the shock. As a result of comparing relationships exposed and non-exposed to road disruptions, the effect appears to be driven by importer relationships and is short-lived.

I then study whether the shock had any impact on firms' portfolio choices in the medium to long run. To measure exposure to road disruptions at the firm level, I use the share of relationships in firms' portfolios that are exposed to the shock and the share of firms' total trade that is exposed to the shock. I find that relationships involving importers who were highly exposed to the shock are more likely to end in the medium to long run, by around 6 percentage points, relative to relationships involving importers that were less exposed. I find no long-term effects on exporters' portfolios with high exposure to shock in their relationships.

Using the relationship-level and firm-level analysis, I can interpret these results from both the exporters' and the importers' perspective. For exporters, there is no incentive to end relationships when they face road disruptions. This is because they are paid upon delivery, and if they cannot deliver flowers to some of their customers, they are forced to rely on their other existing relationships for sales. When roads are no longer disrupted, exporters could be forced to rely more on their existing matches if they did not expand their portfolio during the crisis. As a result, exporters are not willing to restructure their portfolio of relationships after the flooding.

For importers, the empirical results during the crisis and after, highlight that the effect is mostly driven by importers who face disruptions in multiple relationships. Since some importers cannot acquire all the flowers they need in the short run, and sellers can only produce what they have already contracted, they have no incentive to replace their current relationships. In the medium and long-run, importers who had multiple relationships which were exposed to road disruptions, are more likely to

[4] This is equivalent to estimating the hazard probability of a relationship ending, where I condition the probability on those relationships that did not end previously.

end them. A possible explanation, is that as a result of the crisis, importers were forced to experiment and found better alternatives, while keeping their portfolios to sustain demand. Additionally, some importers may have been forced to diversify and build portfolios that are more resilient due to these flooding events.

I relate my results to the empirical and theoretical literature on search costs, on relational contracts, and on product specificity. One explanation for importers restructuring relationships in the long-run is a change in risk perception regarding future extreme weather events in Colombia. Highly affected importers may decide to diversify and divert business to other supplier countries to avoid potential over-reliance on Colombian flower exporters vulnerable to flooding disruptions. I reconcile this explanation with my findings by showing that the number of new relationships initiated by importers that experienced disruptions decreases after the shock.

In the final section, I present a theoretical framework that formalizes the idea that relationship-specific surplus is contingent on a firm's profits over its entire portfolio. Using road disruptions as a shock to flower deliveries in multiple relationships, as is observed in the data, the model predicts that the effect of a shock on relationship-specific surplus will be ambiguous and will depend on two main effects: (1) an *indirect* effect whereby relationship surplus increases when firms have multiple relationships exposed to the shock, and (2) a *direct* effect whereby conditioning on the costs of forming new relationships, a decrease in flower purchases from the current relationship can reduce its surplus. The overall effect of a shock on relationship-specific surplus depends on which of these effects is larger and on the costs of forming new relationships. If the *indirect* effect dominates, then there will be a positive effect on a relationship surplus and would lead firms to keep the current relationship, while if the *direct* effect dominates and is negative, then the effect on the relationship surplus would lead firms to abandon it. The intuition from this framework is that firm decisions on specific relationships are interdependent with profits across their entire portfolio. When replacing multiple relationships simultaneously seems infeasible or highly costly, firms may opt to retain all existing relationships, even those unable to deliver fully contracted quantities.

My paper contributes to the literature on the propagation of idiosyncratic shocks in production networks.[5] In that literature, empirical estimation of the effects of shocks has relied on two types of identification strategies. A first set of papers focuses on one-time natural disasters that are highly disruptive for supply chains. This can yield estimates of causal effects, but the probability of these adverse events occurring is low, and there are thus only a handful of studies that exploit them. For instance, Boehm, Flaaen, and Pandalai-Nayar (2014), Carvalho, Nirei, Saito, and Tahbaz-Salehi

[5]Related to shock propagation in production networks, a recent literature has focused on the COVID-19 pandemic. See Lafrogne-Joussier, Martin, and Mejean (2023), Lebastard and Serafini (2023) and Lebastard, Matani, and Serafini (2023).

(2021) and Todo, Nakajima, and Matous (2015) rely on the 2011 tsunami in Japan and its impact on disrupting supply chains, while Volpe and Blyde (2013) exploits infrastructure damage from the 2010 earthquake in Chile. Kashiwagi, Todo, and Matous (2021) use Hurricane Sandy in 2012 in the US and study the propagation of supply shocks within and across countries. Similar to these papers, my identification strategy also utilizes a one-time extreme event. A second set of papers relies on variation from repeated weather shocks. Barrot and Sauvagnat (2016) use various types of weather events in the United States, including blizzards, floods, earthquakes and hurricanes, as exogenous shocks, while Gigout and London (2021) use disaster data for worldwide events since 1900.

Balboni, Boehm, and Waseem (2023) study firms' adaptation responses to repeated flooding in Pakistan. They examine domestic firms' adaptation decisions when repeatedly exposed to flooding events using VAT data from domestic transactions. This is different from the context I consider in this study, which focuses on firms' responses to an isolated extreme shock. Unlike repeated weather events, firms could have not anticipated and prepared for this type of shock by adopting forward-looking mitigation strategies, and thus can only adapt to it by changing their behavior ex post.

Within the literature on the propagation of shocks in production networks, most studies quantify the short-run economic damage of natural disasters (Volpe and Blyde, 2013; Barrot and Sauvagnat (2016); Boehm et al., 2014; Carvalho et al., 2021), and point to input specificity as a key driver for the propagation and amplification of shocks. In this paper, I do not estimate aggregate effects but add to the few existing studies that examine firm responses over longer time horizons (Gigout and London, 2021; Balboni, 2019; Todo et al., 2015).

I contribute to the literature on firm-to-firm dynamics by studying relationship-specific idiosyncratic shocks rather than aggregate or firm-level shocks.[6] Monarch and Schmidt-Eisenlohr (forthcoming) demonstrate that buyer-seller relationships with longer histories withstood shocks better than those with shorter histories during the 2008-09 financial crisis; Heise (2018) examines the effect of exchange rate shocks on prices in relationships and finds that sellers in older relationships with more accumulated capital have a greater ability to increase markups.

I also contribute to the literature on relational practices when contracts between firms are difficult to enforce.[7] Macchiavello and Morjaria (2015) study the dynamics of contractual relationships focusing on the rose sector in Kenya. The fact that spot markets are well-functioning allows them to estimate lower bounds on relationship values in this context due to the direct measurement of exporters' temptations to depart from contractual arrangements. Unlike the case of Kenyan rose exporters, supply relationships between Colombian flower exporters and US importers do not coexist

[6]See Alessandria, Arkolakis, and Ruhl (2021) for a literature review on the dynamics of firm-to-firm trade.

[7]See Macchiavello and Morjaria (2022) and Macchiavello and Morjaria (forthcoming) for a recent review of the relational contracts literature.

with a spot market. By exclusively focusing on relational contracts, I provide new empirical evidence regarding the dynamics of relationships in a setting where observable incentives from outside options on the seller side are either not available or limited.

There has been important work on the theoretical side to understand the contractual nature of trade relationships. This paper relates to the work on relationship contracts when firms hedge against possible disruptions in the supply chain. Cajal-Grossi, Macchiavello, and Del Prete (2023) develop a model where buyers self-select into the most suitable type of contract when they face supply chain disruptions. Elliott, Golub, and Leduc (2022) and Acemoglu and Tahbaz-Salehi (2023) develop a theoretical framework to systematically understand the macroeconomic consequences of supply chain disruptions using complex networks. I provide empirical evidence that firm-level outcomes are shaped by hedging on the part of importers in response to the risk of nondelivery. This is in addition to the channels incorporated into these theoretical frameworks.

Finally, my paper contributes to the literature on firm networks in trade. Research in this field has demonstrated that large firms often have more customers but sell less to each customer, which raises questions about how firms sustain their customer base as they expand.[8] I contribute to this literature by providing empirical evidence that idiosyncratic shocks at the relationship level can trigger responses at the firm level. Related research focuses on endogenous network formation and examines how responses to shocks differ from those in canonical models. For example, in the static setting of Oberfield (2018) and the dynamic setting of Chaney (2014), 'superstar' firms emerge due to their ability to expand their existing network. In these simple one-sided search models with trade frictions, the existing network matters for adding new links since having more connections can reduce informational barriers.[9] I contribute to this body of work by providing empirical evidence of how, following a negative shock, firms' network exposure can influence decisions about individual relationships.

In the next section I describe the context of the 2010-11 La Niña event and the Colombian flower sector. Section 3 is an overview of the data used in the analysis, and an explanation of the construction of the variables of interest, specifically the variable of *relationship status*, and the variable of *exposure to the shock*. I then describe the sample used in the empirical analysis and present different summary statistics. Section 4 outlines the empirical strategy, presents the main results, and connects them to prior research. Section 5 contains the theoretical model I use to interpret the empirical findings, and Section 6 concludes.

[8] This empirical finding has been documented for different country data sets. Bernard, Moxnes, and Saito (2019) use Japan, Bernard, Dhyne, Manova, and Moxnes (2022) use Belgium, and Bernard, Bøler, and Dhingra (2018b) use Colombia.

[9] See Bernard, Moxnes, and Ulltveit-Moe (2018b) and Eaton, Jinkins, Tybout, and Xu (2022) for models that allow double-sided searching.

2 Context: 2010-11 La Niña and Colombian flower exporters

2.1 The 2010-11 La Niña event

Known as ENSO (El Niño-Southern Oscillation), La Niña is an integral part of Earth's most significant climate pattern and has been observed 24 times since 1903, with the most recent occurrence between 2020 and 2023. During La Niña, specific weather patterns are anticipated but not guaranteed. In an average season, equatorial East Africa tends to experience drier-than-normal conditions from December to February, while in the central Andes, there is typically higher-than-normal rainfall.

The 2010-11 La Niña event was one of the strongest on record. Australian temperatures reached their second and third-highest levels since 1900. The Western United States and Midwest recorded 180% above-average snowfall, with the exception of the Southern Rockies and Western Mountains.[10] Climate change is predicted to intensify extreme weather patterns, including La Niña, and cause significant infrastructure damage in developing countries.[11] In Vietnam, Balboni (2019) finds that a forward-looking allocation of infrastructure investments that avoids flood-prone regions would lead to a 72% welfare gain, where changes in aggregate welfare are measured as the compensating variation averaged across locations when changing locations' fundamentals, i.e., road upgrades. Global prices can also be affected by weather shocks. For instance, major producers could see their exports reduced by weather shocks, resulting in higher prices worldwide.[12] In 2010-11, Colombia was impacted by La Niña-related weather events that resulted in widespread flooding and landslides, causing entire villages to disappear under water. Figure 1 illustrates the total flooded area during the 2010-11 La Niña event. Based on the yellow area, the estimated total flooded area was approximately 3.5 million hectares, accounting for roughly 3.3% of the country's land area (equivalent to 15% of England's land area). Most of the flooded regions were located in the northern and central parts of the country, particularly around the convergence of the main rivers, Magdalena and Cauca, and on the northeastern border with Venezuela.

The heavy rains caused damage to the road infrastructure estimated at \$6.5 million USD.[13] The affected road network comprised roughly 36% of the total, of which 9% were inter-state roads. The transport sector was among the hardest hit, as in 2009 approximately 73% of goods by volume was

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[10] Australian Bureau of Meteorology, National Centers for Environmental Information (NCEI, 2011).

[11] See Geng et al. (2022).

[12] See Fatica, Kátay, and Rancan (2022) on the effect of flooding events on European manufacturing firms, and Forslid and Sanctuary (2023) on export performance for Thailand producers exporting to Swedish importers following 2011 flooding events. See Chatzopoulos, Domínguez, Zampieri, and Toreti (2020), Bednar-Friedl, Knittel, Raich, and Adams (2022), Ghadge, Wurtmann, and Seuring (2019), and Mekbib, Wossen, Tesfaye, and von Braun (2017) for studies on climate change and its effects on prices.

[13] The costs for rebuilding were estimated at \$1.5 billion USD.

transported by trucks. The reported losses in the transport sector amounted to around $222 million USD. In North Santander, at the border with Venezuela, transportation costs increased by an additional million dollars.[14]

As a consequence of the unprecedented rain levels from the 2010-11 La Niña event, the Colombian government initiated measures to reconstruct infrastructure in preparation for future flooding events. As an example, the 'Plan for Climate-Resilient Roads' was launched in 2012 with a goal of identifying the roads most vulnerable to weather shocks and building new roads that could withstand climate change. According to reports on this particular flooding events of 2010-11 (CEPAL, 2012), estimations regarding road disruptions resulting from the failure to make any improvements to roads in response to a 1°C increase in temperatures by 2040 were that 5.9% of roads would become unavailable each year. This implies that without road upgrades, it is anticipated that there will be 21 days of road disruptions per year directly related to higher precipitation levels.[15]

2.2 The Colombian flower sector

Colombia is the second largest exporter of cut flowers in the world, following the Netherlands. As of 2010, Colombia accounted for 68% of US flower imports and held a 16.8% share of the world market. In 2010 and in the present, the US is the primary global buyer of flowers with a 20% market share.[16] The majority of Colombian flower exporters are located in the central regions of the country, near the capital, known as the Bogota-Savannah region, and in the northwest in the Antioquia region. In 2009, 70% of the production of flowers for export was centered in the Bogota-Savannah region, while 18% was in the Antioquia region.[17] High-altitude regions are preferred because flowers thrive at temperatures between 15 and 25 degrees Celsius. There are about 1,600 flower varieties produced in Colombia for international markets, with the main species being roses (31%), followed by hydrangeas (15%), carnations (13%), and chrysanthemums (11%).[18]

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[14]The transportation costs are based on CEPAL (2012). The repair costs are estimates from the National Budget as of December 31, 2015. The estimates of truck volumes are derived from a 2011 report by the Ministry of Transport (Ministry, 2012).

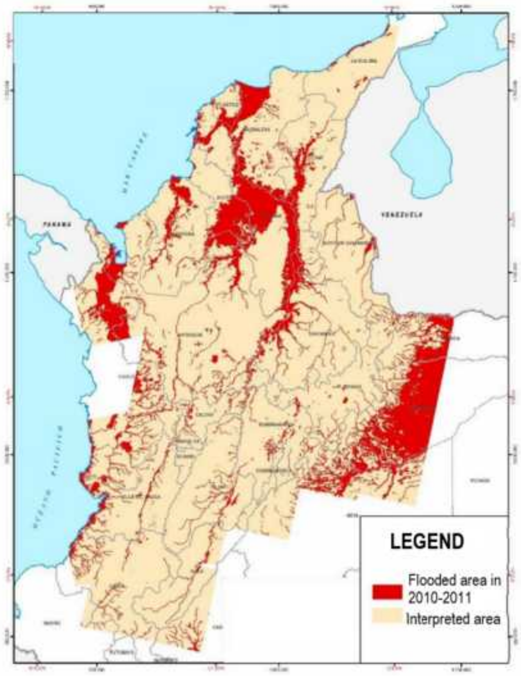
[15]In the flower sector, flooding was mitigated through the use of sandbags. The estimated damage ranged from 5% to 15% of the total national production due to the increased humidity affecting rose producers. As a result, flower producers in these specific areas were compensated by the Ministry of Agriculture and Rural Development (MADR) by around $230,000 USD. My sample contains five municipalities where flower producers may have experienced flooding during this period. I excluded these areas from the main analysis and later added in the robustness checks.

[16]Source: The Economic Complexity Observatory. Data on total import participation is based on averages for 2007-2020.

[17]Figure A.1 displays the quantities of production and exports from 2002 to 2014. Figure A.2 shows road disruptions during La Niña 2010-11 and the location of producers.

[18]While certain species of chrysanthemums, roses, and carnations have become standardized products, other varieties are highly specialized and tailored to individual buyers. For example, 'Galleria Farms' is a company that provides nine

Figure 1: Flooded area in during La Niña 2010-11



Notes: The map displays the total flooded areas as of June 6, 2011, during the La Niña event. The satellite data of flooding only includes information from the area highlighted in pastel yellow, which excluded uninhabited regions like the Amazon. The red regions within this interpreted area represent the flooded zones during the event. Source: Ideam 2010.

The flower market comprising US importers and Colombian producers is suitable for studying trade relationships because of the direct contact between sellers and buyers. First, Colombian flower exporters and US importers have a long history of direct trade and business relationships that date back to the 1970s. The proximity of Colombia to the US not only fosters strong relationships between Colombian firms and US buyers, but also facilitates the formation of other business partnerships. For instance, between 2002 and 2009, the share of flower exports to the US was about 80%.[19] Additionally, many producers emphasize the importance of forming stable relationships with their buyers, a sentiment echoed by buyers when discussing their relationships with their producers. For example, on Silvestres Flowers' web page, a Colombian exporter that grows flowers since 1988 for the US market highlights that "One of the priorities of the company has always been to establish long-lasting business relationships with our customers so that we can grow and prosper together."[20]

types of hydrangeas, each with up to six different stem lengths and head sizes. Detailed information about such specific products cannot be obtained from the 10-digit HS code level.

[19] Source: Colombian Flower Association (Asocolflores).

[20] Source: www.silvestres.com/company. During interviews that I conducted with three other Colombian flower

This is just one example of how important connections between buyers and sellers is in this market.

3 Data, estimation sample, and summary statistics

The following section is devoted to describing the data, the variation used from the road disruptions, the main variables used in the empirical analysis, and the sample. In Sections 3.1 to 3.3, I describe the different data used for the empirical analysis. In Section 3.4 I describe the setting and the method for the measurement for the variables of interest: *relationship status* and *exposure to the shock*, as well as the sample of trade relationships used in the empirical analysis. Section 3.5 contains the summary statistics.

3.1 Data on firm-to-firm trade

Using Colombian customs data from 2007 to 2019, I track all monthly transactions between Colombian flower exporters (tax IDs) and US importers (names). Trade values, quantities, and customs offices used to exit the country are reported for all transactions. I construct an importer identifier and generate a monthly panel of transactions at the buyer-seller level.[21] Using the panel dimension of the transactions, I can follow relationships from January 2007 until their last transaction or until December 2019. I focus on the continental US because about 98% of flower exports to the US go to the continental US.

3.2 Data on road disruptions and routes to ports

For road disruptions I draw on sources compiled by different governmental organizations. This includes a report from the Emergency Office, created in the aftermath of the first closures, which is a snapshot of the status of the roads on May 24, 2011. The report has the location, the dates of closures, and the type of closure, e.g., scheduled for repair, accident, or landslide. To complete the list of road disruptions from May to August 2011, I use the Ministry of Transport summary of the road disruptions for inter-state roads. I also obtain data from the Ministry of Transport, which includes summaries of each major road disruption, along with a 'before' photo of the road at the time of the event and an 'after' photo following repairs. To identify disrupted roads within municipalities, I do a comprehensive review of the Ministry of Transport's news feed and other news reports.

producers, the mention of establishing strong business relationships with sellers was also common sentiment.

[21] See Krizan, Tybout, Wang, and Zhao (2020) who document that "careless" cleaning of this data could result in over counting of US importers by twofold.

Focusing on road disruptions along the routes used by flower exporters to reach cargo terminals, I consider only road disruptions lasting more than one week. The length of disruption is crucial because after being cut, flowers have a limited lifespan and are typically sold for international distribution before they start blooming. I find a total of 34 disruption incidents on different roads (36 when counting roads that closed more than once). Among these disruptions, two roads were shut down for 16 weeks, while the rest were closed for a minimum of 1 week and a maximum of 6 weeks.[22]

I construct the transportation routes using the Ministry of Transport's system SICE-TAC, and information about the cargo terminals used for each transaction obtained from the customs data. The SICE-TAC system provides precise information about transportation routes originating from municipal capitals and compiles data from all transportation service companies. For small towns that do not have designated routes, I calculate the shortest route to the cargo terminals using information from the nearest town with available data. Additionally, I consider only routes where the trade on a specific route (between a farm's municipal center and a cargo terminal) before the shock had been at least 10% of the total trade of that relationship compared to the trade on all other routes. Most exporters rely on the same cargo terminals for all of their relationships, and used on average 1.3 cargo terminals in each relationship before the shock.

3.3 Additional data sets

I use National Statistical Agency reports on La Niña-related flooding and identify the producers located in flooded areas. Flooding only affected flower production municipalities in the Bogota-Savannah region. I classify municipalities as being flooded if they had at least 0.7% or more of their total area flooded. I included municipalities exposed to both unexpected flooding and slow inundations, information on which is also found in these reports. Overall, there are five municipalities with flower producers flooded, affecting 47 producers.

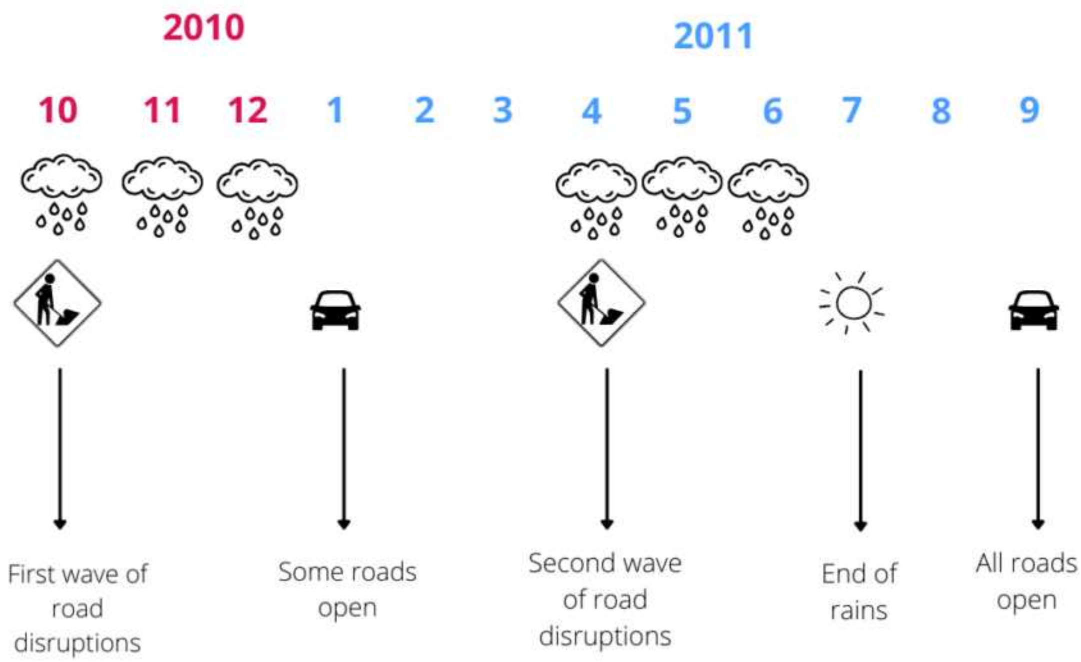
In the customs data there are 1,090 flower exporters for the entire period 2007-2019, and I can find information about the activity of 96% of them.[23] Out of the total, 297 exporting firms were classified as intermediaries (non-producers). For the remaining exporters (758), I visited their websites, when available, as well as Google Maps and online directories, to determine their location and assign them to municipalities if they had multiple farms at different locations.[24]

[22] In Table A.1, I show the road disruptions that are used in the empirical analysis.

[23] Each firm is registered using the tax ID, a unique 7-digit number which can be found in the RUES database and I extract the firm's main activity.

[24] For farms that are no longer active, I referenced government registrations issued in 2007 and 2008, which listed registered exporters for a phytosanitary program. These documents encompassed both small and large farms, along with their municipality.

Figure 2: Timeline of La Niña 2010-11 in Colombia



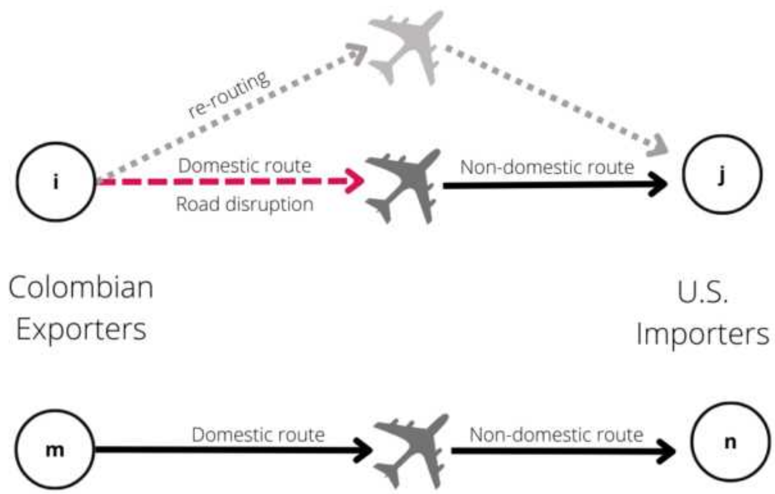
Notes: The diagram shows the timeline of the La Niña event. The rains started in October 2010 and ended in June 2011. The flooding happened in two waves, one from October to December 2010, followed by a second wave from April to June 2011. During both waves multiple road disruptions happened around the country, lasting days, weeks or even months. By September 2011 all disrupted roads during the flooding were reopened.

3.4 Setting

Figure 2 shows that road disruptions occurred only from October 2010 to June 2011. They happened on different dates surrounding the event, but they were grouped into two periods when the rain levels were at their highest: (i) from October to December 2010 and (ii) from April 2011 to June 2011. Some relationships were disrupted multiple times, and some disruptions overlapped from 2010 to 2011.

Exogenous variation. I use the variation in road disruptions between October 2010 and June 2011 and assign them to the routes exporters use to access domestic cargo terminals. Figure 3 provides an example of the variation I exploit in my empirical analysis once I focus on all disruptions within a trade relationship. More precisely, I exploit the variation in domestic road disruptions occurring between the location of the producer's farm (i) and the cargo terminal that the producer uses to deliver flowers to its importer (j) in the US. Because other exporters may be using different routes or they might be situated away from a disruption area, there are other relationships, (mn) in Figure 3, that

Figure 3: Road disruption set up



Notes: The figure shows the variation I exploit to identify the effect of road disruptions in a relationship. The example shows a relationship ij that is exposed to a road disruption in the domestic route to the cargo terminal. Exporter i can re-route or not use that cargo terminal to reach j. Relationship mn is not affected by any domestic road disruptions to reach its cargo terminals.

remain unaffected. Road disruptions affect exporters' decisions about whether to incur the additional effort when roads are disrupted to send their shipments to the US. These firms may need to pay additional transport costs to reach their original cargo terminal or to reroute their shipments through another cargo terminal.

In cases where exporters tend to use similar routes to cargo terminals across all their relationships, identification is primarily based on the variation across importers sourcing from different exporters, especially if importers source from producers from municipalities that do not overlap in their routes to the cargo terminals.

I also exploit the variation across exporters when fixing the importer side of the relationship. Referring to Figure 3, I exploit the variation from comparing relationships ij and mn where importer j is the same as importer n. In this case, when $j = n$, both i and m are linked to j and the variation relies on the importer's side of the relationship across relationships that experience road disruptions and those that do not.

Measuring relationship status. To begin, I use all the buyer-seller transactions from the customs data covering the period from January 2007 to December 2019. I group each buyer-seller transaction into non-calendar six-month periods. I use non-calendar six-month periods so that I have a period that corresponds to the first road disruptions in October 2010. For every buyer-seller transaction, I create a balanced panel of the six-month period intervals. The panel fills out all periods in which firms transact or do not transact between the first and last period that they are observed to be transacting. Finally, I construct the variable *relationship status* from this balanced panel. The *relationship status* variable takes a value of zero during all the periods when the relationship is present in the balanced panel, and a value of one for the period immediately after the relationship has no other transactions within the balanced panel. A relationship with a value of one is considered not active and disappears from the data after this period.

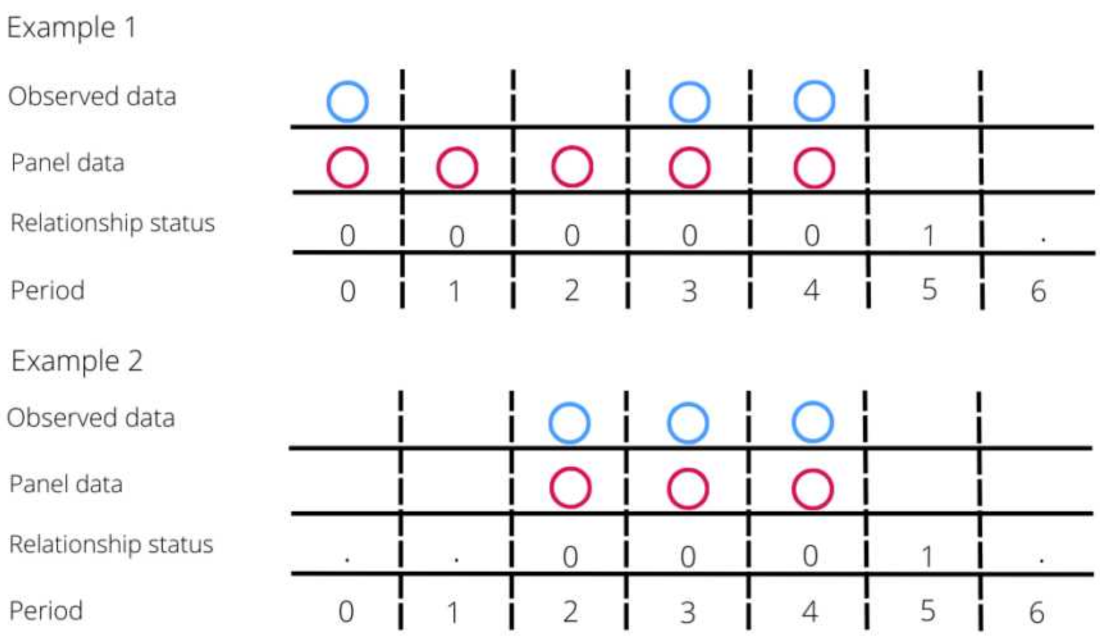
Figure 4 illustrates how the *relationship status* variable would look for two example relationships in the data. In Example 1 there are four rows, the first three are data or constructed by the observed data, and the last row indicates the six-month periods the data points are referring to. The first row refers to the 'observed data'. The green dots indicate that a relationship is observed in the customs data to have a transaction. The second row, the 'panel data', is constructed from the 'observed data'. Green dots indicate that the relationship is active, but not necessarily observed to be transacting at every period. Finally, the last row shows the *relationship status* variable constructed from the 'panel' data. The *relationship status* variable takes a value of 0 from the first period of observed transactions in the data, and a value of 1 after the last period of and observed transaction. Example 2 demonstrates another scenario that is likely to be observed in the customs data set. In this case, the 'observed data' and 'panel data' rows are the same, but are not observed at the beginning of the sample. In this case, the *relationship status* variable will be missing in periods 0 and 1.

Note that the *relationship status* variable assigns a value of one to a relationship in the next period when there are no more observed transactions in the subsequent periods. Therefore, all relationships that end in a given period are those that were active in the period before, and the interpretation of the variable should be understood as indicating whether a relationship was active in period $t-1$ but no longer active in period t.

A final point about the *relationship status* variable is that, given the absence of information beyond December 2019, relationships can remain active but not engage in transactions. Assuming they are no longer active might result in a large number of inactive relationships in the last periods. I deal with this problem by combining the last three years into one period and use the last observed status of activity as the measure of activity for the whole period. The assumption that all firms with active status from the cutoff period that stop transacting in the next three years could resume the relationship after the cutoff period alleviates this measurement error.

Measuring exposure to the shock. Customs data can provide information on whether a relationship had a transaction, but it does not show if a transaction was scheduled but failed to deliver due to road disruptions. To address this, I create a variable of *exposure to the shock* using information on the

Figure 4: Constructing the *relationship status* variable



Notes: The figure illustrates how the *relationship status* variable would look for two example relationships in the data. In Example 1 there are three rows of data, followed by a row indicating the six-month period the data points refer to. In the first row, the 'observed data', blue dots indicate that a relationship is observed to be transacting. The second row, the 'panel data' data, is constructed from the previous row. Red dots indicate that the relationship is active, but not necessarily transacting every period. Finally, the last row shows the *relationship status* variable constructed from the previous row. The *relationship status* variable takes a value of zero from the first period of observed transactions in the data, and a value of one after the last period of an observed transaction. Example 2 demonstrates another scenario that is feasible to observe in the transaction data. In this case, the 'observed data' and 'panel data' rows are the same but are not observed at the beginning of the period. In this case, the *relationship status* variable will be missing in periods 0 and 1.

different cargo terminals used for each buyer-seller transaction available in the customs data. I begin by considering all the routes from the exporter's farm to the different cargo terminals for a given relationship from January 2007 until the month before the first road disruption in September 2010. I then cross-reference this information with the data on road disruptions caused by the flooding events between October 2010 to June 2010. I construct an indicator variable for whether that route from the exporter's farm to the cargo terminal was affected by any road disruption during the flooding events (October 2010 to June 2010). I then aggregate the indicator at the relationship level, creating the binary variable *exposure to the shock*, that takes the value of one if there was any road disruption on any of the routes from the exporter's location to the different cargo terminals, and zero otherwise.

I consider three variations of the variable *exposure to the shock* by varying the number of months considered prior to the shock to include different cargo terminals used in that relationship. A first measure takes all the origin-cargo terminal combinations in a relationship from January 2007 until the month prior to the shock September 2010. A second measure of the variable *exposure to the shock* is restricted to only origin-cargo terminal combinations used 24 months before the shock. A third measure, the most restrictive, relies only on origin-cargo terminal combinations used 12 months before the shock.

Estimation sample. The empirical analysis includes only importers with a unique identifier and excludes importers whose final destination is outside the US or US territories such as Puerto Rico, Guam, Alaska, and Hawaii. I focus on exporters with farms and exclude firms that are not producers, are intermediaries, or have multiple locations across municipalities. I have 676 exporters who have farms in one municipality and 41 producers who have farms in multiple municipalities.

For the empirical analysis, I exclude all new relationships that are active from October 2010 onwards, since for these relationships the shock is no longer random. I end up with a sample for the pre-shock period January 2007 to September 2010 that covers 73% of the total export value of flowers to the US, with around 885 importers and 390 exporters and 7,545 relationships that have a measure of *exposure to the shock* of one or zero. For the main estimations I exclude exporters in municipalities with flooding: these are 349 relationships that are not associated with any road disruption, and 64 that are. Although these firms are located in flood-prone areas, it is not always the case that their production was affected by the rains. I include these firms and their relationships in the robustness exercises, as well as in estimations where it is important to account for all importer relationships.

Table 1 displays the number of relationships considered in all the different measurements of the variable *exposure to the shock*, grouped by relationship cohort. A relationship's cohort is based on its first observed transaction within a six-month period.[25] Each cohort period corresponds to six

[25]The duration of the relationship is chosen based on evidence that trade relationships do not experience frequent

Table 1: Number of relationships per cohort

Cohort	***Exposure to the shock* measure ($E_{ij,0}$)**					
	All months		**24 months**		**12 months**	
	$E_{ij,0} = 0$	$E_{ij,0} = 1$	$E_{ij,0} = 0$	$E_{ij,0} = 1$	$E_{ij,0} = 0$	$E_{ij,0} = 1$
2007m1-m6	1,546	807	1,429	792	1,492	777
2007m7-m12	359	198	349	192	347	190
2008m1-m6	439	289	425	283	425	277
2008m7-m12	307	208	303	206	304	198
2009m1-m6	336	484	336	484	318	465
2009m7-m12	369	856	369	856	366	850
2010m1-m6	514	481	514	481	514	481
2010m7-m9	153	199	153	199	153	199
Total	4,023	3,522	3,946	3,493	3,919	3,437

Notes: The table displays the number of relationships in each cohort for the different measures of the variable *exposure to the shock*, referred to as $E_{ij,0}$. Below columns $E_{ij,0} = 0$ are all the relationships that are classified as not *exposed to the shock*, and below columns $E_{ij,0} = 1$ are all relationships that are classified as *exposed to the shock*. 'All months' refers to the measure of *exposure to the shock* that uses all origin-cargo terminal combinations between ij from the initial sample January 2007 until the month prior to the shock in September 2010. '24 months' refers to the measure of *exposure to the shock* that uses all origin-cargo terminal combinations between ij from September 2008 until the month prior to the shock in September 2010. Finally '12 months' refers to the measure of *exposure to the shock* that uses all origin-cargo terminal combinations between ij from September 2009 until the month prior to the shock in September 2010.

calendar months, with the first cohort containing all relationships observed first transacting between January 2007 and June 2007 (cohort 2007m1-m7), and so on for all other cohorts until the last cohort between July 2010 and September 2010 (cohort 2010m7-m9).[26]

3.5 Summary statistics

This section reports summary statistics for the sample of relationships from the cohort in Table 1. The first section examines the *relationship status* variable by relationship cohort. The second part gives an overview of the location of relationships in Colombia by municipality and by their classification

turnover in very short periods of time. see Martin, Mejean, and Parenti (forthcoming) for evidence on buyer-seller relationship stickiness. Further, given the nature of these contractual relationships, it can take time for a relationship to develop, as buyers and sellers figure out exactly who they are matched with. See Cajal-Grossi (2016) for evidence on new buyer-seller relationships in developing countries. I decided to use six month periods, in order to capture the short and long term dynamics of trade relationship.

[26]My observations are truncated in the left, because I only observe relationships from January 2007. Because I am only interested in churn after they have transacted, this is not much of a concern. I show results when excluding the cohort 2007m1-m6 in the Appendix Figure A.14.

of *exposure to the shock*. The main point is to show the spatial distribution of road disruptions for exporters, which affected disproportionately the west regions (near Antioquia and the Coffee region). The last part presents some summary statistics describing relationship-level variables on the pre-shock period (January 2007 to September 2010).

Relationship status. Figure 5 plots the share of relationships ending for three selected cohorts, where the relationships ending are those with a *relationship status* equal to one. Despite selecting three age cohorts for this figure (2008m1-m6, 2009m1-m6 and 2010m1-m6), the patterns are similar for all eight cohorts. Two observations can be made based on the graph. First, relationships will likely end at a higher rate within the first year from their first transaction.[27] Second, the share of relationships that end each period decreases over time. In the cohort 2009m1-m6, the share of relationships that end within that cohort in the first six months is about 10%, 28% six months later, 24% six months later, and so on until it is stable around 6% for the rest of the periods in my sample.

Based on this analysis, it appears that relationships can only be compared within cohorts because across cohorts they can be at different stages of their duration cycles, e.g., they can be new relationships with high probability of ending in the next period or older relationships with a lower probability of ending in the next period. For example, with reference to Figure 5, consider the older cohorts (2008m1-2009m1 and 2009m1-m6) and 30 and 18 months after their first transaction, respectively, corresponding to the calendar period from October 2010 to April 2011. The share of relationships that end for both cohorts is about 15%; while for the younger cohort (2010m1-m6), the share in the same calendar period, six months after the first transaction, is about twice as high.[28]

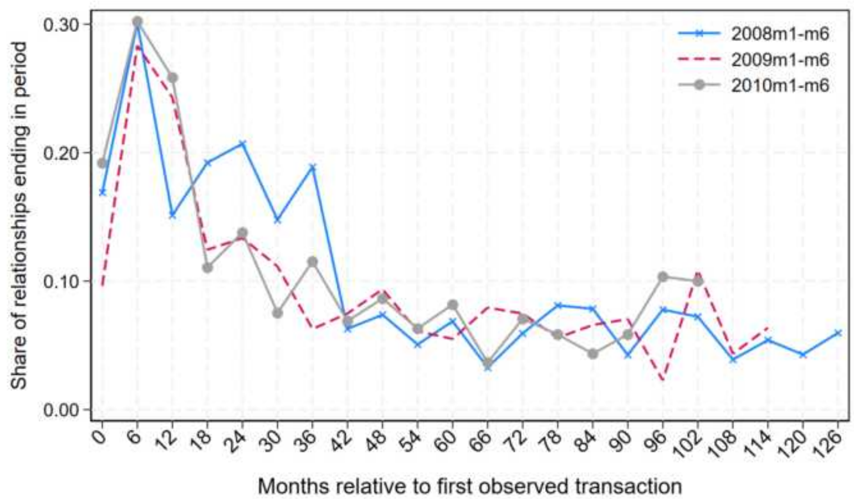
Exposure to the shock. Table 1 counts the share of relationships with a value of one in the variable *exposure to the shock* for each municipality where flower producers are located. Figure 6 is a map showing the distribution of these shares for the country. The municipalities with the highest share of relationships exposed to the shock have a dark blue tone, whilst light shades of blue display municipalities with a lower share of relationships with *exposure to the shock*.

The shock mostly affected firms in the west (Antioquia and the Coffee region), while firms in the Bogota-Savannah region were less likely to be affected. This is unsurprising, given that the road disruptions in the first wave occurred near the cargo terminals of Medellin and Rionegro (Figure A.2 and Table A.1), and roads disrupted in the second wave were on routes connecting the west of the

[27] A high hazard rate in the first year is not unusual. In Eaton, Jinkins, Tybout, and Xu (2022), the US apparel sector has a hazard rate of 0.8. They also show that the hazard decreases once a relationship survives a year. Besedes and Prusa (2006) also find that trade relationships face a high hazard rate in their initial years.

[28] Macchiavello and Morjaria (2015) use age as the number of previous periods with transactions but face the challenge that age and cohort are collinear. Since it is observationally equivalent, I compare cohorts and not ages.

Figure 5: Share of relationships ending in a given period



Notes: The figure plots the share of relationships within a cohort that have a *relationship status* of one in a particular period, where the relationships ending are those with *relationship status* equal to one. The six-month periods coincide coincide with the first road closures in October 2010 to April 2011.

country to the east. Firms in the Bogota-Savannah region use the cargo terminal in the capital city and thus did not experience many disruptions on routes connecting their locations to this cargo terminal.

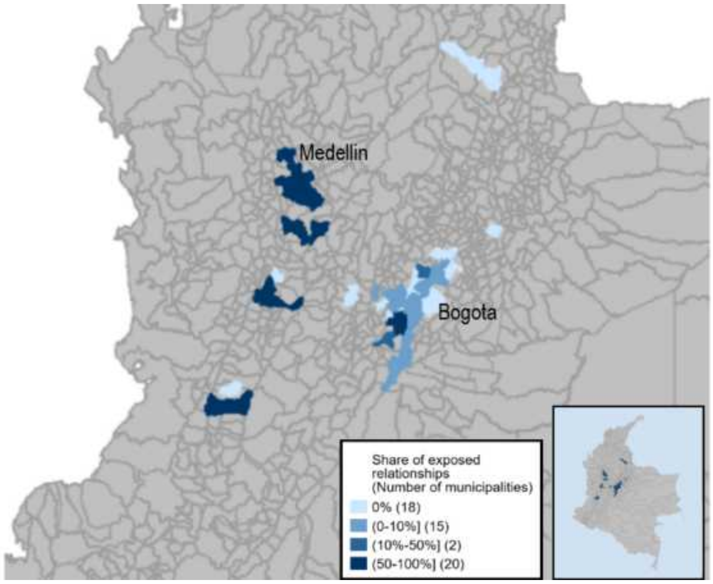
Relationship characteristics. Table 2 shows summary statistics for the relationship level characteristics in the pre-shock period January 2007 to September 2010. All measures are an average across the six-month periods that I created, starting from the period April to September 2007, and ending in the period April to September 2010.[29]

The 'share of active relationships' is the number of relationships with an active status, regardless of a transaction taking place, over the number of all potential relationships – the relationships possible with active firms. An active relationship is measured using the balanced panel of transactions, and is equivalent to using all relationships with the variable *relationship status* equal to zero. All potential relationships are all buyer-seller combinations from active firms at each period. On average 0.5% of the relationships from all exporters and importers in the flower sector are active, among all potential relationships .[30] The second row shows the 'share of relationships ending'. This is equivalent to

[29]For the first period April to September 2007, I include the three months January to March 2007. For the measure 'share of relationships ending' I include the period October 2010 to April 2011 since the variable measures the change in the *relationship status* for the active relationships before the disruptions.

[30]This statistic can be though of as the density of a network. Bernard, Bøler, and Dhingra (2018b) found for all Colombian exporters that 1 in every 15,000 firms are connected. Bernard, Moxnes, and Saito (2019) found one in

Figure 6: Share of relationships exposed to the shock by municipality



Notes: The map zooms in on the flower producing regions. In each municipality I estimate the share of relationships with the *exposure to the shock* that equals one over total relationships with an *exposure to the shock* measure. Darker blue shadings indicate municipalities with a high number of relationships with *exposure to the shock* equal to one. For the measure of *exposure to the shock* I rely on the preferred definition using the origin-cargo terminal combinations between ij from 24 months before the first disruption, from September 2008 until September 2009. The number of municipalities belonging to each interval is displayed in parenthesis.

measuring the number of relationships that end (*relationships status* equal to one) in a given period, given they are active the previous period. The value of the statistic is 17%, and I use it as a benchmark to understand the size of the effects from the empirical estimations.

Figure A.5 illustrates the distribution of exporters and importers by the number of relationships. For exporters, the average number of active relationships is less than 11 and for importers the average number of active relationships is 6. Finally, I examine whether the relationships in my sample exhibit similar assortative patterns to those in other buyer-seller data sets. Figure A.4 in the Appendix illustrates the negative degree assortative pattern present among flower exporters and US importers, which is also present in other contexts. This pattern demonstrates that, on average, firms with many connections tend to trade with firms that are less well-connected.[31]

130,000 in Japan and Bernard, Dhyne, Manova, and Moxnes (2022) found one in 23,000 in Belgium.

[31] See Bernard et al. (2022) for evidence in Belgium firms.

Table 2: Summary statistics in the pre-shock period

Variable	Average
Share of active relationships on all potential relationships	0.005
Share of relationships ending	0.17

Notes: The table shows the summary statistics for the relationship level characteristics of the data in the pre-shock period. All measures are an average across the six-month periods, starting from April to September 2007 and ending with the period April to September 2010. I include the period October 2010 to April 2011 for the row 'share of relationships ending'. An active relationship has a *relationship status* of zero.

4 Empirical strategy and main results

In this section I describe the empirical strategy and the main results. Section 4.1 is a description of the main estimation equation, the control variables and the identifying assumptions. In section 4.2 I show the main results, then a follow up analysis for an alternative specification using exposure to the shock at the firm level. Section 4.3 is a discussion of the results and their connection to the existing literature.

4.1 Main estimating equation

In an event study, I estimate the probability of a relationship ending as[32]

$$\mathbb{1}\{y_{ijt} = 1\} = \sum_{l} \beta_l E_{ij,0} \cdot \mathbb{1}\{t = l\} + \gamma X'_{ij} + \psi_i + \varphi_j + \theta_{ct} + \varepsilon_{ijt}, \tag{1}$$

where $\mathbb{1}\{y_{ijt} = 1\}$ is the *relationship status* variable, which takes on a value of zero during all periods when the relationship is active and a value of one starting from the period immediately after the relationship is no longer active (as discussed in the previous section, a relationship can be considered active even if it is not transacting at every period). $E_{ij,0}$ is the *exposure to the shock* variable defined for each relationship and is time-invariant. The variable *exposure to the shock* takes on a value of one ($E_{ij,0} = 1$) if there was any road disruption on any of the routes from the exporter's location to the different cargo terminals, and a value of zero otherwise.

[32]Estimating non-linear models when using high-dimensional fixed effects gives biased estimates. For a more detailed explanation, refer to Charbonneau (2014) in an application to gravity models.

Since I am interested in estimating the dynamic effects on decisions in current relationships when they are exposed to road disruptions, the coefficients of interest are the leads and lags of the set $\{\beta_{t=l}\}$. These coefficients represent the differential effect on the probability of a relationship ending, for relationships for which *exposure to the shock* is one and those for which it is zero. The indicator $\mathbb{1}\{t = l\}$, reference all six-month periods, with the shock centered at $t = 0$ coinciding with the initial wave of road disruptions in October 2010. As a result, the subscript l indicates the six-month period corresponding to the specific β coefficient. For instance, if we are interested in the coefficient that corresponds to the status of relationships ending 12 months after the shock, we would focus on the coefficient β_{12}. In (1), the β_l coefficients can be directly interpreted as the percentage point change in the probability of a relationship ending. If firms are more likely to end current relationships that are exposed to road disruptions, then estimates for the β_l coefficients should be positive. In contrast, if the estimate is negative, firms are less likely to end relationships that are exposed to the shock.

X_{ij} is a matrix of relationship-level controls, which are discussed in the following section, while ψ_i and φ_j are fixed effects that control for firms' unobserved characteristics. In order to ensure the comparison is between relationships in the same cohort, I include a cohort fixed effect θ_{ct}.[33] I cluster the standard errors at the exporter level.[34]

I estimate a total of seven lagged coefficients covering six-month periods preceding the shock period and fourteen leading coefficients following the shock period. The lagged coefficients include the first period in which it is possible to observe any relationship ending, that is 36 months before the shock (from October 2007 to April 2008). The leading coefficients extend from the periods following the shock period (from April 2011 to October 2011) until a period (from April 2017 to December 2019) that is combined into one to accommodate for the lack of observed data on relationships in the final years.[35] More precisely, I estimate the set of coefficients $\beta_l = \{\beta_{t=-36}, ..., \beta_{t=80}\}$, where l are the months relative to the shock period, that is, when $t = 0$. The benchmark period I select omits the coefficient from relationships that end before they are exposed to road disruptions when $t = 0$, known as $beta_{shock}$. According to this coefficient, relationships that ended in the six months before the shock are those that ended in October 2010 to March 2011 but were active in April 2010 to September 2010.

Control variables. The first set of controls takes potential homophily effects into consideration, thus incorporating controls for the degree assortativity observed in the data. I construct firm size bins based on trade value deciles for each exporter (i), and importer (j), for the period before the shock.

[33]See Dobkin, Finkelstein, Kluender, and Notowidigdo (2018) refer to this specification with θ_{ct} as a "parametric event-study".

[34]See Cameron and Miller (2015) for a discussion of robust inference and clusters. They suggest using a minimum of 50 clusters, which is not feasible at the municipal level in the Colombian data.

[35]See Schmidheiny and Siegloch (2023), who suggest binning the end points from dynamic estimations.

Then, I create interactions between the firm size bins for exporter i with firm fixed effects for importer j, and the firm size bins for importer j with exporter i fixed effects. By introducing this bilateral set of controls to capture assortative patterns in a flexible manner, I am able to account for variations in relationships that cannot be captured solely by including fixed effects.

In my data, there are two waves of disruptions so some relationships may not have been exposed in one of the two waves. Thirty-three percent of the relationships are exclusively exposed in the first wave, while 66% are exposed in both waves. The remaining relationships, accounting for less than 1%, are exclusively exposed in the second wave. To account for any differential effects resulting from relationships being exposed to different waves, I include a categorical control variable based on the classification of periods of disruption: first wave only, second wave only, and both. These categories are mutually exclusive.

Finally, there is a potential confounding effect from indirect linkages (other relationships from a same firm) that are also exposed to road disruptions. The concern is that if road disruptions affect a firm in multiple relationships, they can have an indirect effect on other relationships. I measure the indirect exposure to the shock, both from the perspective of the importer side of the relationship and, alternatively, from the exporter side. The variable takes a value of one when other relationships linked to the firm (either as an exporter or importer) are exposed to the shock and zero otherwise. When examining indirect exposure specifically in relation to relationships with the importer, only 9% of the relationships have a value of zero. This means that very few importers have no variation within their relationship's exposure to shock, meaning that most importer firms have multiple relationships exposed to the shock. On the exporter's side of the relationship, the numbers are very different. I find that 39% of the relationships have a zero in this indirect exposure variable. In this case, less than half of the relationships are linked to exporters that are likely to have either only one exposed relationship or no exposure at all.

Identification assumption. Identification of the causal effect of the road disruption on relationship continuation decisions relies first on the shock being unexpected and second on the validity of the parallel trends assumption. Conditional on the number of connections of the exporter and importer side, if the shock is random, we would not expect to see any difference in the probability of termination between those relationships classified as having *exposure to the shock* and those classified as not having *exposure to the shock* before the disruption occurs. For each relationship cohort, I calculate the conditional lagged coefficients of the share of relationships that terminate in a given period for both groups. The results of this comparison for all cohorts is shown in the Appendix, Figure A.6 for the validation of equation (1). For validating estimations of variants of equation (1) that consider effects within importers and within relationships, the results are shown in the Appendix, Figures A.7 and A.8.

From the parallel trend estimations, the patterns look similar before the shock for both groups of exposed and non-exposed relationships, with the exception of the initial cohort 2007m1-m6 for the period September 2009-March 2010, six months before the shock, which exhibits a slightly different pattern. Overall, this seems to validate the parallel trends assumption by cohort.

Still, to account for the possibility that the parallel trends assumption might not hold exactly in all cohorts and for all specifications, I follow the sensitivity analysis from Rambachan and Roth (2022) that permits robust inferences where the parallel trends assumption is partially violated.[36] For the main result, I report the robust confidence intervals from the tests they suggest.

4.2 Results

In this section, I present estimation results from specification (1). I provide results when the variable *exposure to the shock* is at the relationship level. In the second section I estimate the differential effect on ending a relationship when I use a measure of *exposure to the shock* at the firm level. For all the reported results when the variable *exposure to the shock* is at the relationship level, I use the sample from Table 1 but exclude relationships from exporters in flooded areas, and report the coefficients when using the preferred measure of the *exposure to the shock* variable, restricting to only origin-cargo terminal combinations used 24 months before the first disruptions.

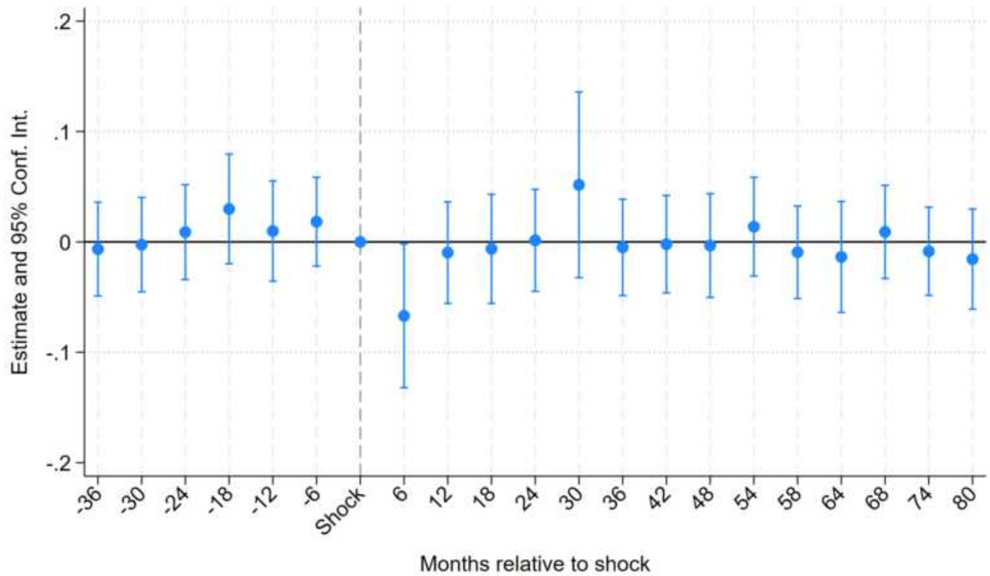
Exposure at the relationship level. Figure 7 shows the point estimates and 95% confidence intervals from the estimating equation (1). The results indicate that relationships with *exposure to the shock* do not systematically differ from relationships without *exposure to the shock* in the lagged periods. Once the roads are flooded, I find a negative and significant effect on the probability of ending for relationships with *exposure to the shock*. I find that six months after the first disruptions, the differential probabilities of ending for a relationship with *exposure to the shock* decline by 7 percentage points. In other words, road disruptions reduce the probability that firms will terminate these relationships, however the effect does not persist in the subsequent periods.

Figure 8 shows the robust confidence intervals for the sensitivity analysis following Rambachan and Roth (2022) for the coefficient β_6. The main take away from the sensitivity analysis is that the β_6 coefficient can still be identified if the parallel trends assumption is slightly violated.[37]

[36]Formally, Rambachan and Roth (2022) decompose the parameter β as $\beta = \begin{pmatrix} 0 \\ \tau_{\text{post}} \end{pmatrix} + \begin{pmatrix} \delta_{\text{pre}} \\ \delta_{\text{post}} \end{pmatrix} = \vec{\tau} + \vec{\delta}$, where τ is the causal parameter of interest when the parallel trends test might not hold. That is, if the null hypothesis $\delta_{\text{pre}} = 0$ is not rejected, a researcher can assume a $\vec{\delta} \in \Delta$ for some set Δ and show that the causal parameter τ_{post} is partially identified under such restrictions.

[37]When referring to the different parallel trends assumption violations, I follow Rambachan and Roth (2022) preferred tests, which are based on two different sensitivity analysis. The first one imposes the restriction that the post-treatment

Figure 7: Effect of road disruptions on the probability of ending a relationship



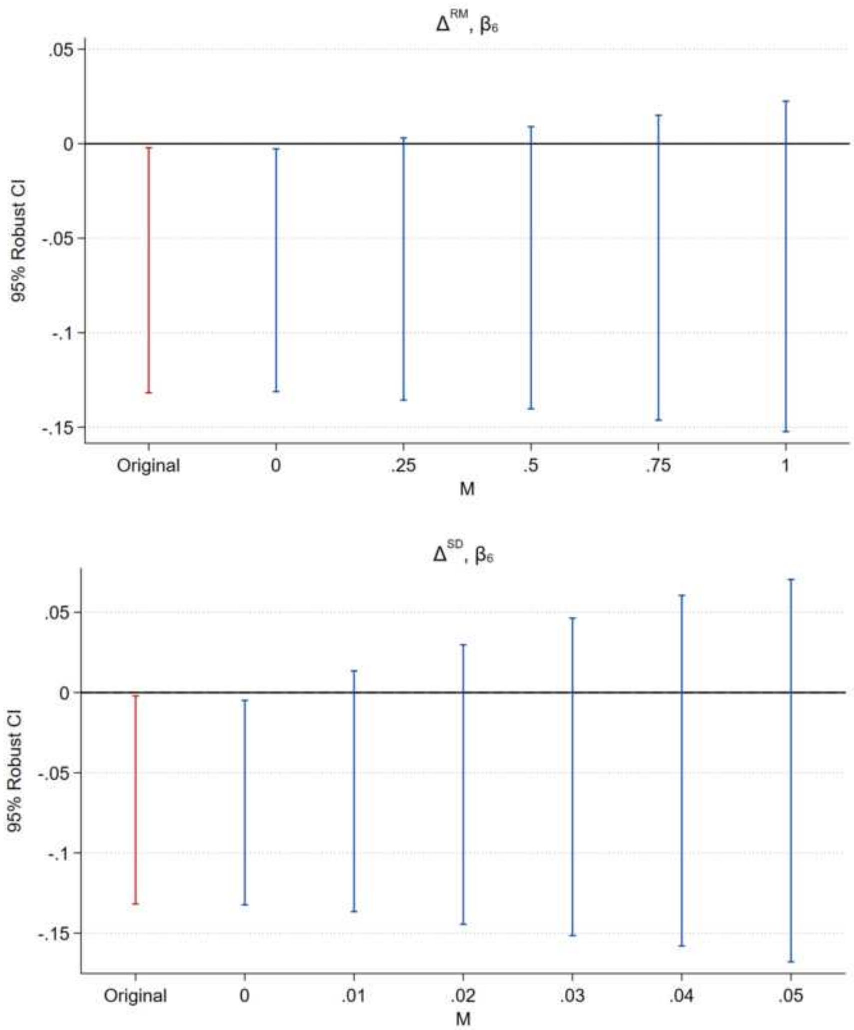
Notes: The figure plots the β_l coefficients from estimating equation (1) and the respective 95% confidence intervals. The variable *exposure to the shock* is restricted to only origin-cargo terminal combinations used 24 months before the shock. The sample includes exporter and importer firms active one year before the disruptions and all their relationships from the eight cohorts starting in 2007m1-m6 until the cohort of 2010m7-m9. All regressions control for firm fixed effects and firm size bin interactions, wave of exposure, indirect effects from exporter and importer, and fixed effects for importer, exporter, and cohort. The reported confidence intervals are estimated using standard errors clustered at the exporter level.

Variation within firms. I look at whether the previous result comes from variation within firms. To do so, I estimate the probability that an importer ends a relationship with *exposure to the shock* relative to relationships without *exposure to the shock* within its portfolio. To do so, I add importer-time fixed effects ψ_{jt} to the specification (1) and focus only on the importers that experience variation in the exposure of their relationships. The results are displayed in Figure 9, and they corroborate those in the previous analysis. Following the road disruptions, the probability of ending relationships with *exposure to the shock* decreases by 9.3 percentage points. Below the estimates, Figure 10 shows the robust confidence intervals following Rambachan and Roth (2022)'s sensitivity analysis for the β_6 coefficient. On the within exporter side, the within analysis is not informative since most exporter variation occurs between firms.[38]

violation of the parallel trends assumption must be no more than some constant value M that is above the maximum size of the violation of the parallel trends assumption in the pre-treatment period. The second one imposes that the slope of the pre-trend can change by no more than M across consecutive periods.

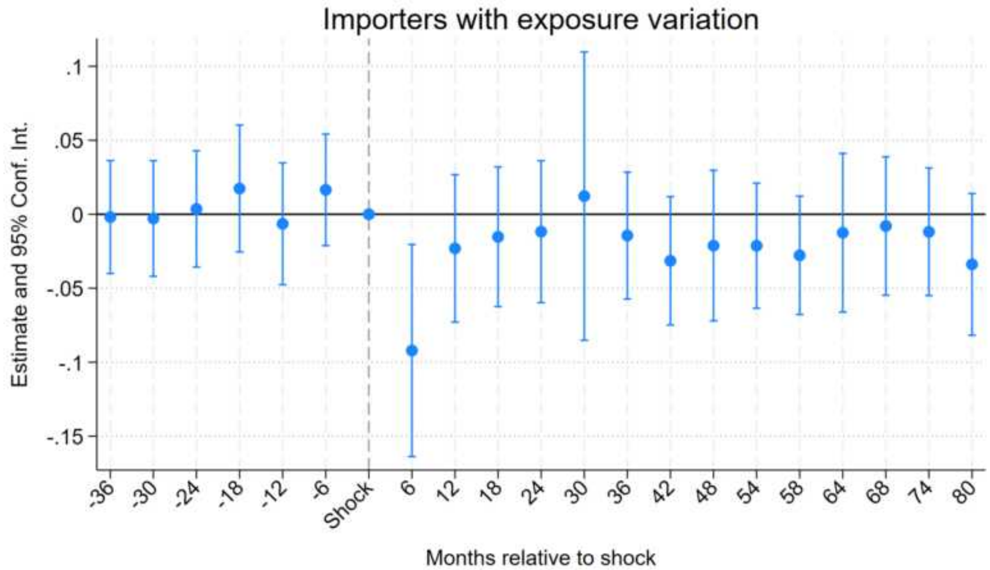
[38]Figure A.11 shows the results when modifying equation (1) and adding ψ_{ij}, that is only looking at changes within a

Figure 8: Sensitivity analysis for the parallel trends assumption: confidence bands for β_6



Notes: The figure shows 95% confidence intervals for β_6 from Figure 7 following Rambachan and Roth (2022). In both panels the 'original' confidence intervals are taken from the estimations in Figure 7 and the confidence intervals for the suggested methods following Rambachan and Roth (2022) for different values of M that violate the parallel trends assumption. For both panels $\bar{M} = 0$ assumes no violation of the parallel trends assumption. The top panel display the confidence bands for different deviations Δ^{RM} that assume the post-treatment violation of the parallel trends assumption is no more than some constant M larger than the maximum violation of the parallel trends assumption in the pre-shock period. The "breakdown value" is below 0.25, which means the estimates are significant even when allowing for a deviation of 1.25 times in the pre-shock period. The bottom panel displays the confidence bands for different deviations Δ^{SD} that impose that the slope of the pre-trend can change by no more than M across consecutive periods. The "breakdown value" is below 0.01, which means that the estimates can only be violated under a very slight deviation from linear trends in the pre-shock period.

Figure 9: Effect of road disruptions on the probability of ending a relationship, within-importer variation



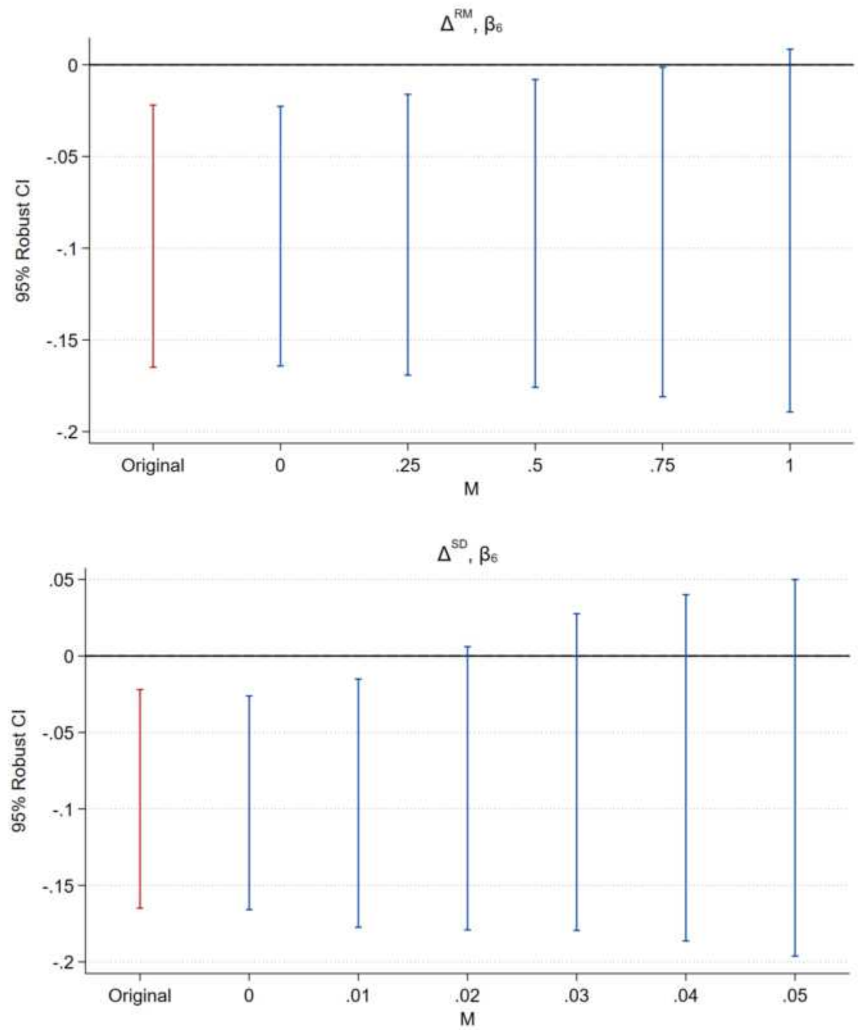
Notes: The figure plots the β_l coefficients from estimating equation (1) with an importer time fixed effect ψ_{jt} and the respective 95% confidence intervals. The variable *exposure to the shock* is restricted to only origin-cargo terminal combinations used 24 months before the shock. The sample includes exporter and importer firms active one year before the disruptions and all their relationships from the eight cohorts starting in 2007m1-m6 until the cohort of 2010m7-m9. All regressions control for firm fixed effects and firm size bin interactions, wave of exposure, indirect effects from exporter and importer, and fixed effects for importer, exporter, and cohort. The reported confidence intervals are estimated using standard errors clustered at the exporter level.

According to these results, the differential probability in the short run that is observed across different relationships is mainly attributed to importers with multiple shocks and with exporters that are mainly exposed in all their relationships.On the exporter side of the relationship, since most exporters are paid upon delivery, exposure across their portfolio would make them cash-constrained and even more reliant on their existing relationships. Hence they will not have any incentive to end current relationships during the weather event: by holding on to all of their customers, they maximize the chance of being able to sell all of their output. On the importer side of the relationship, most importers are facing multiple non-deliveries from the disruptions, making then supply constrained. So, likewise, importers do not have any incentive to abandon their existing relationships during the weather event: by holding on to relationships that are exposed, they maximize the chance of receiving deliveries from them.

Exposure at the firm level. Here I examine whether the shock affected the portfolios firms had at

relationship. The results suggest that the effect is only significant at the 90% level.

Figure 10: Sensitivity analysis for the parallel trends assumption: confidence bands for β_6



Notes: The figure shows 95% confidence intervals for β_6 from Figure 7 following Rambachan and Roth (2022). In both panels the 'original' confidence intervals are taken from the estimations in Figure 7 and the confidence intervals for the suggested methods following Rambachan and Roth (2022) for different values of M that violate the parallel trends assumption. For both panels $\bar{M} = 0$ assumes no violation of the parallel trends assumption. The top panel display the confidence bands for different deviations Δ^{RM} that assume the post-treatment violation of the parallel trends assumption is no more than some constant M larger than the maximum violation of parallel trends assumption in the pre-shock period. The "breakdown value" is below 1, which means the estimates are significant even when allowing for a deviation of 2 times in the pre-shock period. The bottom panel displays the confidence bands for different deviations Δ^{SD} that impose that the slope of the pre-trend can change by no more than M across consecutive periods. The "breakdown value" is below 0.02, which means that the estimates can only be violated under a slight deviation from linear trends in the pre-shock period.

the time of the shock, as well as whether those effects had short-term or long-term implications. I construct a measure of *exposure to the shock* for the firms. I call this measure *firm exposure*. This is separately constructed for exporters and for importers as

$$\text{IE}_j = \frac{\sum_i \mathbb{1}\{E_{ij,0} = 1\}}{\sum_i \mathbb{1}\{E_{ij,0} = 1\} + \sum_i \mathbb{1}\{E_{ij,0} = 0\} + \sum_i \mathbb{1}\{E_{ij,0} = 1 \cup E_{ij,0} = 0\}^c}, \tag{2}$$

and

$$\text{EE}_i = \frac{\sum_j \mathbb{1}\{E_{ij,0} = 1\}}{\sum_j \mathbb{1}\{E_{ij,0} = 1\} + \sum_j \mathbb{1}\{E_{ij,0} = 0\}}, \tag{3}$$

where IE_j is the measure of *importer exposure through relationships* and EE_i is the measure of *exporter exposure through relationships*. The measures count the number of relationships with *exposure to the shock* equaling one over the total number of active relationships. For the measure of *importer exposure*, I include an additional term in the denominator, that is $\sum_i \mathbb{1}\{E_{ij,0} = 1 \cup E_{ij,0} = 0\}^c$. The term adds up all other relationships that are linked to an importer and that do not have an *exposure to the shock* measure. These are the relationships with intermediary exporter firms, exporters with multiple farms, and sellers in flooded areas. There is no need to add this additional term for exporters since all relationships are classified as exposed or not. For all measures of *firm exposure*, I restrict the count to all relationships that are active at least one year before the disruptions.

I also construct a measure of *firm exposure* that uses the total trade from relationships:

$$\text{IE}_j(x) = \frac{\sum_i \mathbb{1}\{E_{ij,0} = 1\}x_{ji}}{\sum_i \mathbb{1}\{E_{ij,0} = 1\}x_{ji} + \sum_i \mathbb{1}\{E_{ij,0} = 0\}x_{ji} + \sum_i \mathbb{1}\{E_{ij,0} = 1 \cup E_{ij,0} = 0\}x_{ji}{}^c}, \tag{4}$$

and

$$\text{EE}_i(x) = \frac{\sum_j \mathbb{1}\{E_{ij,0} = 1\}x_{ij}}{\sum_j \mathbb{1}\{E_{ij,0} = 1\}x_{ij} + \sum_j \mathbb{1}\{E_{ij,0} = 0\}x_{ij}}, \tag{5}$$

where x_{ij} is the total trade value of relationship ij a year before the shock. $IE_j(x)$ is the measure of *importer exposure through trade* and $EE_i(x)$ is the measure of *exporter exposure through trade*. For all the measures of *firm exposure*, I use the variable of *exposure to the shock* that restricts to only the origin-cargo terminal combinations used 24 months before the shock.

Figure 11, shows the distributions of relationships for all four measures of *firm exposure*. The vertical lines for the exporter measures indicate the mean of the distribution, and the 75th percentile for the importers.[39] The distributions within the *exporter exposure* measures are similar, but the distri-

[39] I rely on the mean for the *exporter exposure* measures because the median is 0 and the 75th percentile is 98.

butions within the *importer exposure* measures are different. For the IE_j measure, most observations fall in the 20% to 40% range; for the $IE_j(x)$ measure, most relationships fall below 20%.

To carry out the analysis at the firm level using the different *firm exposure* measures, I construct an indicator $E_{h,0}$. The indicator $E_{h,0}$ is calculated separately for each *firm exposure* measure, and it classifies relationships into 'low' exposure or 'high' exposure groups if their *firm exposure* measure is above the chosen thresholds. In particular, I use the mean threshold for the exporters and the 75th percentile threshold for the importers as shown in Figure 11. The subscript h generalizes that the indicator is calculated for exporters and importers separately. With the indicator $E_{h,0}$ that links a relationship to a *firm exposure* measure, I estimate the following probability model for all four *firm exposure* measures

$$\mathbb{1}\{y_{ijt} = 1\} = \sum_l \beta_l E_{h,0} \cdot \mathbb{1}\{t = l\} + \gamma X'_{ij} + \psi_i + \varphi_j + \theta_{ct} + \lambda_t + \varepsilon_{ijt}, \tag{6}$$

where the coefficients of interest are the β_ls, which measure the differential probability that relationships linked to a firm in the 'high' exposure group end, relative to the 'low' exposure group.

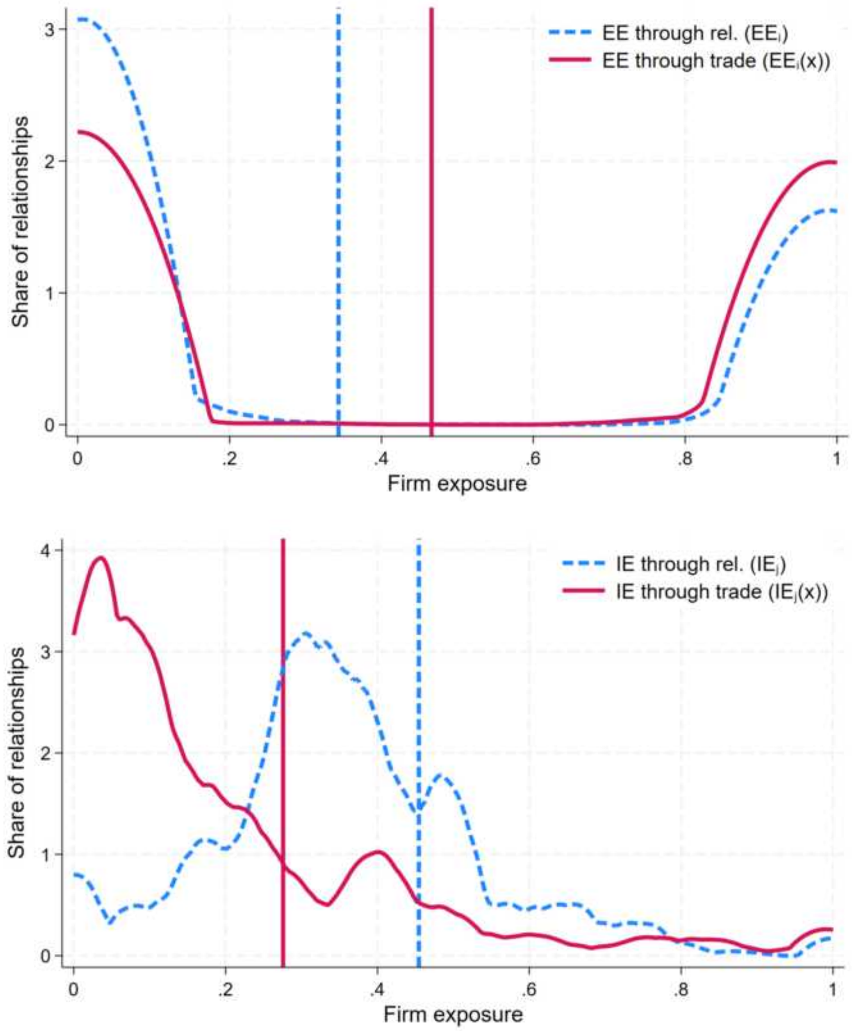
Figure 12 illustrates the results for exporters. The figure indicates that, for the *exporter exposure on relationships* measure EE_i (top panel), there is no significant difference in the probability of relationships ending when they belong to exporters with 'high' exposure. However, when focusing on the *exporter exposure through trade* measure $EE_i(x)$ (bottom panel), relationships linked to exporters with 'high' exposure based on trade value exposed have a decrease in the probability of ending after the shock. In the years preceding the shock, for both *exporter exposure* measures EE_i and $EE_i(x)$, the estimates suggest there are no differential effects.

Figure 13 presents the results for importers. The figure displays a similar pattern for both *importer exposure* measures IE_j (top panel) and $IE_j(x)$ (bottom panel). The estimation shows that relationships linked to importers with a 'high' exposure in terms of trade relationships and trade value are more likely to end in the years following the shock. Overall, the results from the firm analysis indicate a pattern: relationships linked to 'high' exposure exporters are less likely to end in the short run. From the importer side, the effect after the shock is not statistically different from zero, but in the medium and long run, relationships linked to 'high' exposure importers end with a higher probability, and the effect is persistent. The firm-level analysis highlights how idiosyncratic shocks to relationships could permeate firms' decisions on their portfolio.

4.3 Discussion

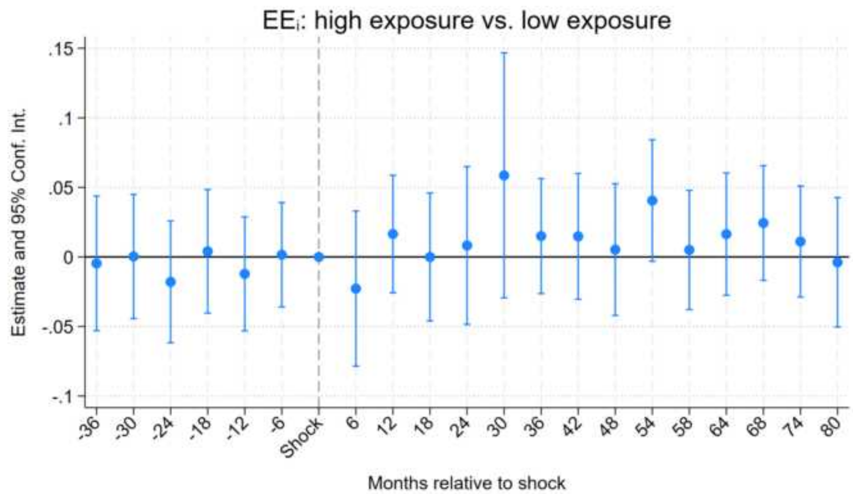
Based on the empirical evidence presented in the previous section, firms are less likely to end relationships exposed to road disruptions in the short run. In this section, I look at the channels that are

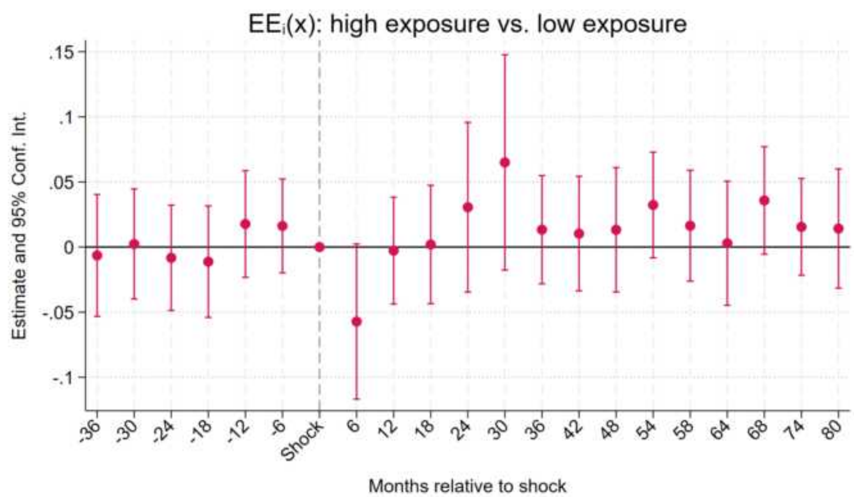
Figure 11: Distribution of *firm exposure* measures



Notes: The figure shows the distribution of relationships for the different measures of *firm exposure*. The distribution in blue represents the measure of *firm exposure through relationships*, which counts the number of exposed relationships. The distribution in red represents an alternative measure of *firm exposure through trade*, which includes trade values of relationships with *exposure to the shock*. The vertical line serves as the cutoff used to separate relationships into 'high' and 'low' exposure categories. This cutoff corresponds to the mean for the exporters and the 75th percentile for the importers.

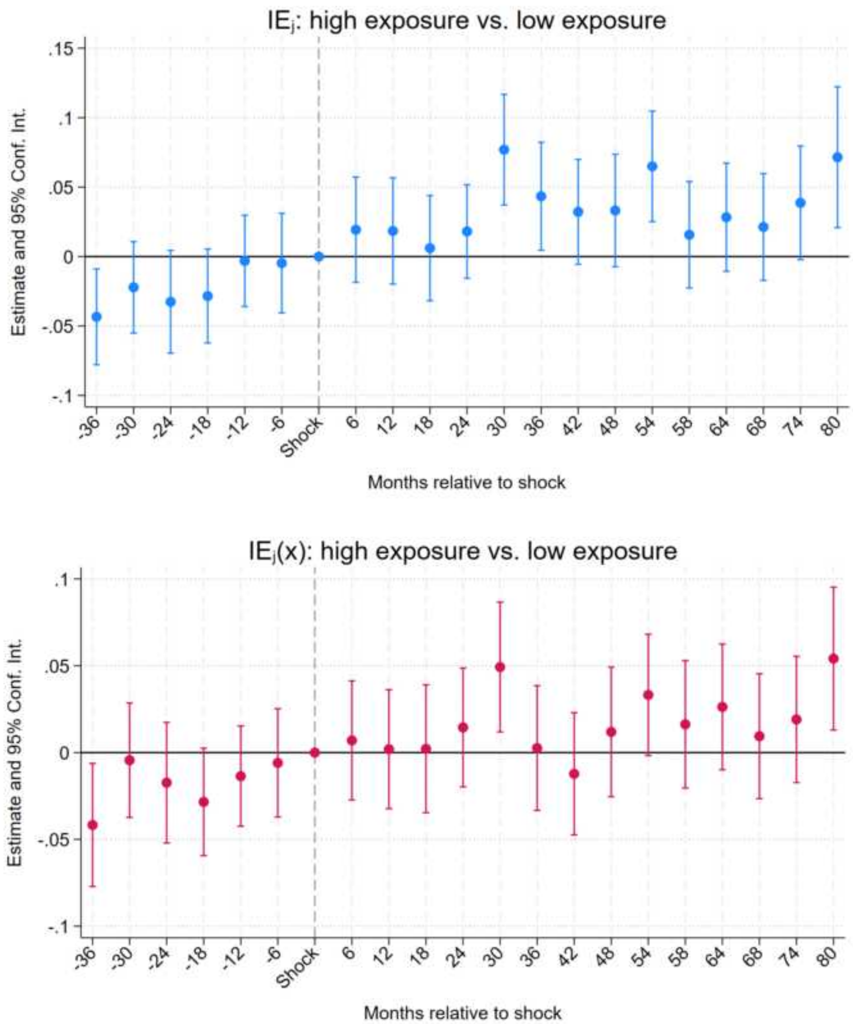
Figure 12: Probability of relationships ending by *exporter exposure*





Notes: The figure plots the β_l coefficients obtained from estimating equation (6), along with their respective 95% confidence intervals. The top panel displays the results when $E_{i,0} = 1$ is based on the threshold derived from the distribution of the measure of *exporter exposure through rel.* (EE_i). Meanwhile, the bottom panel showcases the results when $E_{i,0} = 1$ is determined using the threshold derived from the distribution of the measure of *exporter exposure through trade* ($EE_i(x)$). The variable *exposure to the shock* is limited to only origin-cargo terminal combinations used 24 months before the shock. The sample consists of exporter and importer firms that were active one year before the disruptions, along with all their relationships from the eight cohorts spanning from 2007m1-m6 to 2010m7-m9. All regressions include controls for firm fixed effects times firm size bin interactions, as well as fixed effects for importer, exporter, and cohort. The reported confidence intervals are estimated using standard errors clustered at the exporter level.

Figure 13: Probability of ending relationships by *importer exposure*



Notes: The figure plots the β_l coefficients obtained from estimating equation (6), along with their respective 95% confidence intervals. The top panel displays the results when $E_{j,0} = 1$ is based on the threshold derived from the distribution of the measure of *importer exposure through rel.* (IE_j). Meanwhile, the bottom panel showcases the results when $E_{j,0} = 1$ is determined using the threshold derived from the distribution of the measure of *importer exposure through trade* ($IE_j(x)$). The variable *exposure to the shock* is limited to only origin-cargo terminal combinations used 24 months before the shock. The sample consists of exporter and importer firms that were active one year before the disruptions, along with all their relationships from the eight cohorts spanning from 2007m1-m6 to 2010m7-m9. All regressions include controls for firm fixed effects times firm size bin interactions, as well as fixed effects for importer, exporter, and cohort. The reported confidence intervals are estimated using standard errors clustered at the exporter level.

consistent with the empirical findings, to identify those that are supported by the empirical evidence and those that are not. I first relate the results to the literature on search costs, then to the literature on relational contracts, and finally to the literature on product specificity. In the last part of the discussion, I show some evidence that supports the results found in the firm level analysis, where relationships that have a higher probability of ending in the long run are those linked to the 'highly exposed' buyers.

Search costs. The information frictions firms face when finding buyers or sellers might explain the findings of the previous section. Eaton et al. (2021) look at the cost of forming relationships from the exporter side. They argue that to find a buyer a firm needs to engage in costly search, and more visible firms can access markets more easily. To test this channel I split the distribution of relationships into two groups: relationships linked to firms with more than the median number of connections and less than the median number of connections, where the number of connections is measured from all active relationships of importers and exporters a year before the road disruptions.[40]

I find that for relationships involving exporters with a below-median number of connections ('low-connected' exporters) the probability of ending a relationship decreases upon impact to the shock. Results are shown in Figure A.17 when looking at the relationships from the exporter side as well as from the importer side. Due to the negative degree assortativity patterns of these relationships, relationships involving exporters with a below-median number of connections involve, on average, importers with an above-median number of connections. Hence the effects can be observed on both sides of the relationship.

This suggests that the number of an exporters' connections, a proxy for search costs, can be a predictor of their portfolio responses to shock. When faced with road disruptions, exporters with few connections might prefer to absorb the higher transportation costs to maintain their current relationships, rather than incurring costly search.[41]

Relational contracts. Macchiavello and Morjaria (2015) highlight the idea that reputation can explain why flower producers keep delivering flowers during the political turmoil affecting rose exporters in Kenya. As in the setting I consider, the Kenyan rose producers suffered an unanticipated shock that made it impossible for them to deliver roses without incurring additional costs. Macchiavello and Morjaria (2015) find evidence for an inverted U-shape between the age of the relationship and the reliability of delivery. Since these exporters can sell flowers on a spot market, relationships that are

[40] Figure A.13 shows the distribution of relationships by their *exposure to the shock* classification when counting the number of buyers on the exporter and the importer side of the relationship.

[41] Based on interview that I conducted for flower exporters in Colombia, in extreme circumstances exporters may even resort to buying flowers from other suppliers in order to hold on to their customers when they cannot deliver their own product.

underpinned by an established stock of reputation and that do not deliver during the turmoil would likely resume afterwards, whereas relationships without an established stock of reputation and that do not deliver during the turmoil would likely terminate.

My findings for the Colombian flower sector could be reconciled with those findings if Colombian exporters also had an outside option, such as a well–functioning spot market. However,there are no spot markets for Colombian flower exporters. Hence, in the Colombian case, there would be no reason for any relationship, even those with weak enforcement and a weak level of commitment, i.e., no history of past transactions, to be abandoned by sellers.[42] If flowers can be sourced from other countries, US buyers would be the ones that might be motivated to deviate.

Product specificity. Barrot and Sauvagnat (2016) find empirical evidence that input specificity is a key propagator of weather shocks affecting the supply side of relationships, making buyers less flexible in finding alternative suppliers when they rely on specific products. If products are not relationship-specific, then importers exposed to road disruptions would be able to replace their current relationships. If flowers are a differentiated product, then it will be difficult to replace suppliers promptly.

This channel could explain the empirical results. Flowers differ in more than just species and quality. Additional sources of product specificity in flowers are not directly observable in the product. For example, some buyers provide technical assistance directly to sellers, sometimes even providing specific types of seeds.[43] Another type of product specificity is seasonality. Valentine's Day, Mother's Day, Thanksgiving, and Christmas are the four high seasons for Colombian producers. Flower importers have specific and different demands for flowers within these time periods.

Change in risk assessment. I consider as a possible channel to explain the increase in the probability of relationships ending years after the shock has ended that after the shock firms might change their relative risk assessment. I rely on the findings by Balboni, Boehm, and Waseem (2023) in which they asses whether temporary flooding disruptions can induce firms to undertake long-term adaptive changes to reduce their vulnerability to future flooding. A change in importers' relative risk of flooding events may lead to a different pattern of new relationship formation after the shock.[44] I

[42]It would in principle be possible for Colombian exporters to sell to European markets through aution markets without the need to have a direct relationship with the buyers, but the cost of transportation would be greater. As of 2002, Colombian flower exports to the Netherlands, the largest flower market that purchases flowers through auctions, remain stable at around 2 percent of Colombian flower exports.

[43]An example of such investment is an importer firm called "Elite Flowers". This firm operates their own research and development (R&D) centers, offering technical advice and collaborating with their growers to develop specific flower products.

[44]I cannot test directly that firms change their risk perception in my data, but I can check if firms change their portfolios

estimate the probability of new relationships being formed within those importers that were active during the road disruptions that had 'high' *importer exposure* relative to those with a 'low' *importer exposure*. First, I construct a full vector of all potential matches in addition to the active ones, and to compare similar firms I split relationships into those linked to importers with a below median number of connections ('low' connected) and above ('high' connected).

Figure A.18 shows the estimation results when considering only potential matches within firms that are already supplying the US market (the incumbent firms). Figure A.19 shows the results for only potential matches among new firms that are new to the US market (entrant firms). The patterns in Figure A.18 indicate that importers with above median connections were forming more relationships prior to the shock, but not in the year before. After the shock, these patterns reverse, and these firms are less likely to form new relationships within the incumbent set of flower exporters. When looking at importers with below median connections, before the shock there is no difference between firms with 'high' *importer exposure* and 'low' *importer exposure*, but two to three years after the shock the formation of new relationships starts to divert. New relationships involving firms with 'high' *importer exposure* are less likely to be formed. Figure A.19 shows a slight, but imprecise, increase in new connections from firms with 'high' *importer exposure* six months from the first wave of disruptions with entrant firms.

In related empirical work about network responses on the buyer side, Gigout and London (2021) and Bernard, Moxnes, and Ulltveit-Moe (2018b) find that higher trade costs and lower efficiency leads to a fall in the number of buyer-seller connections. I reconcile these patterns with their findings. My results suggest that buyers 'highly affected' by the shock in time are forming less connections with the incumbent Colombian exporters, and that new connections with new Colombian sellers do not compensate for the consistent negative effect. To some extent, it is plausible that some of the most affected importers might decide that they do not want to find themselves in the same position as during the La Niña 2010-11 flooding events, i.e., that their long-run risk perception of Colombian exporters would change. This could induce them to divert some of their business to other supplier countries.

4.4 Robustness

I estimate (1) using the alternative *exposure to the shock* measures discussed in Section 3.4, using all the origin-cargo terminal combinations from January 2007, and using only the origin-cargo terminal combinations for the 12 months before the shock. I also present the results when changing the

within Colombian sellers. An additional story that can lead importers to change the portfolio structure can also be linked to how the shock forced some firms to search for better matches which could h ave replaced the current ones.

threshold for a route to be considered part of the set of origin-cargo routes by focusing on routes within relationships with a share of trade above 20% instead of 10%. Finally, I repeat the estimations when I include all exporters located in the flooded areas. For all of the above, the results have the same sign for all these specifications and remain significant. All these results can be found in Figure A.15, and for the within importer variation results in Figure A.16.

5 Theoretical framework

This is a model to rationalize the mechanism behind the empirical results, specifically the short-run result that relationships exposed to road disruptions are less likely to end.

Setting and assumptions. The market is comprised of two types of firms, domestic sellers (exporters) and foreign buyers (importers). I assume markets are in equilibrium at each period, t, and so the final demand and final prices in the US are taken as given. Buyers and sellers meet randomly in period t and once they meet, firms choose the prices and quantities optimally and trade in t and in $t+1$.[45]

I assume that the discount factor is unity and so revenues and costs for both periods are known and constant, given that the final demand for each buyer is the same. For both importers and exporters I assume that revenue is a concave function in quantities, $R'(Q) > 0$ and $R''(Q) < 0$, and that the cost function is convex in quantities, $C'(Q) > 0$ and $C''(Q) > 0$.

Finally, I assume that the revenue net of production costs is always positive and larger than costs of maintaining the relationship λ. I also assume that firms must pay a cost ρ_x, where x denotes importers and exporters, whenever they decide to form a new match.[46] In other words, any transaction is profitable even when paying the maintenance cost λ, and the cost of forming a relationship is larger than the cost of maintaining it: $\rho_j + \rho_i > \lambda$.

Firm decisions. Firms make two decisions in period t: they can either decide to keep or not keep one of their current matches, and, simultaneously, whether or not to add a new match to their portfolio in

[45]As in Macchiavello and Morjaria (2015), buyers and sellers meet and form optimal contracts for each period. As in Eaton, Jinkins, Tybout, and Xu (2022) I assume that buyers and sellers engage in efficient bargaining and split the surplus.

[46]Cost of forming a new relationship can be thought of as search costs as in Aker (2010), Allen (2014), and Goyal (2010) among others, that arise from exporters' lack of full information. In this context, exporters search information to appeal their products in international markets. In Monarch (2016), Alessandria (2009), Drozd and Nosal (2012) and Rauch and Watson (2003) the information friction is on the buyer side. Buyers gather information on prices and the quality. The cost of continuing a relationship is assumed, as in Eaton, Jinkins, Tybout, and Xu (2022), to be a fixed cost that could reflect maintenance of the account, technical support, or client-specific product adjustments. Bernard, Moxnes, and Ulltveit-Moe (2018b) also model relationship specific costs, these costs are assumed to be payed in labor units by the seller and to vary by country.

period $t+1$. If a firm decides to keep a relationship in $t+1$, the firm has to pay the maintenance cost λ. Alternatively, the firm can decide to add a new match in $t+1$, in which case the firm pays a cost of forming a new relationship ρ that is incurred at t. In $t+1$ firms do not make any decisions, they just obtain the profits from their choices at t.

The possible payments for a firm at t and $t+1$ depend on the firm's choices of keeping and matching of relationships at t. The profits of an importer (or similarly of an exporter when changing the subscript j for i), given decisions at t, are

$$\begin{aligned}\pi_t^j = \;& \mathbb{1}\{y_{ijt}=0\}\,\mathbb{1}\{m_{ijt}=0\}\left(R(S_{j,-i}+q_{ij}) - C(S_{j,-i}+q_{ij}) - N\alpha\lambda\right)\\ &+\mathbb{1}\{y_{ijt}=1\}\,\mathbb{1}\{m_{ijt}=1\}\left(R(S_{j,-i}) - C(S_{j,-i}) - (N-1)\alpha\lambda - \rho\right)\\ &+\mathbb{1}\{y_{ijt}=0\}\,\mathbb{1}\{m_{ijt}=1\}\left(R(S_{j,-i}+q_{ij}) - C(S_{j,-i}+q_{ji}) - N\alpha\lambda - \rho\right)\\ &+\mathbb{1}\{y_{ijt}=1\}\,\mathbb{1}\{m_{ijt}=0\}\left(R(S_{-j,-i}) - C(S_{j,-i}) - (N-1)\alpha\lambda\right),\end{aligned} \tag{7}$$

where $\mathbb{1}\{y_{ijt}=0\}$ indicates a firm's binary decision of whether to hold on to a relationship, and $\mathbb{1}\{m_{ijt}=1\}$ indicates the firm's decision of whether to add a new match.[47] $S_{j,-i}$ is the total quantity of flowers that j buys from the rest of its relationships excluding the flowers from the current relationship. The flowers traded between the buyer and seller are denoted as q_{ji}. Importers pay a fraction α of the maintenance cost, while exporters pay $(1-\alpha)$. N refers to the total number of relationships currently in the firm's portfolio.

The possible payments in $t+1$ following the decisions of j in period t are

$$\begin{aligned}\pi_{t+1}^j = \;& \mathbb{1}\{y_{ijt}=0\}\,\mathbb{1}\{m_{ijt}=0\}\left(R(S_{-ij}+q_{ij}) - C(S_{j,-i}+q_{ij})\right)\\ &+\mathbb{1}\{y_{ijt}=1\}\,\mathbb{1}\{m_{ijt}=1\}\left(R(S_{j,-i}+q_{jk}) - C(S_{j,-i}+q_{jk})\right)\\ &+\mathbb{1}\{y_{ijt}=0\}\,\mathbb{1}\{m_{ijt}=1\}\left(R(S_{j,-i}+\omega q_{ji}+(1-\omega)q_{jk}) - C(S_{j,-i}+\omega q_{ji}+(1-\omega)q_{jk})\right)\\ &+\mathbb{1}\{y_{ijt}=1\}\,\mathbb{1}\{m_{ijt}=0\}\left(R(S_{-j,-i}) - C(S_{j,-i})\right).\end{aligned} \tag{8}$$

Note that a firm that decides to keep the existing match and add a new one would only be able to sell a fraction ω, as final demand is constant and contractually agreed in period t.

Relationship surplus. Importer and exporter decisions cannot be mutually exclusive since they decide on the same relationship. This reduces the choices firms can make. For instance, if the importer keeps a relationship, the exporter must also decide to keep it for it to continue. Not keeping and not

[47] Time subscripts are not relevant here since final demand is the same for both periods $Q_{ij,t} = Q_{ij,t+1}$ and so for all $q_{ij,t} = q_{ij,t+1}$

matching is the less profitable option, but a firm can choose this option if it decides to reduce its participation in the market since all transactions are profitable and revenues are concave in Q.

I consider the relationship surplus for the combinations of decisions that firms are most likely to face during the road disruption period. First I consider the comparison between the profitable choices for the firm: keeping a relationship but deciding whether to match with a new one, and between keeping or not keeping a relationship when firms choose to add a new match. In both cases, the surplus from a firm keeping and adding a new relationship is always negative. This is because when a firm chooses to add a new relationship and keep the current one, there is always an additional cost, either λ or ρ, that firms are paying to have one additional relationship in their portfolio at $t+1$. The surplus from these choices is in Appendix D.1.

I focus on the choice between keeping a relationship and not matching with a new one ($\pi_{ij}\mathbb{1}\{y_{ijt} = 0\}\,\mathbb{1}\{m_{ijt} = 0\}$), compared to not keeping a relationship but matching with a new one ($\pi_{ij}\mathbb{1}\{y_{ijt} = 1\}\,\mathbb{1}\{m_{ijt} = 1\}$). In this case, the relationship surplus is

$$
\begin{aligned}
\Delta\pi_{ij} = \Delta(\pi_j) + \Delta(\pi_i) = \quad & \left(R^j(S_{j,-i} + q_{ij}) - C_t^j(S_{j,-i} + q_{ij}) - R^j(S_{j,-i}) + C^j(S_{j,-i})\right) \\
& + \left(R^i(S_{i,-j} + q_{ij}) - C^i(S_{i,-j} + q_{ij}) - R^i(S_{i,-j}) + C^i(S_{i,-j})\right) \\
& - \lambda + \rho_j + \rho_i.
\end{aligned} \tag{9}
$$

To relate this result to how road disruptions change the relationship surplus, I consider a decrease in the quantities of flowers delivered. A change in q_{ij} or $S_{j,-i}$ directly impacts the profit of the selling and buying firms. I separate the effect on the surplus from a decrease in flower deliveries in the relationship q_{ij} (*direct* effect), from a decrease in flower deliveries in other relationships linked to that firm (*indirect* effect) $S_{j,-i}$ or $S_{i,-j}$.

Prediction 1. *A decrease in the quantities in a firm's other relationships will increase the surplus from a given relationship.*

This follows from the assumptions on the concavity and convexity of the cost and revenue functions. The intuition is that the marginal revenues from a decrease in $S_{j,-i}$ or $S_{i,-j}$ without q_{ij} are lower than with q_{ij}. Hence, the net profit is positive given that the rest of the terms in the surplus are positive following the assumption that $\lambda < \rho^j + \rho^i$.[48]

Prediction 1 rationalizes the results from Figure 9 in which firms that keep relationships are importers with multiple relationships exposed to the shock. I refer to the channel as the *indirect* effect, where if the circumstances of the firm's portfolio worsen, i.e., multiple failures on deliveries occur, firms can still obtain revenue from any relationship that delivers. In this case, importers have

[48]The proof is in Appendix D.2.

no incentive to end any of their current relationships.

Prediction 2. *A decrease in the number of a firm's relationship quantities will decrease the firm's profits; moreover,*

(i) if the cost of establishing a new relationship is lower than the decrease in the profits, relationship surplus decreases;

(ii) if the cost of establishing a new relationship is higher than the decrease in the profits, relationship surplus increases.

This follows from the assumptions on the concavity and convexity of the cost and revenue functions. The sign of the effect on the relationship surplus will depend on how much the net profits from a decrease in the quantities are offset by the net cost of forming a relationship, which is positive under the assumption $\lambda < \rho_i + \rho_j$.[49]

I refer to the channel in Proposition 2 as the *direct* effect. The intuition is that firms can consider their decisions to replace a current match as a choice between the profitability of the existing relationship and the cost of replacing them. In Figure 7, firms are more likely to maintain an existing relationship that is exposed to road disruptions. It is possible to rationalize these results when the *direct* effect is negative and case (i) of Prediction 2 applies, that is if the cost of establishing a new relationship is lower than the decrease in the profits making the relationship surplus decrease. In this case, if the *indirect* effect is larger than the *direct* effect and firms will be more likely to keep the relationship. Similarly, if the *direct* effect is positive and case (ii) of Prediction 2 applies, that is he cost of establishing a new relationship is higher than the decrease in the profits making the relationship surplus increase, then the *direct* and *indirect* effects go in the same direction; in this case, the effect is unambiguously an increase in the total surplus of the current relationship.

To conclude, this model highlights a channel that can explain the empirical results in which firms' decisions on their specific relationships are a function of their profits over their entire portfolios. I link the short-run results in Figures 7 and 9 to the *indirect* effect being larger than the *direct* effect. Similarly, as shown in Figure A.18, in the shock period, importers are also not forming new relationships. This evidence may point to higher costs of forming new relationships ρ during the shock period, thus contributing to the firms' decisions on their existing relationships.

[49] The proof is in Appendix D.3.

6 Conclusion

Trade transactions involve buyers and sellers. In less-than-perfect markets, firms that access international markets can only do so by establishing relational contracts as an informal mechanism to guarantee their entry. Understanding how business react to relationship-specific shocks is important, and this is likely to become even more important as weather-related shocks increase in frequency and severity as a result of climate change. At the firm level, adverse shocks can erode a firm's relationship portfolio, deterring its growth potential. In the aggregate, understanding the channels that disrupt these relationships is important for developing countries that often lack institutional capacity to attract buyers and may heavily rely on export sector growth.

By focusing on a specific setting – the flower industry in Colombia, which produces almost exclusively for exports and is a significant player in the global flower market – I investigate how international supply relationships respond to disruptions caused by a severe La Niña event. I find evidence that relationships affected by road disruptions are less likely to end in the short run. But in the medium and long run, I find that relationships involving importers with a high exposure to the shock are more likely to end. These negative effects jointly occur with a decrease in the formation of new relationships between Colombian sellers and US buyers in subsequent periods. These patterns highlight possible channels that could be at play during the shock period, such as frictions in forming new relationships when firms do not have a high number of connections, as well as contractual frictions where firms produce or demand products that are specific and harder to find replacements for. To conclude, I emphasize an additional channel that is important to understand firms' responses to shocks. A firm's decision to maintain or dissolve any relationship affected by a temporal shock depends not only on that particular relationship, but also on how the firm's overall portfolio is exposed to the shock, and its impact on the firm's profits. More broadly, this paper shows that the exposure of a firm's full portfolio is an important determinant of how it responds to idiosyncratic shocks to any of its individual relationships.

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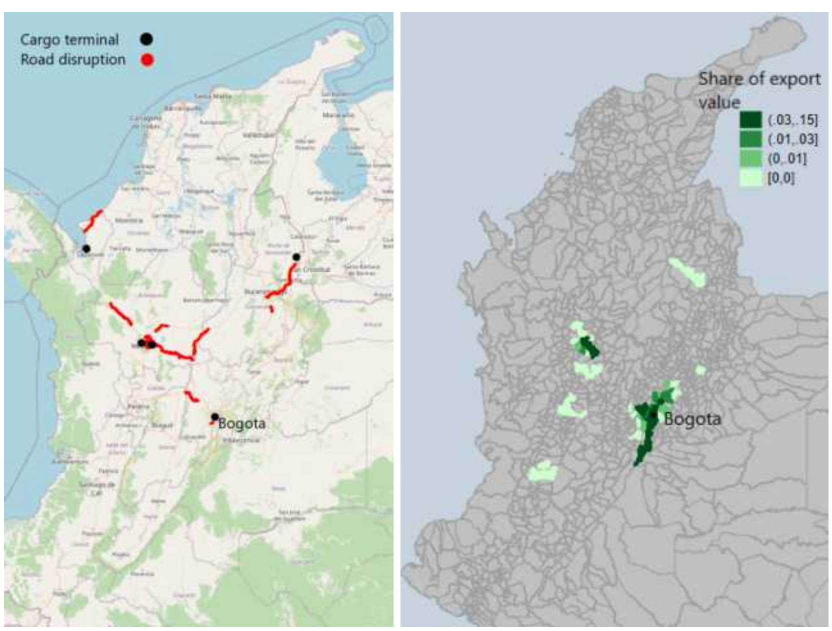
A Figures

Figure A.1: Production and exports of cut flowers

Source: MADR - ICA (2016).

Figure A.2: Disrupted roads, cargo terminals and production of flowers

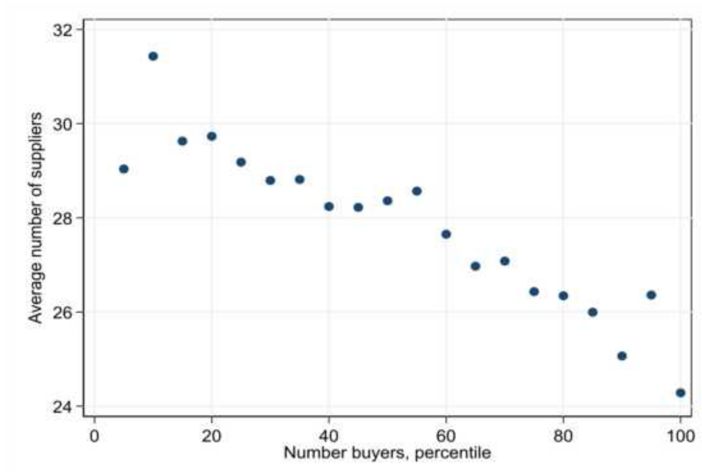


Notes: The figure on the left displays the roads disrupted between flower farms in red during La Niña 2010-11, and the cargo terminals used by flower exporters in black dots. Four out of the five cargo terminals are airports, while one (Apartado) in the North is a seaport. The figure on the right illustrates the market share of the municipality for all flower exporters during 2008-2009.

Figure A.3: Example of a reported road closure

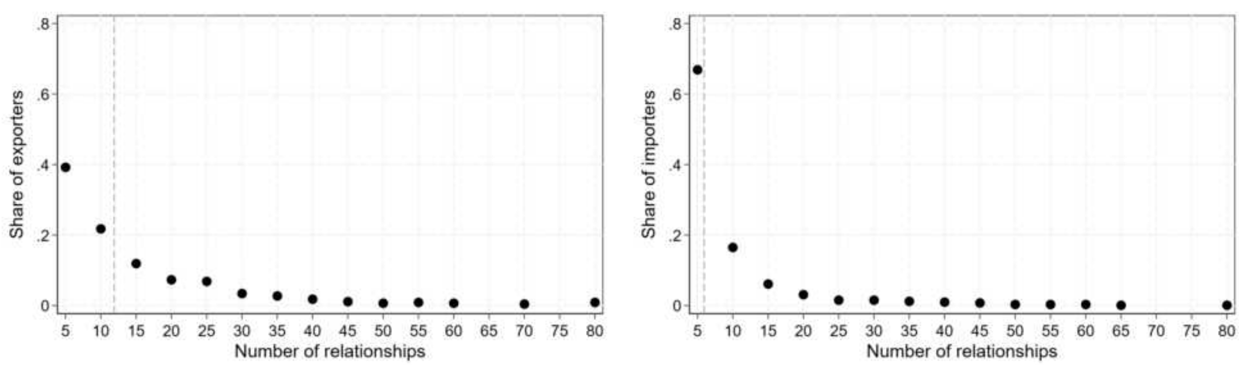
Notes:The figure illustrates an example of a road disruption. In the top panel, there's a photograph of the road shortly after the landslide, and in the bottom panel, there's a photograph of the same road after it was repaired.

Figure A.4: Degree assortativity for flower exporters with US importers



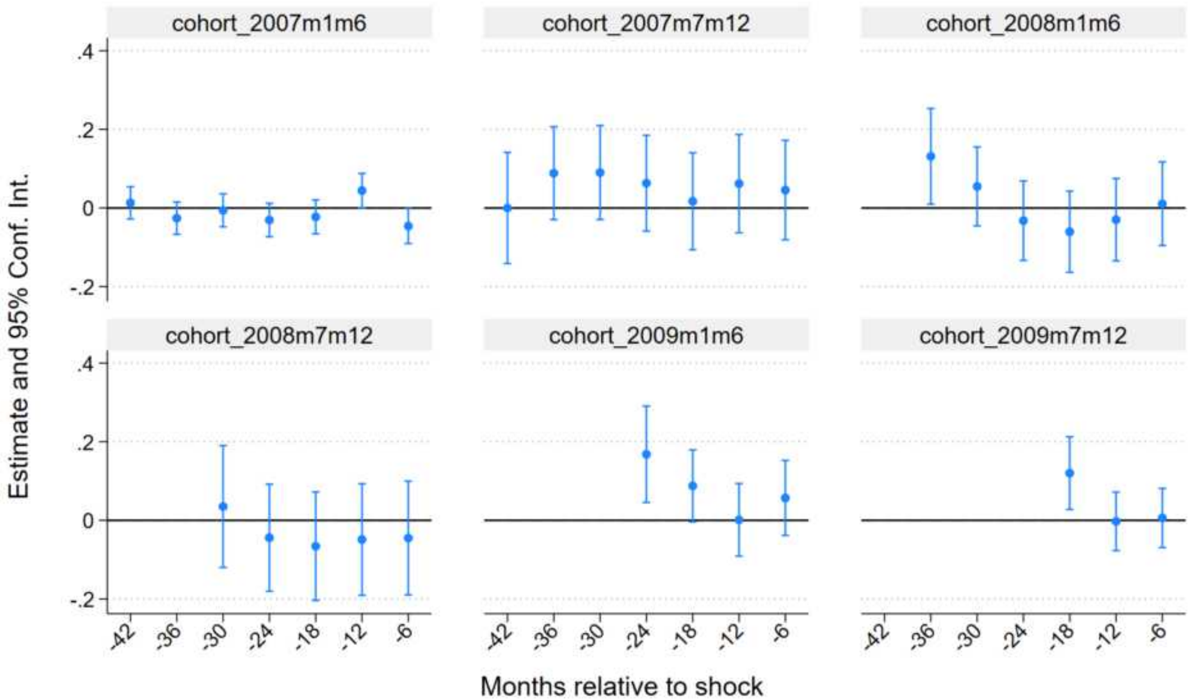
Notes: The figure shows the correlation between the average number of suppliers and the number of suppliers. Each bin shows groups of firms divided into 20 equal-sized bins by their log number of costumers, and computes the mean of the variables on the y and x-axis in each bin.

Figure A.5: Distribution of firms' portfolio in the pre-shock period



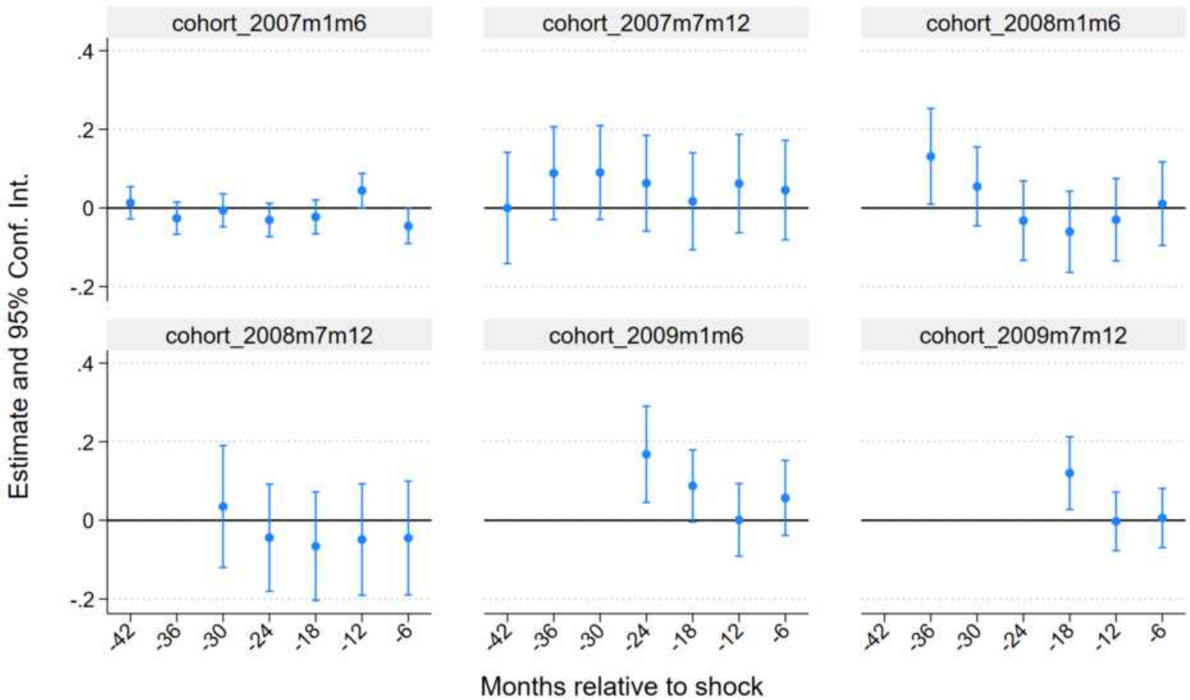
Notes: The figure shows the distribution of exporters and importers based on the number of relationships. The term "number of relationships" refers to the maximum total of active relationships a firm has within a specific six-month period. I group this number into bins of 5, with the last bin representing firms with more than 80 active relationships during a given six-month period. The analysis covers seven six-month periods from April 2007 to September 2010. I have also included data from January to March 2007 in the first period. The vertical line represents the mean of number of active relationships. The sample includes only firms that operate as producers, excluding intermediaries or firms with multiple locations.

Figure A.6: Validating the identification assumption



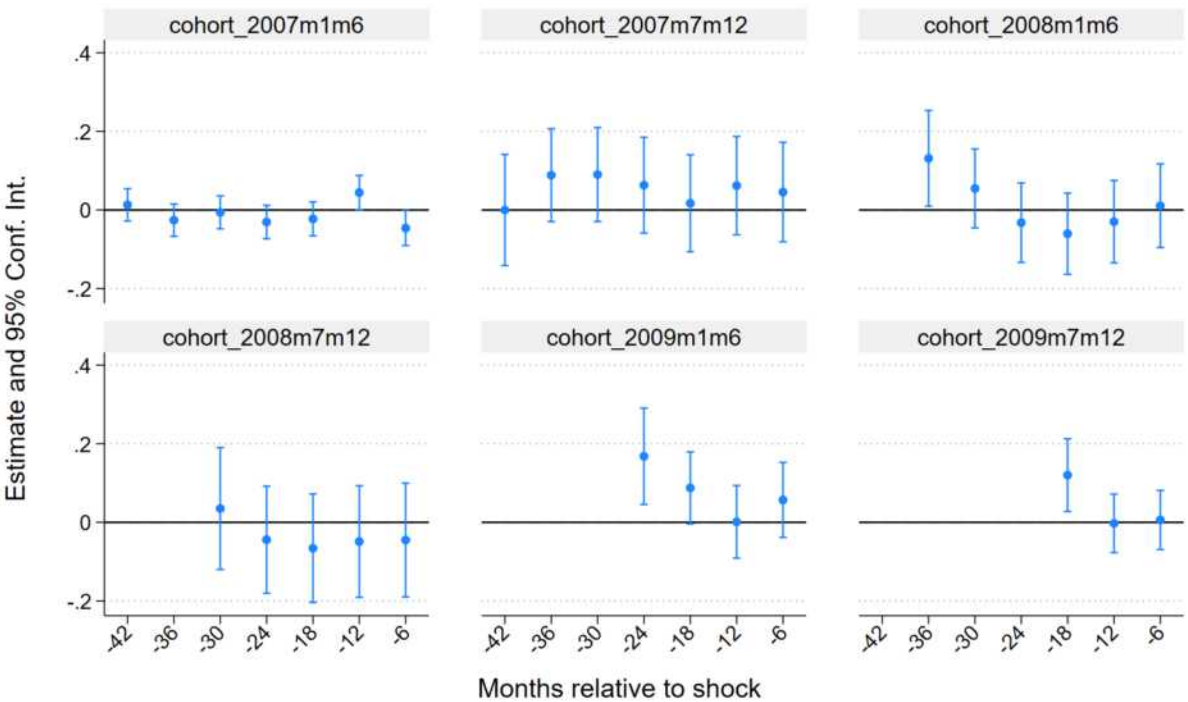
Notes: The figures shows estimated coefficients of the *relationship status* variable for each cohort for all the pre-shock periods between exposed and non-exposed relationships. Control variables are: importer, exporter fixed effects, and firm size bin interactions. The variable *exposure to the shock* is restricted to only origin-cargo terminal combinations used 24 months before the shock.

Figure A.7: Identification assumption: within importer variation



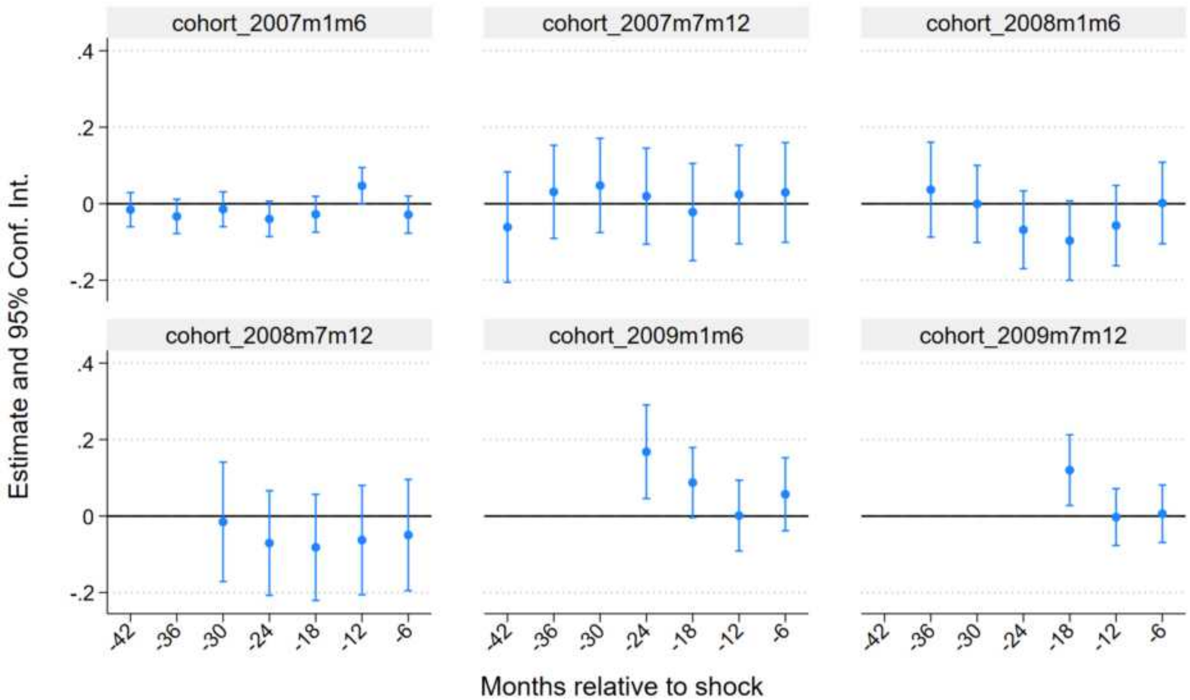
Notes: The figures shows estimated coefficients of the *relationship status* variable for each cohort for all the pre-shock periods between exposed and non-exposed relationships. Control variables are: importer-time, and exporter fixed effects, and firm size bin interactions. The variable *exposure to the shock* is restricted to only origin-cargo terminal combinations used 24 months before the shock period.

Figure A.8: Identification assumption: within relationships



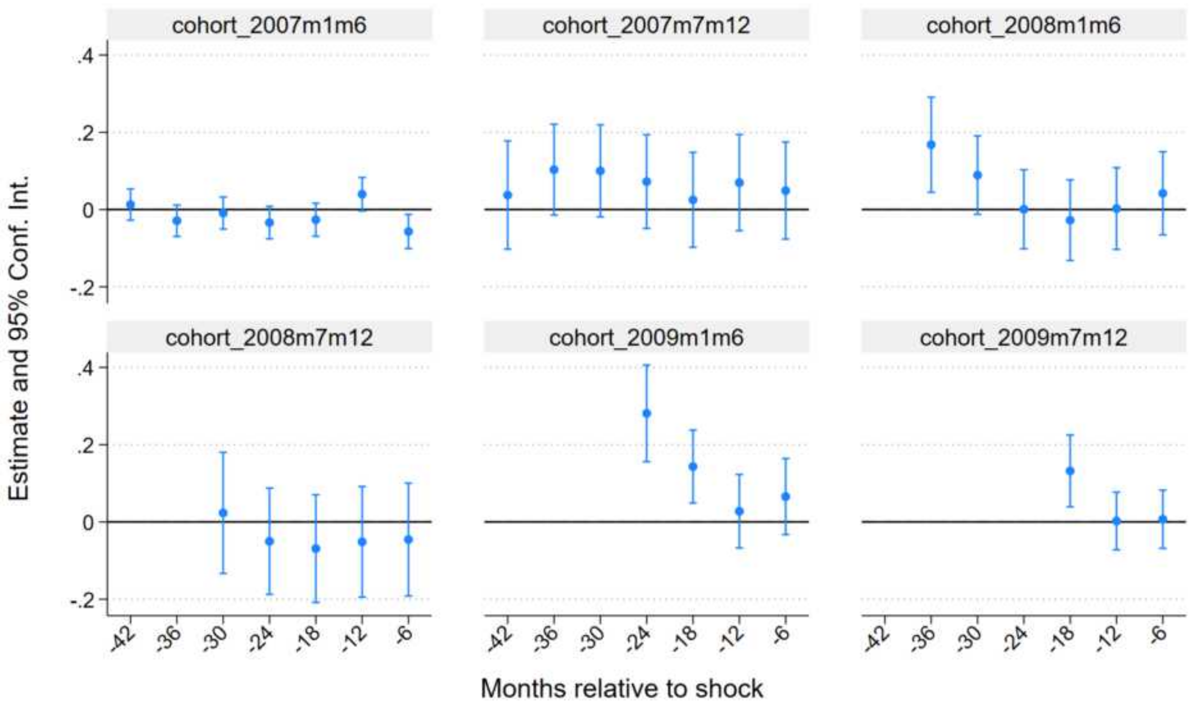
Notes: The figures shows estimated coefficients of the *relationship status* variable for each cohort for all the pre-shock periods between exposed and non-exposed relationships. Control variables are: importer, exporter and relationship fixed effects, and firm size bin interactions. The variable *exposure to the shock* is restricted to only origin-cargo terminal combinations used 24 months before the shock period.

Figure A.9: Identification assumption: alternative exposure to the shock measure



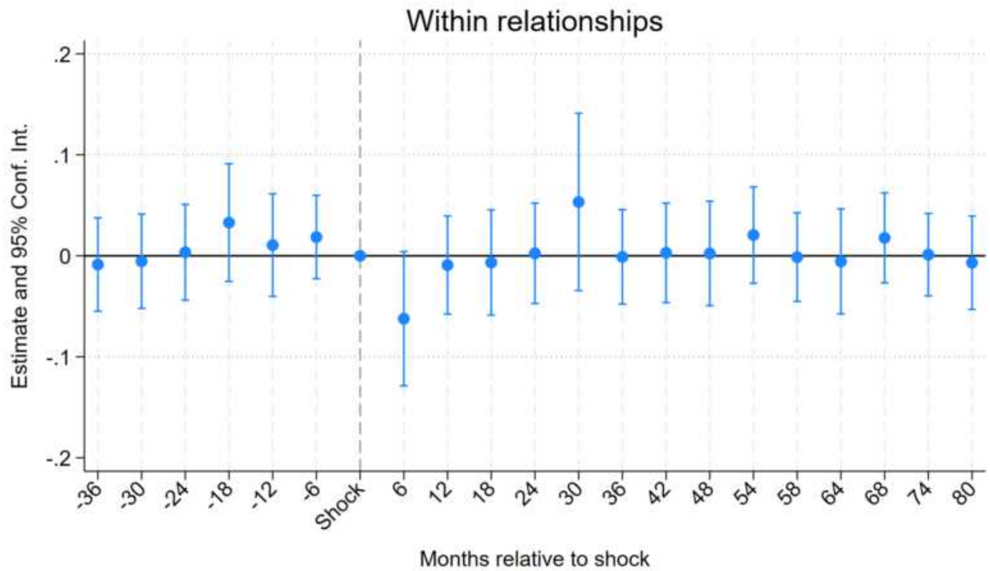
Notes: The figures shows estimated coefficients of the *relationship status* variable for each cohort for all the pre-shock periods between exposed and non-exposed relationships. Control variables are: importer, exporter and relationship fixed effects, and firm size bin interactions. The variable *exposure to the shock* is restricted to only origin-cargo terminal combinations used all months before the shock.

Figure A.10: Identification assumption: alternative exposure to the shock measure



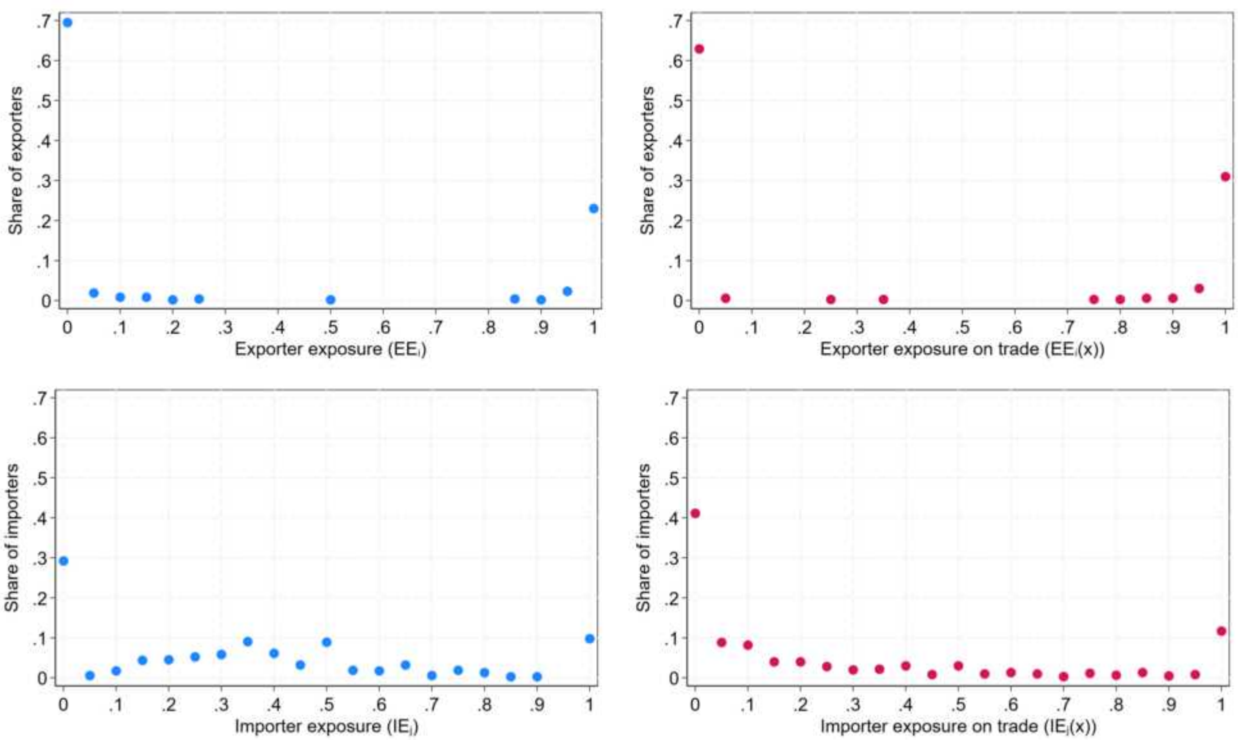
Notes: The figures shows estimated coefficients of the *relationship status* variable for each cohort for all the pre-shock periods between exposed and non-exposed relationships. Control variables are: importer, exporter and relationship fixed effects, and firm size bin interactions. The variable *exposure to the shock* is restricted to only origin-cargo terminal combinations used 12 months before the shock.

Figure A.11: Effect of road disruptions on the probability of ending a relationship, within-relationship variation



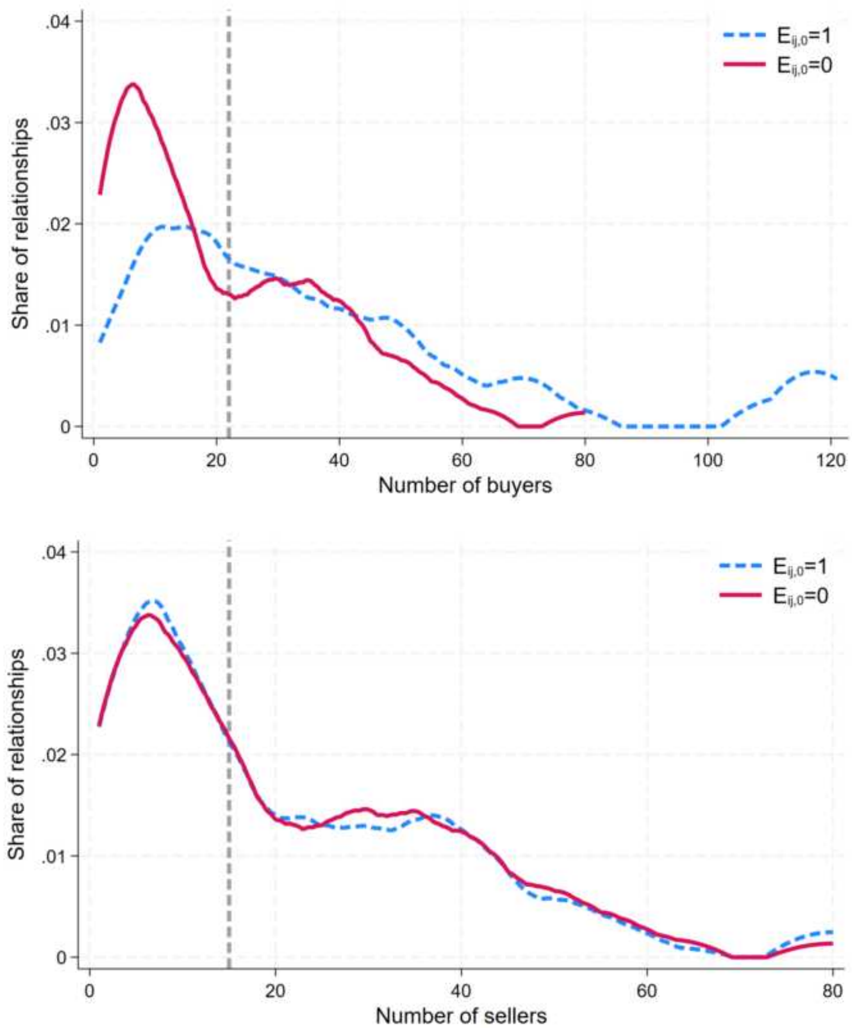
Notes: The figure plots the β_l coefficients from estimating equation (1) with an importer time fixed effect ψ_{jt} and the respective 95% confidence intervals. The variable *exposure to the shock* is restricted to only origin-cargo terminal combinations used 24 months before the shock. The sample includes exporter and importer firms active one year before the disruptions and all their relationships from the eight cohorts starting in 2007m1-m6 until the cohort of 2010m7-m9. All regressions control for firm fixed effects and firm size bin interactions, wave of exposure, indirect effects from exporter and importer, and fixed effects for importer, exporter, and cohort. The reported confidence intervals are estimated using standard errors clustered at the exporter level.

Figure A.12: Distribution of *exporter exposure* and *importer exposure*



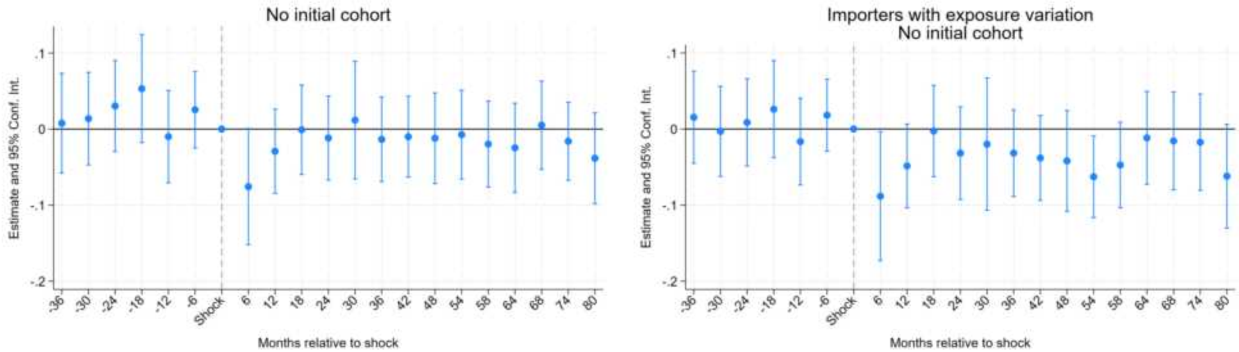
Notes: The figures show the distribution of the different measures of *firm exposure* for equally sized bins of 0.1. The top panel plots the *exporter exposure* and the *exporter exposure on trade*. The bottom panel plots the the *importer exposure* and the *importer exposure on trade*. The variable *exposure to the shock* used restricts to only origin-cargo terminal combinations used 24 months before the shock. For the *importer exposure* measures I include relationships with intermediaries, sellers with multiple farms and sellers in flooded areas.

Figure A.13: Distribution of firms' portfolios by *exposure to the shock* measures



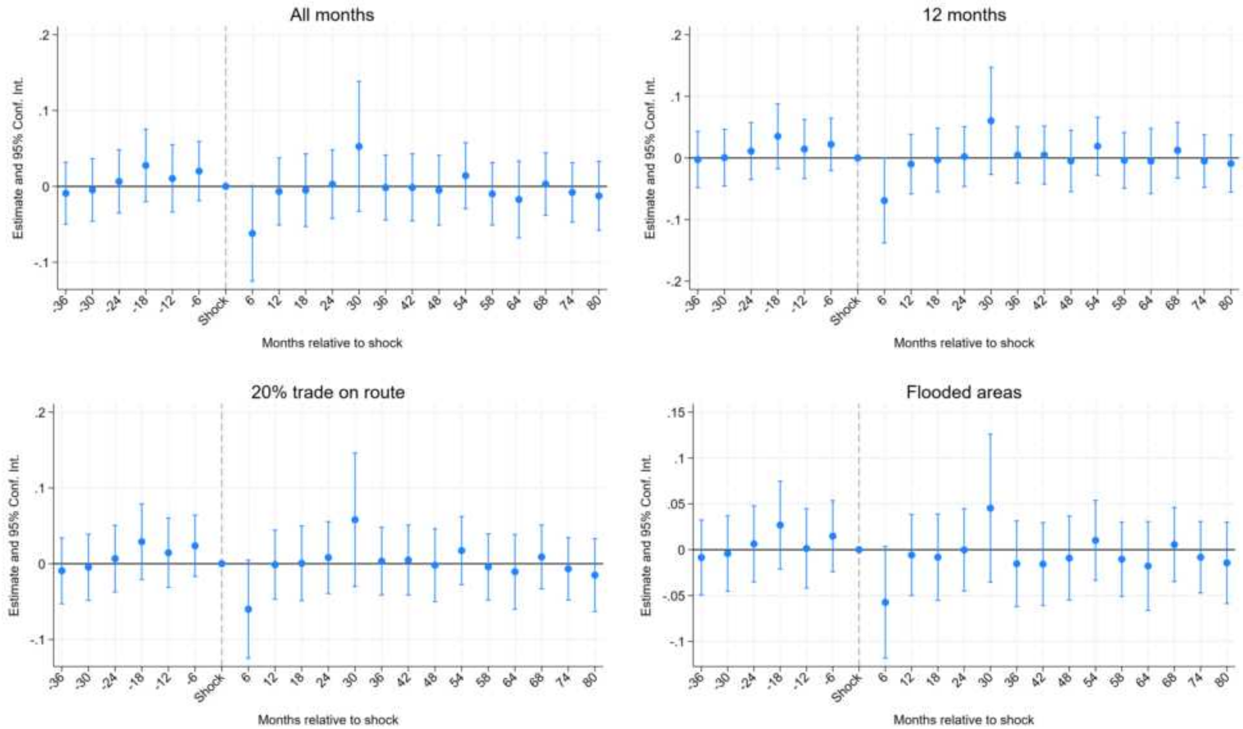
Notes: The figure shows the distribution of relationships by their *exposure to the shock*. The top panel groups relationships by the number of buyers from the exporter side of the relationship. The bottom panel groups relationships by the number of sellers from the importer side of the relationship. The vertical line shows the median of the distribution.

Figure A.14: Robustness: effect of road disruptions on the probability of ending a relationship



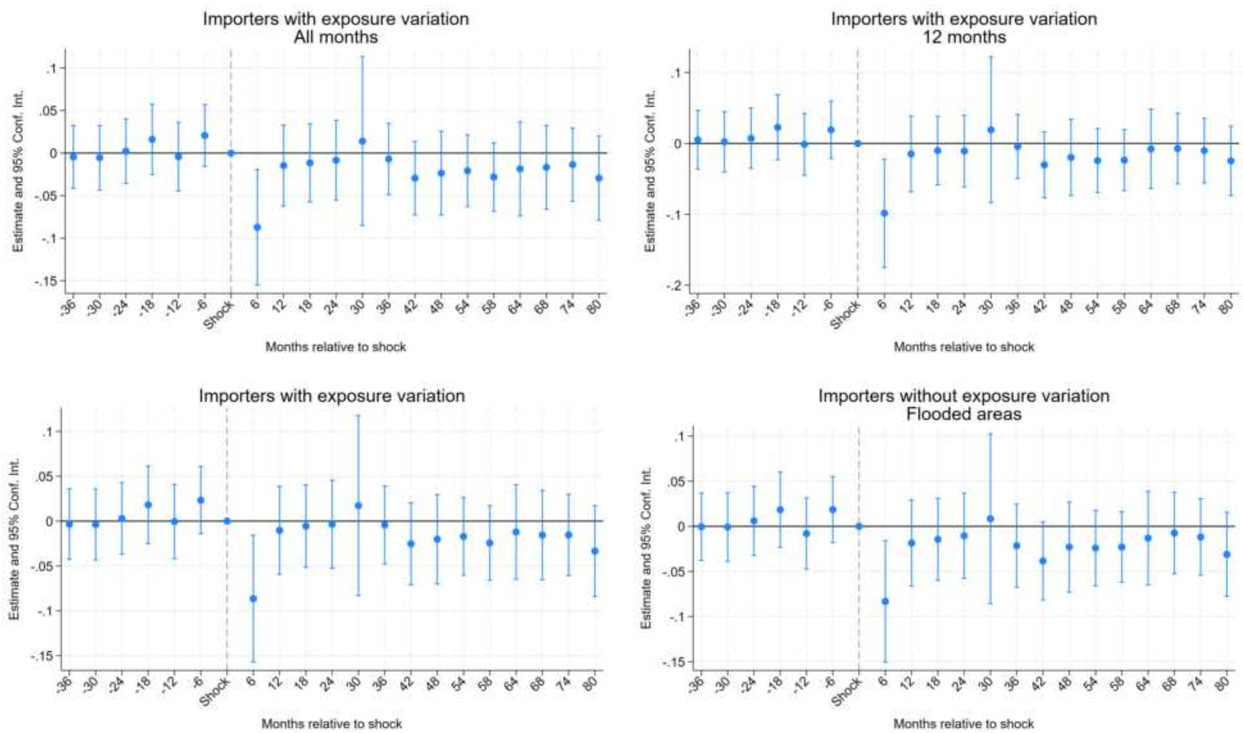
Notes: The figure plots the β_l coefficients from estimating equation (1) and the respective 95% confidence intervals. The variable *exposure to the shock* is restricted to only origin-cargo terminal combinations used 24 months before the shock. The sample includes exporter and importers firms active one year before the disruptions and all their relationships from the eight cohorts from 2007m1-m6 to 2010m7-m9. All regressions control for firm fixed effects and size bin interactions, wave of exposure, indirect effects from exporter and importer, and fixed effects for importer, exporter, and cohort. The reported confidence intervals are estimated using standard errors clustered at the exporter level.

Figure A.15: Robustness: effect of road disruptions on the probability of ending a relationship



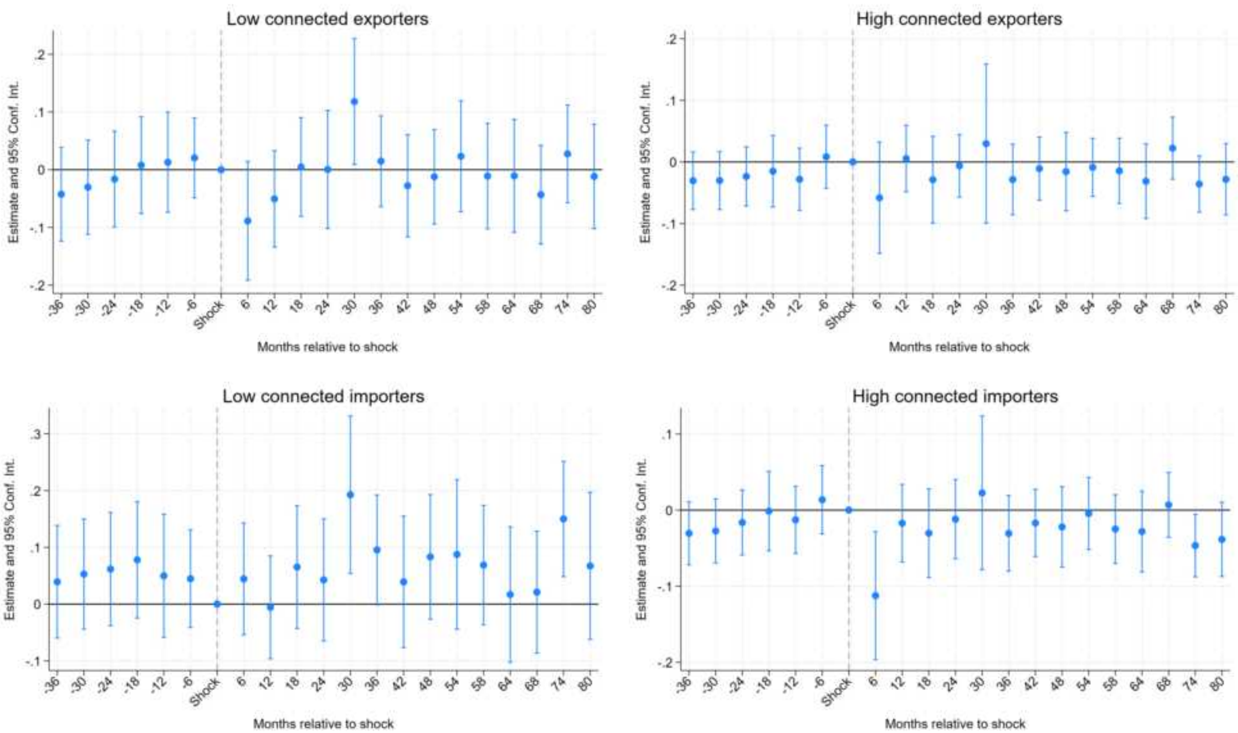
Notes: The figure plots the β_l coefficients from estimating equation (1) and the respective 95% confidence intervals. The variable *exposure to the shock* is restricted to only origin-cargo terminal combinations used 24 months before the shock. The sample includes exporter and importers firms active one year before the disruptions and all their relationships from the eight cohorts from 2007m1-m6 to 2010m7-m9. All regressions control for firm fixed effects and size bin interactions, wave of exposure, indirect effects from exporter and importer, and fixed effects for importer, exporter, and cohort. The reported confidence intervals are estimated using standard errors clustered at the exporter level.

Figure A.16: Robustness: effect of road disruptions on the probability of ending a relationship, within importers variation



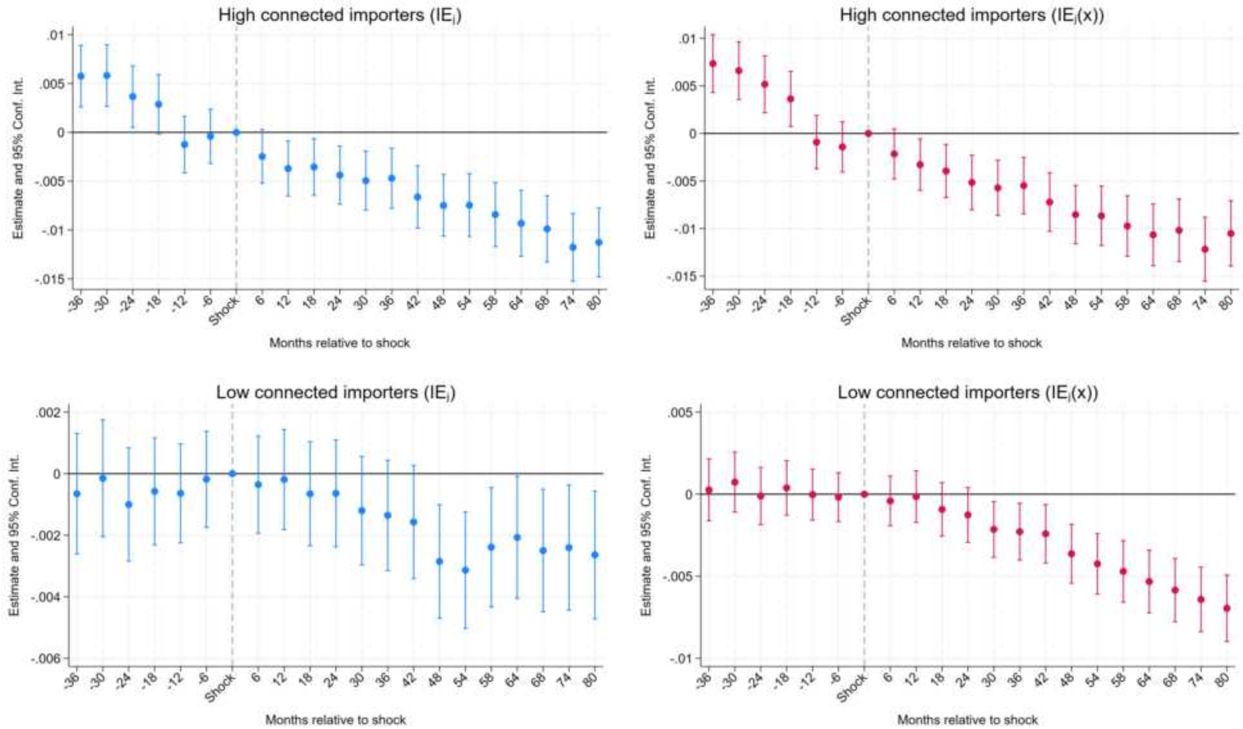
Notes: The figure plots the β_l coefficients from estimating equation (1) with an importer time fixed effect ψ_{jt} and the respective 95% confidence intervals. The variable *exposure to the shock* is restricted to only origin-cargo terminal combinations used 24 months before the shock. The sample includes only importers with within relationship variation in the *exposure to the shock* variable and only considers exporters and importers firms active one year before the disruptions and all their relationships from the eight cohorts from 2007m1-m6 to 2010m7-m9. All regressions control for firm fixed effects and size bin interactions, wave of exposure, indirect effects from exporter and importer, and fixed effects for importer, exporter, and cohort. The reported confidence intervals are estimated using standard errors clustered at the exporter level.

Figure A.17: Probability of ending relationships by *importer exposure*



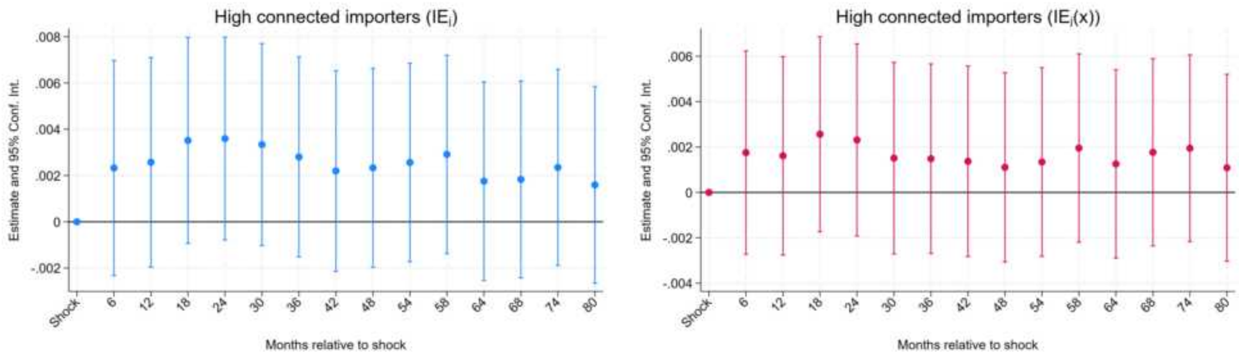
Notes: The figure plots the β_l coefficients from estimating equation (1) for sub-sample of 'low' connected exporters ans importers and 'high' connected importers and exporters with their respective 95% confidence intervals. The variable *exposure to the shock* is restricted to only origin-cargo terminal combinations used 24 months before the shock. The 'low' connected firms are classified as those below the median number of connections the year before the road disruptions, and 'high' connected firms above the median. The sample includes only importers with within relationship variation in the *exposure to the shock* variable and only considers exporters and importers firms active one year before the disruptions and all their relationships from the eight cohorts from 2007m1-m6 to 2010m7-m9. All regressions control for firm fixed effects and size bin interactions, wave of exposure, indirect effects from exporter and importer, and fixed effects for importer, exporter, and cohort. The reported confidence intervals are estimated using standard errors clustered at the exporter level.

Figure A.18: Probability of forming a new relationship with incumbent seller



Notes: The figure plots the β_l coefficients from estimating the following equation for each sub-sample of 'high' and 'low' connected importers and their respective 95% confidence intervals: $\mathbb{1}\{y_{ijt} = 1\} = \sum_l \beta_l E_{j,0} \cdot \mathbb{1}\{t = l\} + \gamma X'_{ij} + \psi_i + \varphi_j + \varepsilon_{ijt}$, where $\mathbb{1}\{y_{ijt} = 1\}$ takes the value of one for an active relationship and zero otherwise. Relationships that are no longer active are not included in the sample. $E_{j,0}$ takes the value of one for relationships linked to an importers with a 'high' exposure to the shock using the measures IE_j and $IE_j(x)$. The variable *exposure to the shock* is restricted to only origin-cargo terminal combinations used 24 months before the shock. The 'low' connected firms are classified as those below the median number of connections the year before the road disruptions, and 'high' connected firms above the median. The sample includes only importers active one year before the disruptions and exporters that before the shock are serving the US market. All regressions control for exporter fixed effects and importer lagged size bin interactions, importer fixed effects and exporter lagged size bin interactions, as well as fixed effects for importer, exporter, and period.

Figure A.19: Probability of forming a new relationship with entrant seller



Notes: The figure plots the β_l coefficients from estimating the following equation for each sub-sample of 'high' and 'low' connected importers and their respective 95% confidence intervals: $\mathbb{1}\{y_{ijt} = 1\} = \sum_l \beta_l E_{j,0} \cdot \mathbb{1}\{t = l\} + \gamma X'_{ij} + \psi_i + \varphi_j + \varepsilon_{ijt}$, where $\mathbb{1}\{y_{ijt} = 1\}$ takes the value of one for an active relationship and zero otherwise. Relationships that are no longer active are not included in the sample. $E_{j,0}$ takes the value of one for relationships linked to an importers with a 'high' exposure to the shock using the measures IE_j and $IE_j(x)$. The variable *exposure to the shock* is restricted to only origin-cargo terminal combinations used 24 months before the shock. The 'low' connected firms are classified as those below the median number of connections the year before the road disruptions, and 'high' connected firms above the median. The sample includes only importers active one year before the disruptions and exporters serving the US market for the first time after the shock. All regressions control for exporter fixed effects and importer lagged size bin interactions, as well as fixed effects for importer, exporter, and period.

B Tables

Table A.1: Sample of roads disrupted

Route	Closing date
Las Palmas-Medellin	Nov-10
Santa Elena-Medellin	Nov-10
Necocli - Arboletes	Nov-10
Dabeiba - Sta Fe de Antioquia	Sep 2010 ; April 2011
Honda-Villeta	Apr-11
Autopista Medellin-Bogota	Nov-10
Los curos - Pescadero	May-11
Puerto Berrio - Puerto Boyaca	Apr-11
Autopista Sur - Soacha	Nov-10
Barbosa - Cisneros	Sep 2010, April 2011
Bucaramanga - Cucuta	Nov 2010 ; April 2011

Notes: The table displays all the road disruptions considered in the analysis based on the criteria: 1) closed during the rain season due to landslides or flooding events, 2) closed for more than one week, 3) located in between the routes to the cargo terminals of flower exporters.

C Classification of road disruptions

I estimate the route to the cargo terminals using the farms' municipality center or main city. SICE-TAC software from the Ministry of Transport provides routes offered by transportation service companies providing inter-municipal transport services. As a baseline, I used a truck with two edges and a container trailer, estimated 1 hour for each load and unloaded waiting times. The software supplies information from specific locations, mainly distribution centers such as Bogota and Medellin and other secondary cities. It also gives the time and cost per km for the specified origin destination. Most importantly, it gives the exact route by giving the tolls trucks will go through. For some routes, there are two main alternatives; I consider both if there is such a case.

For simplicity, on the multiple dates of disrupted routes, I collapsed the disruptions in two waves: the first occurring from October 2010 to April 2011 and the second from May 2011 to June 2011. For any closure in the wave, I estimate the benchmark route using the software and benchmark configuration available for inter-state trips only. The routing is done for all the possible combinations of origin-cargo terminal combinations and then repeated when a road disruption happens. In this second repetition, I estimate the possible route considering the road disruption and take the total distance of the best new alternative course. If the alternative is a longer distance, I consider the disruption valid; otherwise, I do not.

D Mathematical appendix

D.1 Relationship surplus: additional cases

Keeping and matching compared to keeping and not matching. The relationship surplus is

$$\Delta\pi_{ij} = \Delta(\pi^j) + \Delta(\pi^i) = -(\rho^j + \rho^i). \tag{10}$$

Keeping and matching compared to not keeping and matching. The relationship surplus is

$$\Delta\pi_{ij} = \Delta(\pi^j) + \Delta(\pi^i) = -\lambda. \tag{11}$$

D.2 Prediction 1

Proof. Revenues are concave in Q, with $\frac{\partial R(.)}{\partial Q} > 0$ and $\frac{\partial^2 R(.)}{\partial Q} < 0$, and that costs are convex in Q, with $\frac{\partial C(.)}{\partial Q} > 0$ and $\frac{\partial^2 C(.)}{\partial Q} > 0$. Given these convexity and concavity assumptions, the following holds:

$$\frac{\partial R(S_{j,-i} + q_{ij})}{\partial S_{j,-i}} < \frac{\partial R(S_{j,-i})}{\partial S_{j,-i}};$$

as well as

$$\frac{\partial C(S_{j,-i} + q_{ij})}{\partial S_{j,-i}} > \frac{\partial C(S_{j,-i})}{\partial S_{j,-i}}.$$

Assuming that $\rho^j + \rho^i - \lambda > 0$, we then have

$$\Big(R(S_{j,-i} + q_{ij}) - C(S_{j,-i} + q_{ij})\Big) + \rho - \lambda > \Big(-R(S_{j,-i}) + C(S_{j,-i})\Big).$$

□

D.3 Prediction 2

Proof. I assume revenues are concave in Q, with $\frac{\partial R(.)}{\partial Q} > 0$ and $\frac{\partial^2 R(.)}{\partial Q} < 0$, and that costs are convex in Q, with $\frac{\partial C(.)}{\partial Q} > 0$ and $\frac{\partial^2 C(.)}{\partial Q} > 0$. Given these convexity and concavity assumptions, the following holds:

$$\frac{\partial R(S_{j,-i} + q_{ij})}{\partial q_{ij}} > \frac{\partial R(S_{j,-i})}{\partial q_{ij}};$$

as well as

$$\frac{\partial C(S_{j,-i}+q_{ij})}{\partial q_{ij}} > \frac{\partial C(S_{j,-i})}{\partial q_{ij}}.$$

A decrease in q_{ij} therefore results in

$$\Big(R(S_{j,-i}+q_{ij}) - C(S_{j,-i}+q_{ij})\Big) < R(S_{j,-i}) + C(S_{j,-i}).$$

Assuming that $\rho^j + \rho^i - \lambda > 0$ the effect on the surplus is then

(i) negative when

$$\Big(R(S_{j,-i}+q_{ij}) - C(S_{j,-i}+q_{ij}) - R(S_{j,-i}) + C(S_{j,-i})\Big) > \rho^j + \rho^i - \lambda;$$

(ii) positive when

$$\Big(R(S_{j,-i}+q_{ij}) - C(S_{j,-i}+q_{ij}) - R(S_{j,-i}) + C(S_{j,-i})\Big) < \rho^j + \rho^i - \lambda.$$

□