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

Alejandra Martinez

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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 percentage points *less* likely to end during the road disruptions. These results are driven by importers that can hedge against non-deliveries by relying on current relationships. A firm-level exposure measure shows that relationships linked to importers who cannot rely on other current relationships for sourcing are *more* likely to end. I present a theoretical framework that rationalises the decision to keep or replace a relationship based on (1) the relative cost of establishing a new trade relationship, and (2) firm profits affected by other exposed relationships. 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 mostly 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] I find that during the first six months of the shock, relationships exposed to road disruptions are actually *less* likely to be terminated by 7 percentage points. Importers are fixed in these estimations, so these are comparisons within importers' portfolios of relationships. A year after the first road closures the effect is still negative and only significant at the 90% and the probability is around 5 percentage points. The 7 percentage point decrease represents a 37% deviation from the baseline population mean of 0.19 of the share of relationships ending in any given period before the shock.

The second analysis examines whether a relationship-level shock generates a firm response, given that some importers have more extreme exposures. I calculate the share of relationships in an importer's portfolio that are exposed to the shock and the share of the importer's total trade that is exposed to the shock to measure exposure to road disruptions at the importer level. With the importer exposure measures through relationships and through trade, I compare importers with high exposure to the shock to importers with low exposure to the shock. I find that relationships from importers who are highly exposed to the shock are more likely to end after the shock by 6 percentage points, and the effect persists in the medium to long run.

Using the relationship-level and firm-level analysis, I can interpret these results. There is not enough variation for exporters to understand differential responses within a portfolio of relationships, since all relationships are exposed or not since they are routed to the same cargo terminals. Alternatively, since the empirical analysis relies on the variation in relationships between importers and Colombian exporters that are affected or not by road disruptions, we can gain a deeper understanding of importers' responses within their portfolios. I find that interestingly exposed relationships that importers source from during the crisis are less likely to end. A crisis tends to make importers more dependent on deliveries already contracted with suppliers. Most importers source from producers in regions where all firms in those regions have experienced disruptions or from producers in regions where none have. When a crisis occurs, importers maintain relationships with sellers who are located in areas with road disruptions to the cargo terminals since they cannot afford to find new contracts in these areas. My findings are similar to Goldberg and Reed (2023) who find that the separation rate for US firms falls during the COVID pandemic. The explanation the authors give is also related to the fact that firms subject to disruption depend on current relationships during a crisis.

Additionally, I discuss some evidence regarding firm characteristics that may contribute to under-

[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.

standing the empirical results. First, I construct a measure of importer dependence on and supplier outdegree, following Khanna, Morales, and Pandalai-Nayar (2022), and a measure of importer connectivity. Rather than having higher separations during the crisis, high-connected importers are incapable of replacing their exposed relationships. These results can be explained by the fact that these importers rely heavily on their suppliers (high outdegree) since these relationships are less likely to end during a crisis.

As a conclusion to the empirical results discussion, I discuss some possible explanations based on the long-term effects of temporary disruptions. One possible explanation comes from importers changing their perception on the flooding risk from extreme weather events as in Balboni, Boehm, and Waseem (2023). In other words, after these unprecedented flooding and firms experiencing delays on their flower deliveries, affected importers may decide to diversify and divert business to other supplier countries to avoid future over-reliance on Colombian flower exporters that are vulnerable to flooding disruptions. In addition to a change in the flooding risk perceived by importers, an alternative explanation can be that importers highly exposed are forced to find new suppliers during a crisis. If those importers that had to search for new suppliers are able to match with sellers with better deals, this can trigger importers willingness to restructure their current portfolio.

I test in the data whether high exposed importers create or not new matches within Colombia. I find that high exposed importers initiate more new relationships after the shock, and the effect lasts no more than three years. The effect only applies to new relationships involving entrant firms that aren't serving the U.S. market. Additionally, the probability of matching with an incumbent exporter–those that had already been serving the US market before the crisis–is negative, and the effect lasts for a long time. The diversification away of these firms cannot be assured without knowing their entire portfolio of importers in other countries, but these results suggest that while importers find substitutes in the years following the shock, there is a more persistent effect where importers highly affected by the shock do not create new relationships with Colombian exporters.

In the final section, I present a theoretical framework that formalises 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 (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 utilises 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 behaviour 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 (forth-

[5]Related to shock propagation in production networks, a recent literature has focused on the COVID-19 pandemic. See Goldberg and Reed (2023), Khanna, Morales, and Pandalai-Nayar (2022), Lebastard and Serafini (2023) and Lebastard, Matani, and Serafini (2023).

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

coming) 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. Because spot markets are well-functioning, they can estimate lower bounds on relationship values in this context by evaluating exporters' temptations to depart from contractual obligations. Unlike the case of Kenyan rose exporters, supply relationships between Colombian flower exporters and US importers do not coexist 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

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

[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.

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.

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

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

[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

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 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.

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.[15]

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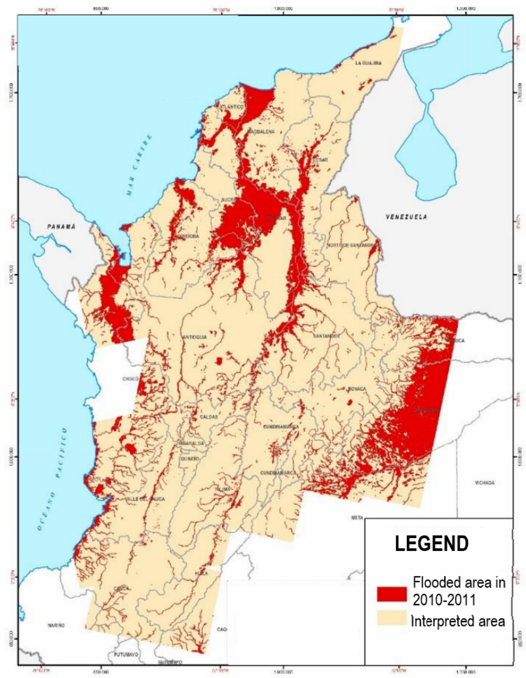
flooding events. See Chatzopoulos, Domínguez, Zampieri, and Toreti (2020), Bednar-Friedl, Knittel, Raich, and Adams (2022), Ghadge, Wurtmann, and Seuring (2019), and Mekbib, Wossen, Tesfaye, and von Braun (2017) for studies on climate change and its effects on prices.

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

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

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 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 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.[16] 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%).[17]

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

[16]Figure A.1 displays the quantities of production and exports from 2002 to 2014. Figure A.2 shows the total KG of exported flowers from Colombia to all trading partners and the trade value in USD. There is a drop if the KG of flowers exported in 2009 (when the financial crisis hit) and after the rain season that lasts for two years. Figure A.3 shows road disruptions during La Niña 2010-11 and the location of producers.

[17]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 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.

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%.[18] 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."[19] This is just one example of how important connections between buyers and sellers is in this market.

During La Niña episode in 2010-11 flooding to flower production 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.[20]

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

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

[19]Source: www.silvestres.com/company. During interviews that I conducted with three other Colombian flower producers, the mention of establishing strong business relationships with sellers was also common sentiment.

[20]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.

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.

In the customs data there are 29,178 buyer-seller relationships for the US and Colombian flower market classified in the Harmonised System 2-digit code 06 which encompasses all "Trees and other plants, live; bulbs, roots and the like; cut flowers and ornamental foliage".[22] 94% of the monthly transactions are on "cut flowers" products (Harmonised System code "0603"). Within these firms there are around 1,151 flower exporters that trade with 1,716 importers that are based in the US mainland or Puerto Rico. The continental US and Puerto Rico are about 98% of flower exports to the US.

3.2 Data on road disruptions and routes to ports

For road disruptions I draw on sources compiled by different governmental organisations. 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.

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.[23]

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

[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.

[22] This number of relationships only considers importers in the US and Puerto Rico in addition to importers were is possible to construct a unique name identifier. The number of relationships without these criteria is 29,827.

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

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.

I use the Chamber of Commerce web page to find information about the activity of 96% of them.[24] From the 1,151 flower exporters, 304 firms are classified as intermediaries (non-producers), 760 as producers and the remaining 87, 52 of them were not found at all in the registry, and 35 do not have an activity. For the producers 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.[25] After locating the sites of production if existent, I found 678 flower producers with farms in one municipality and 41 producers who have farms in multiple municipalities. Only 44 producers have missing farm location.

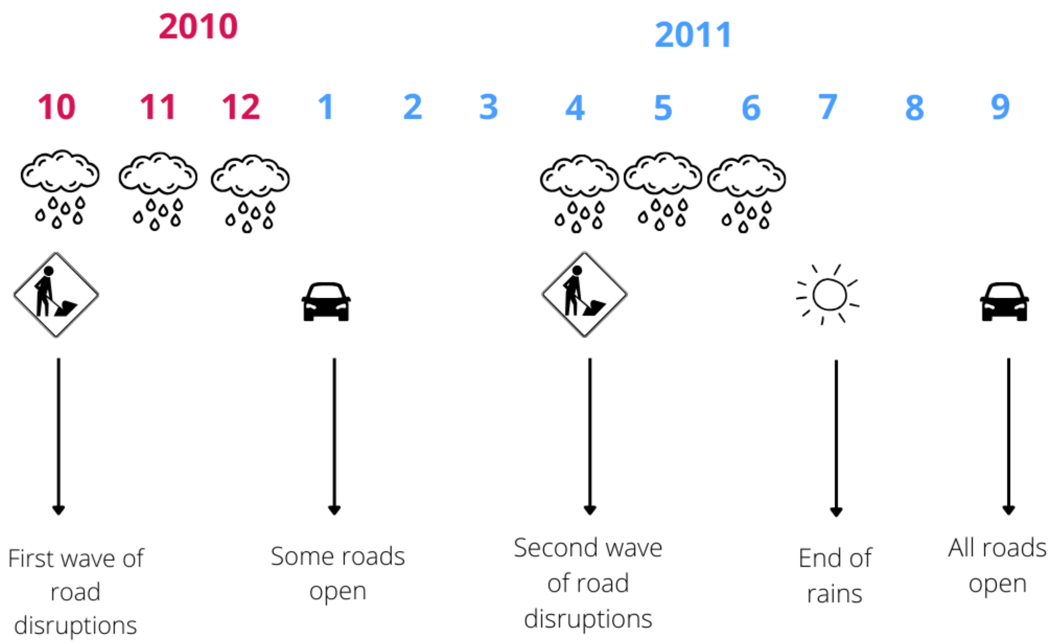
3.4 Setting

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

[24]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.

[25]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



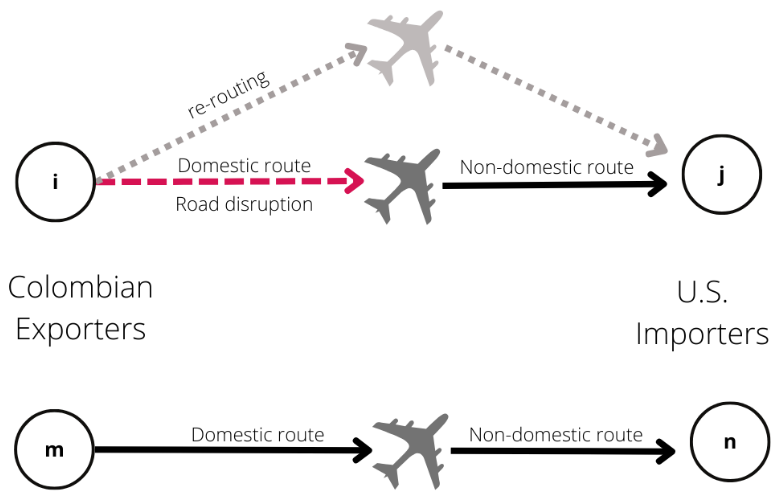
Notes: The diagram shows the timeline of the La Niña event. The rains started in October 2010 and ended in June 2011. The flooding happened in two waves, one from October to December 2010, followed by a second wave from April to June 2011. During both waves multiple road disruptions happened around the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

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 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.

It is most likely that exporters tend to use similar routes to cargo terminals across all their relationships. Because of this reason, the identification is primarily based on the variation across

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.

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 exploit the variation across exporters in different regions when fixing the importer side of the relationship. Referring to Figure 3, in the empirical analysis I compare 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. Using non-calendar six-month periods, 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 month transactions. The panel fills out all months in which firms transact or do not transact between the first and last month 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 in a six-month period if the relationship is active in the balanced panel. If a relationship's last transaction occurs in any month within a six-month period, then I give a value of one in this period. This measure is a complete duration, which means a relationship is only active if it is observed during the entire length of the period. Once a relationship has a value of one in a given period, it's status is considered not active and the relationship observation disappears from the data in the following period.

Figure 4 illustrates how the *relationship status* variable would look for two example relationships in the data when using the time divided into similar length periods. In Example 1 there are four rows, the first row is the raw data, and the second and third row are constructed from the raw data. The last row indicates the period respectively. The first row refers to the 'observed data'. The blue dots indicate that a relationship is observed in the customs data, which means any transaction observed within the period. The second row, the 'panel data', is constructed from the 'observed data'. Red dots indicate that the relationship is active, but not necessarily observed to be transacting at every period. 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 the last period a relationship is active. A relationship ends when there are no more transactions observed, and the last transaction could occur before the end of the period.

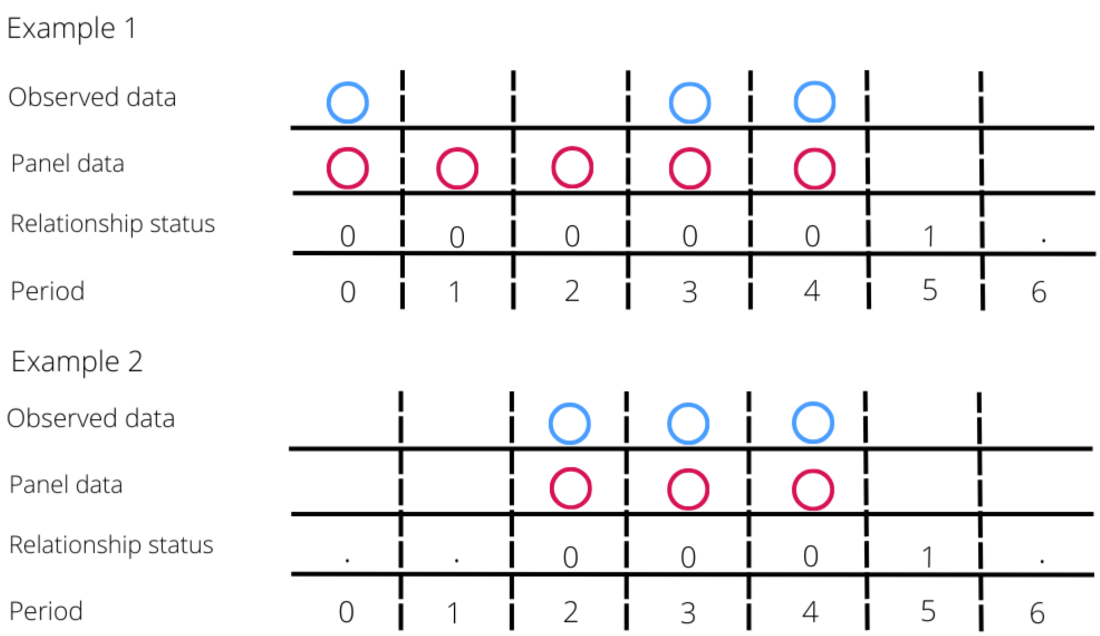
Example 2 demonstrates another scenario that is likely to be observed in the customs data set. This example shows how to deal with observations that are not observed throughout the entire timeline. In this specific example, the 'observed data' and 'panel data' rows are the same, but are not observed at the beginning of the sample. In this case, the *relationship status* variable will be missing in periods 0 and 1.

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 which can result in classifying them as not active. As a solution to the right censoring problem, I have cut the timeline in 2017. The assumption here is that firms are less likely to stop trading for more than three years in a row.[26]

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 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

[26]There are 28,679 exporter-importer relationships with identified names and locations for the entire US and Colombian flower sector. About 7% of them have stopped trading for at least a year in a row, and approximately 74% of these spells lasted less than three years. A spell, i.e. no transaction, that lasts more than three years occurs in only 2% of the universe of relationships.

Figure 4: Constructing the *relationship status* variable



Notes: Figure 4 illustrates how the *relationship status* variable would look for two example relationships in the data when using the time divided into similar length periods. In Example 1 the first row refers to the 'observed data'. The blue dots indicate that a relationship is observed in the customs data, which means any transaction observed within the period. The second row, the 'panel data', is constructed from the 'observed data'. Red dots indicate that the relationship is active, but not necessarily observed to be transacting at every period. 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 the last period a relationship is active. A relationship ends when there are no more transactions observed, and the last transaction could occur before the end of the period. Example 2 demonstrates another scenario that is likely to be observed in the customs data set. 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.

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.

3.5 Summary statistics

The first section describes the estimation sample used in the empirical analysis. The second section examines the *relationship status* variable by relationship cohort. The third section gives an overview of the location of relationships in Colombia by municipality and by their classification 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). In the final section, some summary statistics are presented describing relationship-level variables for the pre-shock period, which is based on equal six-month periods starting in April 2007 and ending in September 2010.

Estimation sample. The empirical analysis includes: importers with a unique identifier and excludes importers whose final destination is outside the US or US Puerto Rico, i.e. Guam, Alaska, and Hawaii. In the main estimations, I exclude all new relationships that are active from October 2010 onwards, since for these relationships the shock is no longer random, but new relationships are included in other analysis.

For the pre-shock period, January 2007 to September 2010, the sample includes 10,666 relationships within, 742 exporters and 1,013 importers. For the estimations comparing between exposed and not exposed to the shock, which excludes exporters with multiple farms and intermediaries and in flooded areas I end up with 6,854 relationships. The trade share of this selected sample of relationships is 56%. 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

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	1,284	697	1,238	682	1,233	667
2007m7-m12	321	198	311	192	310	190
2008m1-m6	412	289	399	283	399	277
2008m7-m12	278	200	274	198	276	190
2009m1-m6	317	477	317	477	300	456
2009m7-m12	344	854	344	854	341	848
2010m1-m6	473	492	473	492	473	492
2010m7-m9	90	128	90	128	90	128
Total	3,519	3,335	3,446	3,306	3,422	3,248

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.

exercises, as well as in estimations where it is important to account for all importer relationships.

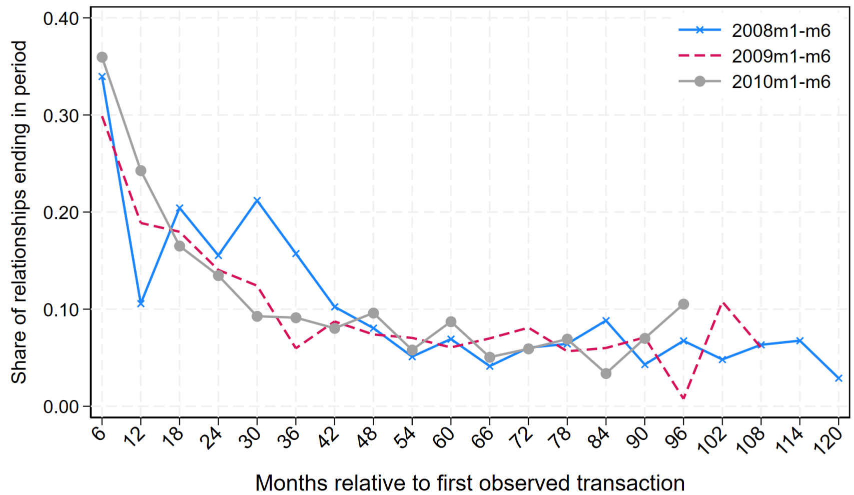
Table 1 displays the 6,854 relationships according to their classification of the three versions of the variable *exposure to the shock*. I split relationships in cohorts, where a relationship's cohort is based on its first observed transaction within a six-month period.[27] Each cohort period corresponds to six 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).[28]

Relationship status. Figure 5 plots the share of relationships ending for three selected cohorts, where

[27]The duration of the relationship is chosen based on evidence that trade relationships do not experience frequent 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 also split the data in three-month periods for robustness analysis (see Figure A.8)

[28]My observations are truncated in the left, since I only observe relationships from January 2007. I also estimate a set of results when excluding the cohort 2007m1-m6 in the Appendix Figure A.7.

Figure 5: Share of relationships ending in a given period



Notes: The figure plots the share of relationships within the selected cohorts that end in a particular period from the remaining relationships.

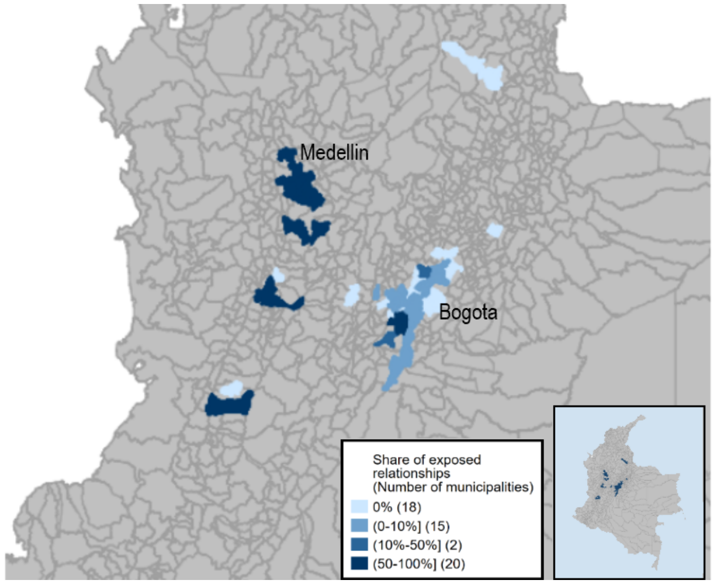
the relationships ending are those with a *relationship status* equal to one. Despite selecting three age cohorts for this figure (2008m1-m6, 2009m1-m6 and 2010m1-m6), the patterns are similar for all eight cohorts. Two observations can be made based on the graph. First, relationships will likely end at a higher rate within the first year from their first transaction.[29] Second Figure 5 shows that the share of relationships ending the first year from their observed first transaction can be between 30 and 40%. However, two years after the first transaction, the share of relationships that end is already between 10% and 20% if the relationship was active during the previous period. The shares are more stable after three years and range between 5 and 10%. Based on this analysis, it appears that comparing ending probabilities of different relationships should be within cohorts.

Exposure to the shock. 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

[29] 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.

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



Notes: This map zooms in on municipalities with flower producers. In each municipality I estimate the share of relationships that are exposed to the shock. Darker blue shadings indicate municipalities with a high number of relationships that are exposed to the shock. 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.

disruptions in the first wave occurred near the cargo terminals of Medellin and Rionegro (Figure A.3 and Table A.1), and roads disrupted in the second wave were on routes connecting the west of the 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 six-month periods before the shock. All measures are an average across the six-month periods starting from the period April to September 2007, and ending in the period April to September 2010. the 'share of relationships ending'. This is equivalent to measuring the number of relationships that end (*relationships status* equal to one) in a given six-month period, given they are active the previous period. The value of the statistic is 18.6%, and I use it as a benchmark to understand the size of the effects from the empirical estimations.

The 'share of active relationships on all potential relationships' is the number of relationships with an active status from all exporter-importer combinations On average 14% of the relationships of all the possible buyer-seller matches are active in average each six-month period before the shock.[30] The 'share of new relationships on all potential relationships' is the share of new relationships that are established within a period. This metric omits all relationships that are already formed or that are already not active. The share of exporter-importer combinations formed in a particular period is in average 0.005, from the pool of firms that have not yet traded.

Table 2: Summary statistics in the pre-shock period

Variable	**Average across periods**
Share of relationships ending	0.186
Share of active relationships on all potential relationships	0.014
Share of new relationships on all potential relationships	0.005

Notes: The table shows the summary statistics. All measures are an average across the six-month non-calendar periods from April 2007 to September 2010. For the 'share of relationships ending' the statistic use 6,854 relationships from the estimation sample. For the 'share of active relationships on all potential relationships' I used 674,845 combinations of relationships that include active and non-active relationships in the period before the shock. For the 'share of new relationships on all potential relationships' I used 674,845 relationships that only include relationships non-active and relationships active for the first time.

Figure A.5 illustrates the distribution of number of relationships before the shock for those importer and exporters that are in the estimation sample. Exporters have an average of 8 active connections over three years, and importers have an average of 6. The majority of exporters, the 54%, have in average less than five connections. Even more skewed is the distribution of importers, with 70% having less than five connections.

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

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

literature.

4.1 Main estimating equation

In an event study, I estimate the probability of a relationship ending as[31]

$$
\begin{aligned}
\mathbb{1}\{y_{ijt}=1\} = & \sum_{l} \beta_l E_{ij,0} \cdot \mathbb{1}\{t=l\} + \sum_{q} \left(\alpha_i^O \, \mathbb{1}\{\mathcal{Z}(\bar{x}_j)=q\} + \alpha_j^D \, \mathbb{1}\{\mathcal{Z}(\bar{x}_i)=q\} \right) \\
& + \sum_{w} \varrho_w \mathbb{1}\{C_{ij}(E_{ij,0})=w\} + \zeta \mathbb{1}\left\{\# \, C_{ik}^{O}(i, k \neq j) > 0\right\} + \eta \mathbb{1}\left\{\# \, C_{kj}^{D}(k \neq i, k) > 0\right\} \\
& + \alpha_i^O + \alpha_{jt}^D + \theta_{ct} + \varepsilon_{ijt},
\end{aligned} \tag{1}
$$

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 ends once there are no other transactions happening between that particular buyer an seller). $E_{ij,0}$ is the *exposure to the shock* variable defined for each relationship and the subscript 0 reflects that the exposure happens at this period. 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.

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 $\beta = \{\beta_{l-t}, \ldots, \beta_{l+t}\}$. 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 the period of analysis, with the shock centred at $t=0$ coinciding with the initial wave of road disruptions in October 2010. As a result, the subscript l indicates the period corresponding to the specific β coefficient. For instance, if we are interested in the coefficient that corresponds to the status of relationships ending during the shock, and if periods are corresponding to six-months, then the coefficient we focus is the coefficient β_0. This coefficient contains the probabilities of a relationship ending for the first sixth months after the first disruption (from October 2010 to March 2011).

In equation (1), the β_l coefficients can be directly interpreted as the percentage point change in the probability of a relationship ending. Because I include the α_{jt}^D and θ_{ct} the comparison is done

[31] 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.

comparing between relationships within an importer and within relationships from the same cohort. This also means that the variation used mostly relies on importers with relationships exposed and non-exposed, whereas importers with no variation of exposure in their portfolio do not contribute to the effect. 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.

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 45 months before the shock (from April 2007 to April 2008). The leading coefficients extend from the periods following the shock period (from April 2011 to October 2011) until 80 months after the shocks (October 2017 to March 2018).[32] More precisely, I estimate the set of coefficients $\beta_l = \{\beta_{t=-45}, ..., \beta_{t=80}\}$, where l are the months relative to the six months prior to the first road disruptions, that is, when $t = -6$.

Following the coefficient of interest, I include a set of controls. The first summation takes potential homophily effects into consideration, thus incorporating controls for the attractiveness of a specific firm based on their size, ($\bar{x}_h$ for $h = \{i, j\}$), to retain or create new relationships. I create a flexible control for the bins by interacting 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. q are the deciles corresponding to the average firm size constructed from $\bar{x}_i$ and $\bar{x}_j$. The average firm sizes are constructed as a three year moving average and using the last measure before the shock.[33]

The second summation of controls distinguishes if a relationship was exposed to the first, second or both waves of disruptions, where w classifies exposure of a relationship in three groups: i) exposure only from October 2010 to March 2011, ii) exposure of relationships in April 2011 to October 2011, or iii) exposure in i) and ii). ϱ takes a value of one if relationship exposure $E_{ij,0} = 1$ happened in a particular group w, and 0 if not.

Finally, the third set of controls accounts for any 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. Let $C^O_{ik}(i, k \neq j)$ be the group of relationships linked to exporter i that exclude importer j that are exposed to the shock (with $E_{ij,0} = 1$). The indicator function $\mathbb{1}\{\# \, C^O_{ik}(i, k \neq j) > 0\}$ takes the value of one if any of the relationships in $C^O_{ik}(i, k \neq j)$ are exposed to the shock. Similarly, $C^D_{kj}(k \neq i, j)$ is the group of relationships linked to importer j that exclude i and are exposed to the shock (with $E_{ij,0} = 1$).

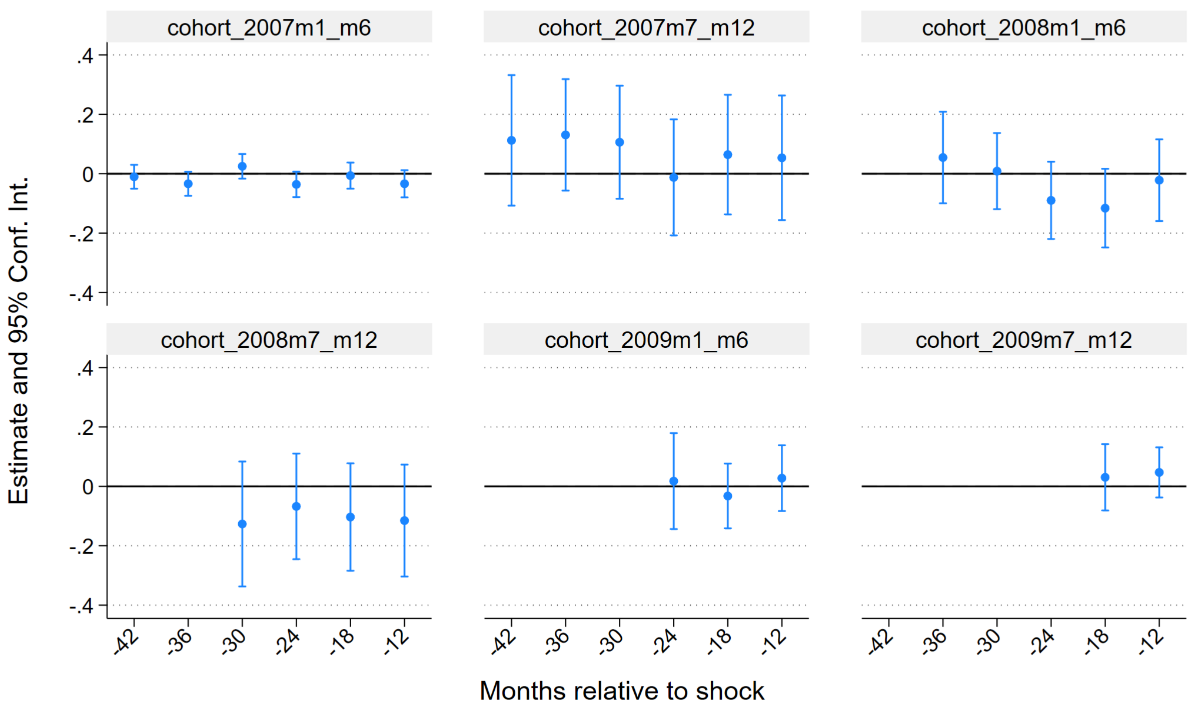
[32]See Schmidheiny and Siegloch (2023), who suggest binning the end points from dynamic estimations.

[33]Specifically, I estimate the following average of trade value for both importers and exporters. For exporter i the total trade is $\bar{x}_i = \frac{1}{T}\sum_{t=\tau-6,\tau<0}^{\tau} x_{it}$, where x_{it} is the deflated trade value in US dollars of firm i at period t, and τ is the last period of x_{it} that is observed before the shock at $t = 0$. The same estimation applies for j.

The indicator function $\mathbb{1}\{\# \ C^D_{kj}(k \neq i, j) > 0\}$ takes the value of one if any of the relationships in $C^D_{kj}(k \neq j, j)$ are exposed to the shock.

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 comparing similar relationships and controlling for firm characteristics, 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 equation (1) and plot the conditional lagged coefficients.

Figure 7: Parallel trends: Lagged effects on relationships exposed and non-exposed to the shock



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. The variable *exposure to the shock* is restricted to only origin-cargo terminal combinations used 24 months before the shock period.

Figure 7 shows that for each cohort where the baseline is β_{-6}. The estimates show that there are not differential effects on the probabilities of relationships ending. Additionally, 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 and report the confidence intervals.[34]

4.2 Results

In this section, I present estimation results from equation (1). In the second part of the chapter I construct a firm-level measure of the exposure and report the results. The third part of the chapter looks at different channels by estimating heterogeneity in the number of connections. The last section of the results looks at different outcome variables beyond the relationship status variable.

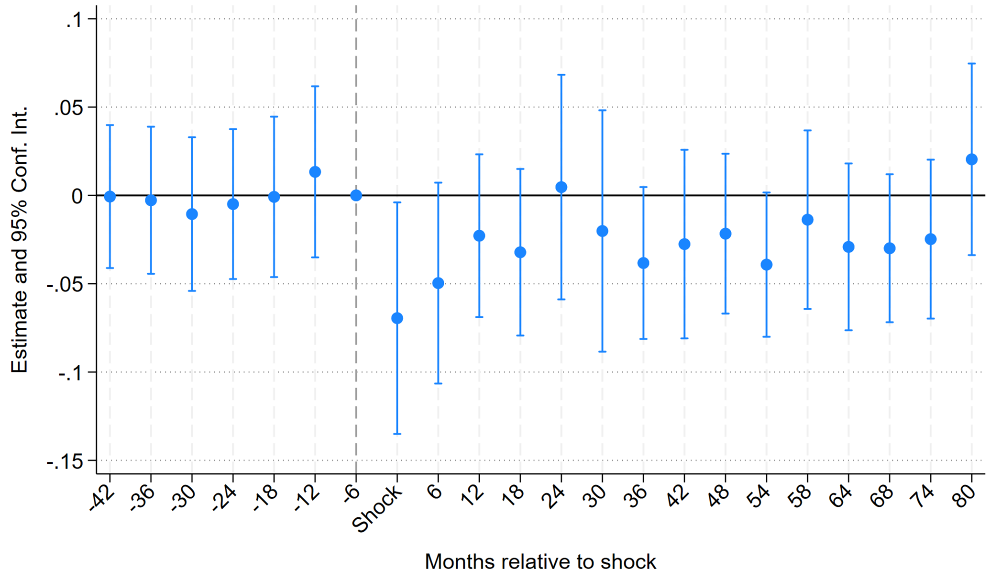
Main results. I estimate equation 1 and show the estimates in Figure 8. Following the road disruptions (β_{shock}), the probability of a relationships ending decreases by 7 percentage points. Half to a year later from the first road closures (i.e., the effect in the second wave of disruptions estimated by β_6), the effect is only significant at the 90% confidence level. The effect remains to be negative, and the magnitude is a decrease in the probability of a relationship ending of 5 percentage points. According to Table 2, the estimated effect during the first six months of road closures corresponds to a 37% of the baseline of relationships ending, which is 0.18. For the second wave of closures the decreased by about 26% on the same baseline. It is not surprising that the effect of the second period is lower, given that most of the exposed to the shock relationships were affected by the first wave of closures. Figure 9 shows the robust confidence intervals following Rambachan and Roth (2022)'s sensitivity analysis for the β_{shock} coefficient.

It can be surprising to see the decrease in the probability of a relationship ending, but Goldberg and Reed (2023), also find similar results. They find that the separation rate for US firms falls during the COVID pandemic. This is because domestic firms maintained existing relationships with trading partners and sought to develop new ones. These results can be interpreted similarly. In average, there is a number of sellers within an importer's portfolio who face delivery disruptions, and these sellers are located in specific regions. Importers can protect themselves from a shortage of flowers caused by road disruptions if they keep all their customers in exposed areas.

Exposure at the importer level. Baseline estimates are primarily based on importers who source from exposed and non-exposed sellers. In order to evaluate how firms respond to temporary disruptions, the following analysis examines how importers with a high exposure to disruptions respond compared

[34]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.

Figure 8: Effect of road disruptions on the probability of ending a relationship, within-importer variation



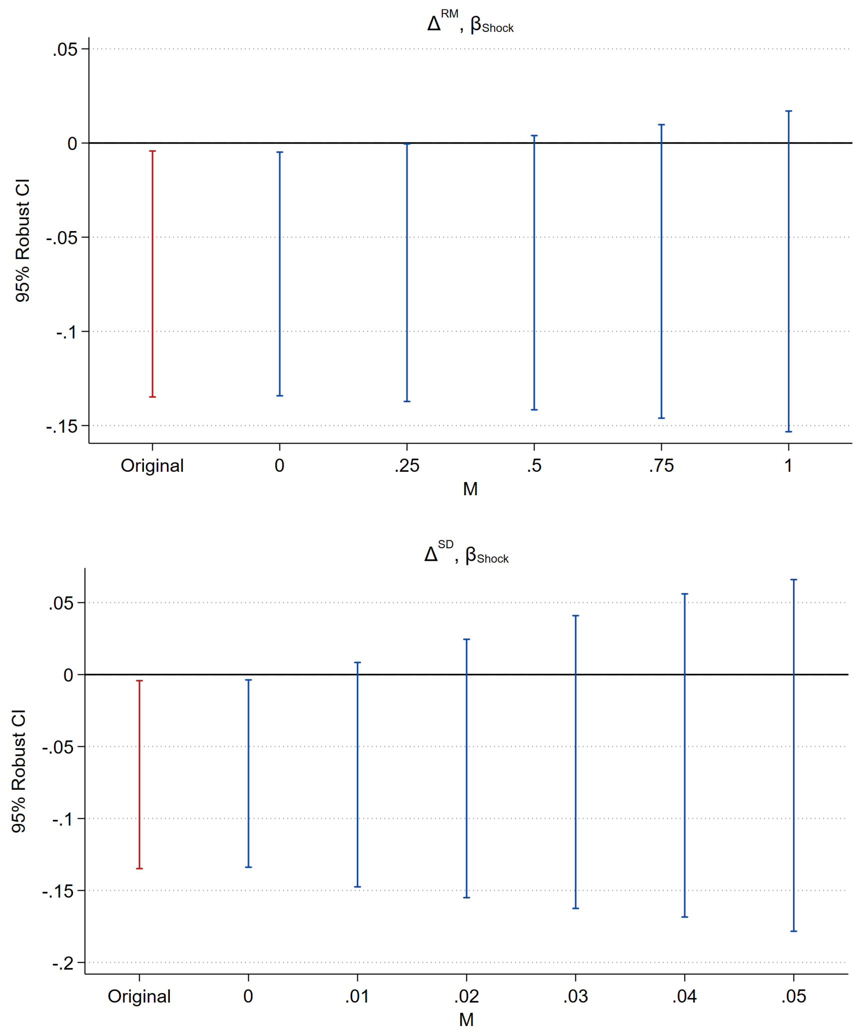
Notes: The figure plots the β_l coefficients from estimating equation (1) and the respective 95% confidence intervals. The variable *exposure to the shock* is restricted to only origin-cargo terminal combinations used 24 months before the shock. The sample includes exporter and importer firms active 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.

to importers with a lower exposure. To identify high and low exposed importers, I construct a measure of *importer exposure*:

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

where IE_j is the measure of *importer exposure through relationships*. The measure counts the number of relationships with *exposure to the shock* equalling one over the total number of active relationships. I include a term in the denominator, that is $\sum_i \mathbb{1}\{E_{ij,0} = 1 \cup E_{ij,0} = 0\}^c$. This 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. To fix the number of active relationships used in the measure, I count all relationships that are active at least one year before the disruptions. In other alternative measures I use active firms using different time intervals of six-months before and two years before the disruptions.

Figure 9: Sensitivity analysis for the parallel trends assumption: confidence bands for β_{shock}



Notes: The figure shows 95% confidence intervals for β_{shock} from Figure 8 following Rambachan and Roth (2022). In both panels the 'original' confidence intervals are taken from the estimations in Figure 8 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 0.5, which means the estimates are significant only when allowing for a deviation of 1.5 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 slight deviation from linear trends in the pre-shock period.

When exposure is not only about the number of links that are exposed, but also about the trade that might not be delivered, then I construct the following measure:

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

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*. For all the measures of *importer 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.

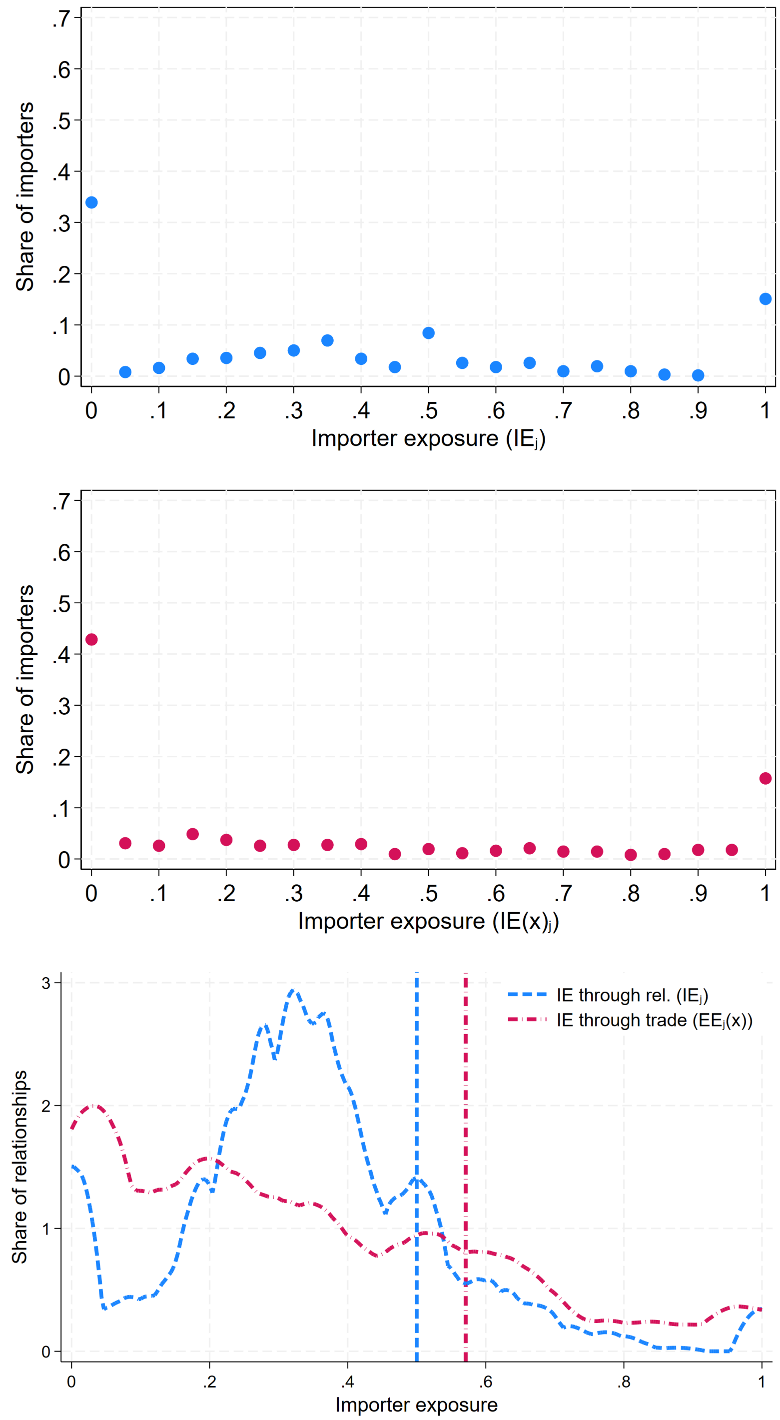
Figure 10 shows the distribution of importers by their firm exposure using the measures of *exposure through relationships* (IE_j), and *exposure through trade* ($IE_j(x)$). Two things are important to highlight. First, on average an importer has around 34% of their relationships or trade value exposed for relationships and trade respectively. Around 90% of importers have all their portfolio exposed, while around 25% don't have any exposure. To split importers between high and low exposed, I use a threshold, the 75^{th} percentile of the distribution of the importer exposure measure. For the importer exposure measures through relationships this cut corresponds to 56% of exposure share IE_j, and for the measure of exposure through trade value this corresponds to 63% of exposure share $IE_j(x)$. The bottom panel of Figure 10 displays the distribution of relationships according to their importer exposure, and the vertical line are the 75^{th} percentile cuts from the firm-level distributions.

To carry out the analysis at the firm level using the different *firm exposure* measures, I construct an indicator $E_{j,0}$. The indicator $E_{j,0}$ is calculated separately for each *importer exposure* measure, and it classifies relationships into 'low' exposure or 'high' exposure groups if their *importer exposure* measure is above the chosen threshold. With the indicator $E_{j,0}$ that links a relationship to a *importer exposure* measure, I estimate the following probability model

$$\begin{aligned}\mathbb{1}\{y_{ijt} = 1\} = &\sum_l \beta_l E_{j,0} \cdot \mathbb{1}\{t = l\} + \sum_q \left(\alpha_i^O\, \mathbb{1}\{\mathcal{Z}(\bar{x}_j) = q\} + \alpha_j^D\, \mathbb{1}\{\mathcal{Z}(\bar{x}_i) = q\}\right) \\ &+ \sum_w \varrho_w \mathbb{1}\{C_{ij}(E_{ij,0}) = w\} + \zeta\mathbb{1}\left\{\#\, C_{ik}^O(i, k \neq j) > 0\right\} + \eta\mathbb{1}\left\{\#\, C_{kj}^D(k \neq i, k) > 0\right\} \\ &+ \alpha_i^O + \alpha_j^D + \phi_{bjt} + \varphi_{bit} + \theta_{ct} + \varepsilon_{ijt},\end{aligned} \tag{2}$$

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. The control variables are the same as equation (1) and in addition I add two set of control variables ϕ_{bjt} and φ_{bit}. These controls are referring to firm bins of their number of connections before the shock. These bins are built similar to the bins used for $\bar{x}_j$ and $\bar{x}_i$. By adding the bins of importers or

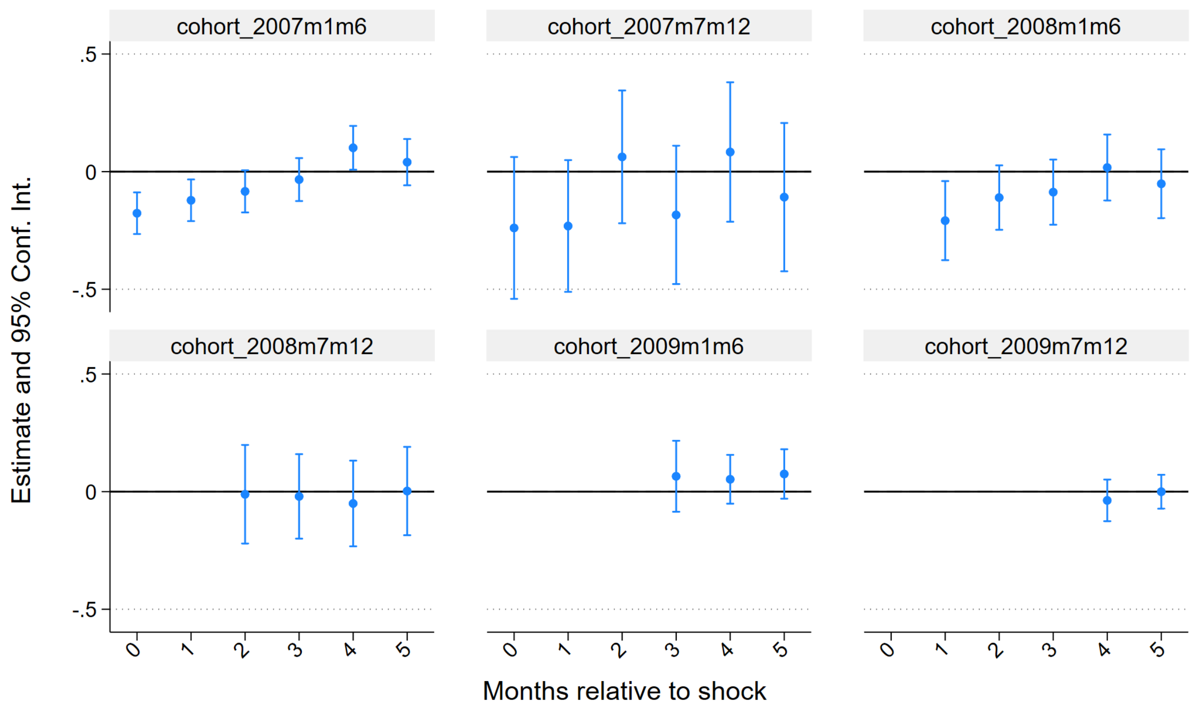
Figure 10: Distribution of *importer exposure* measures



Notes: The figure shows the distribution of relationships for the different measures of *importer exposure*. The distribution in blue represents the measure of *importer exposure through relationships*, which counts the number of exposed relationships. The distribution in red represents an alternative measure of *importer exposure through trade*, which includes trade values of relationships with *exposure to the shock*. The bottom panel shows the distribution of relationships for the importer exposure measure. The vertical line serves as the cutoff used to separate relationships into 'high' and 'low' exposure categories equivalent to the 75^{th} percentile of the firm distributions. For the exposure through relationship this is 56% and for exposure through trade this is 63%.

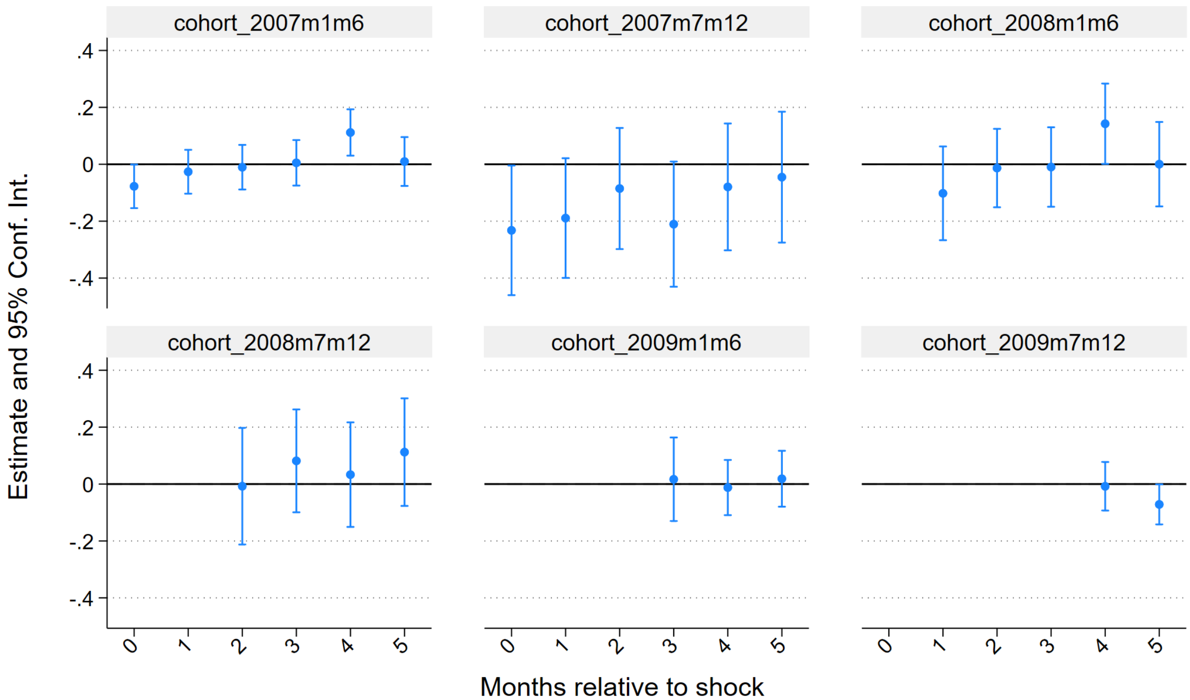
exporters as fixed effects, the estimates compare between relationships that belong to firms that are in the same bin of number of pre-shock connections. If there is a concern that firms with a large number of connections (high-connected firms) are more likely to have relationships affected by a disruption than firms with few connections (low-connected firms), adding fixed effects helps address this. The validation of the identification assumption also relies on the conditional comparison of relationships linked to high and low exposed importers. Figure 11 displays the results for the measure of exposure through relationships IE_j and Figure 12 shows the results for the measure of exposure through trade $IE_j(x)$.

Figure 11: Parallel trends: Lagged effects by relationship cohort using importer exposure through relationships (IE_j)



Notes: The figures shows estimated coefficients on equation (2) of the *relationship status* variable for each cohort for all the pre-shock periods between high and low exposed importers. 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, initial connections, and cohort. The reported confidence intervals are estimated using standard errors clustered at the exporter level.

Figure 12: Parallel trends: Lagged effects by relationship cohort using importer exposure through trade $IE_j(x)$



Notes: The figures shows estimated coefficients on equation (2) of the *relationship status* variable for each cohort for all the pre-shock periods between high and low exposed importers. 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, initial connections, and cohort. The reported confidence intervals are estimated using standard errors clustered at the exporter level.

Figure 13 presents the results 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. The results of the firm analysis indicate a pattern: relationships with high-exposed importers are more likely to end in the long run. Similar to the findings by Khanna, Morales, and Pandalai-Nayar (2022) that look at the COVID shock, find a higher separation rate from suppliers in strict lockdown zones relative to other suppliers.[35]

Results show that high exposed importers who cannot source from within their current portfolio due to the disruption tend to end their relationships only after the shock has passed. It is also important to note that the effect is larger when considering *exposure through trade* rather than *exposure through*

[35]Khanna et al. (2022) find that firms with supplier risk of one standard deviation above the mean experience an increase of 4.5 percentage points in the separation rate from suppliers.

relationships. As a result, disruptions affecting importers' trade share are more concerning than exposure based on the number of relationships affected.

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 the first section, I try to understand firm characteristics that can be associated with the relationship-level responses. In the second section, I look at evidence that can explain the results found in the firm level analysis.

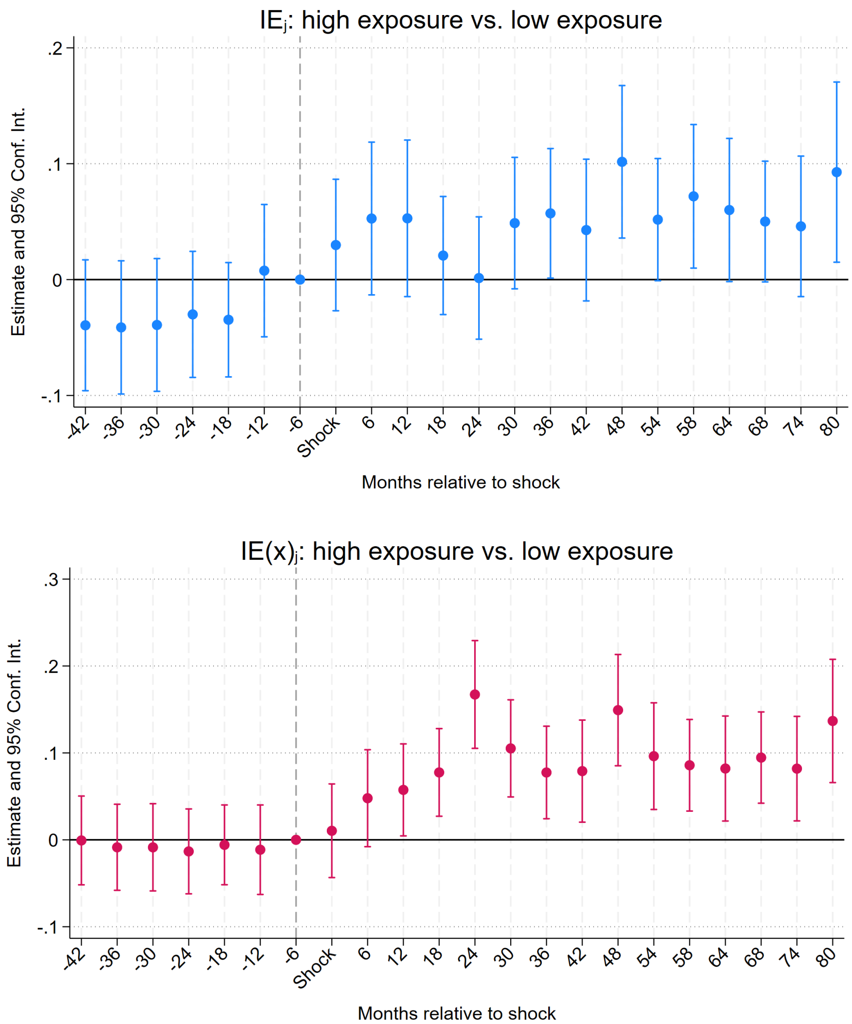
Firm characteristics. Firms may face information frictions when searching for buyers or sellers. Eaton, Eslava, Jinkins, Krizan, and Tybout (2021) examine the cost of forming relationships from the exporter's perspective. Their argument is that more visible firms –with larger portfolios– have fewer barriers to accessing markets than firms with smaller portfolios. In this section I build two metrics based on Khanna, Morales, and Pandalai-Nayar (2022) that can relate to supplier characteristics. The first metric is the average outdegree of a firm's suppliers. This measures how nodal suppliers of a buyer j are. To estimate the supplier's outdegree, I estimate the share of exports of a supplier i to a buyer j using $\bar{x_{ij}}$ as in the firm-level measure of *exposure through trade*. Then, I add these shares for each supplier i and estimate the average of these summations at the buyer level j. A high number means that suppliers of a buyer j represent a larger share of their buyer's purchases.

The second metric also used in Khanna et al. (2022) is the connectivity of the importers, which is a metric on the number of suppliers. I compute the number of suppliers relying in the number of active relationships used in the denominator on the measure exposure through relationships. It may be less costly for firms with multiple relationships to break current ties as they can source from other relationships in their portfolio. Or as in Eaton et al. (2021), as a result of their greater visibility, it is easier to find new suppliers if these firms already have connections in other places where they can source from.

I study if there is a different response between importers with a high supplier's average outdegree or a high number of connections. Having a high supplier's average outdegree means that these importer are in average connected to exporters that export a large share of their sales to their costumers, including them. The figure 14 top panel displays the distribution of relationships for exposed and non-exposed relationships according to the importer measure of supplier's outdegree and in the vertical line the median of the importer's distribution. Below the figure the following panels show the estimates of equation (1) for each group -above and below the median. When experiencing a shock, importers who buy more from an exporter are more likely to keep their current match.

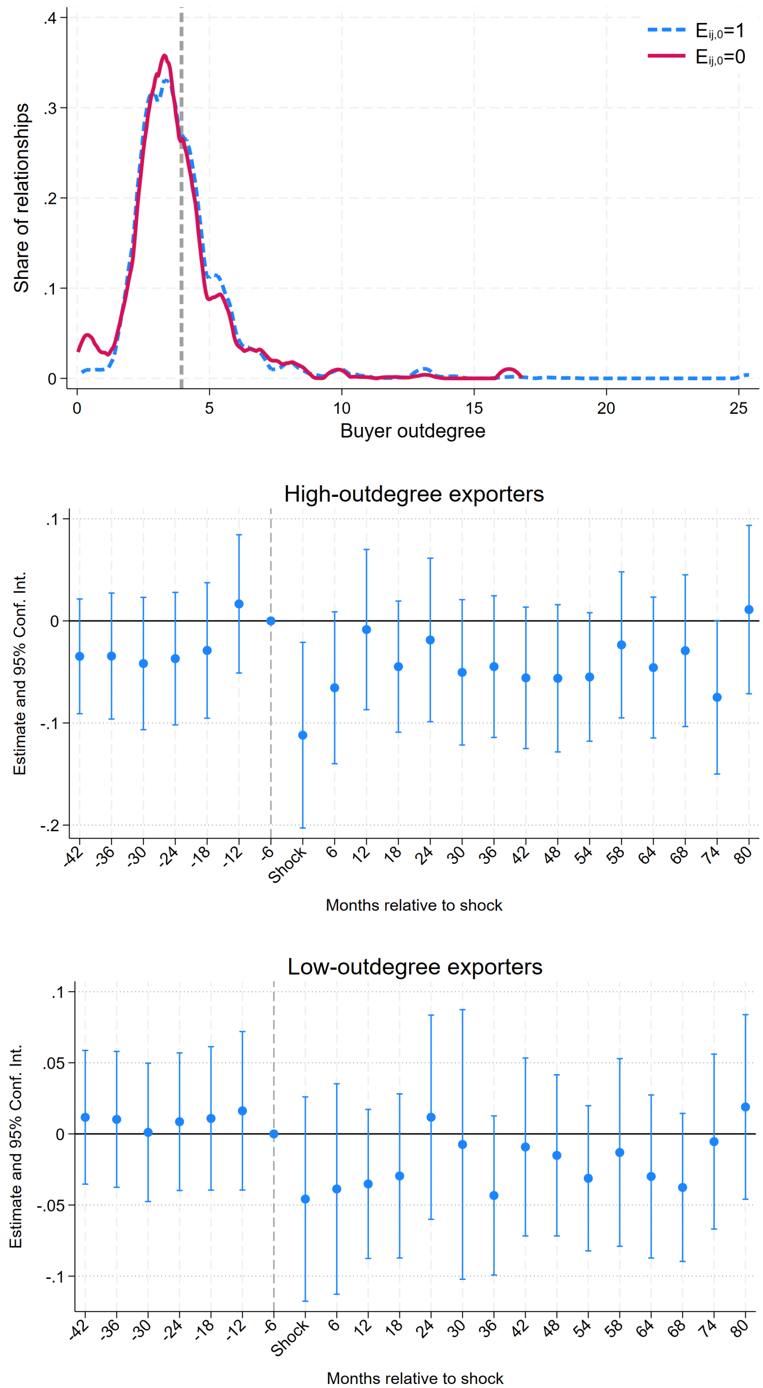
Figure 15 top panel displays the distribution of relationships for exposed and non-exposed rela-

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



Notes: The figure plots the β_l coefficients obtained from estimating equation (2), 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 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, initial connections, and cohort. The reported confidence intervals are estimated using standard errors clustered at the exporter level.

Figure 14: Probability of ending relationships by supplier's average outdegree



Notes: The figure plots the β_l coefficients obtained from estimating equation (1), along with their respective 95% confidence intervals. The top panel displays the distribution for relationships exposed ($E_{ij,0} = 1$) and non-exposed ($E_{ij,0} = 0$) for the importers distribution of supplier's outdegree metric. Meanwhile, the bottom panel showcases the results when using importers with an above median outdegree and below median outdegree. 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, initial connections, and cohort. The reported confidence intervals are estimated using standard errors clustered at the exporter level.

tionships according to the importers connectivity. The bottom panel shows the results of equation (1) for each group -above and below the 75^{th} percentile. I find that importers that rely on a high number of active connections are more likely to keep current relationships. Importers with fewer connections do not show these effects. This indicates that importers might not be able to replace exposed exporters within their portfolio as easily, especially if they have a higher reliance on them.

Understanding long-term importer response to disruptions. Results at the firm-level indicate that the shock had a persistent effect on the continuation of relationships. By using the *firm exposure* measures, I examine importers' responses regarding the probability of forming new relationships. Due to the fact that I cannot observe other countries from which US importers source, the analysis is limited to Colombian firms. To do the analysis, I construct a vector of all buyer-seller relationships between January 2007 to December 2019. I create variable of *active relationship* that takes the value of zero if a relationship is not active and one if it is active. All observations of ongoing relationships always take a value of one, as they are always active, and for those that go from active to non-active, they disappear from the data once they are no longer active. I estimate the following probability model

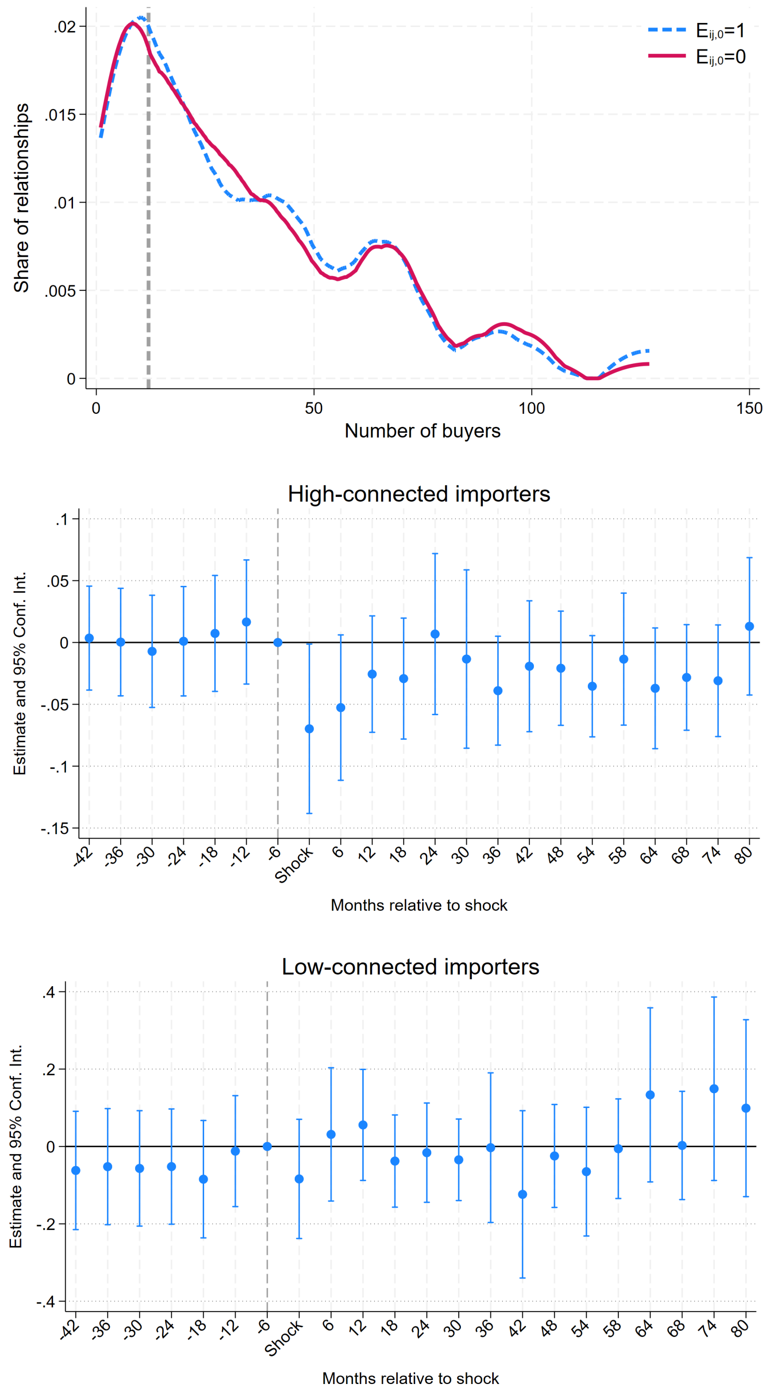
$$\begin{aligned}\mathbb{1}\{y_{ijt} = 1\} = &\sum_l \beta_l E_{h,0} \cdot \mathbb{1}\{t = l\} + \sum_q \left(\alpha_i^O\, \mathbb{1}\{\mathcal{Z}(\bar{x}_{jt-1}) = q\} + \alpha_j^D\, \mathbb{1}\{\mathcal{Z}(\bar{x}_{it-1}) = q\}\right) \\ &+ \alpha_i^O + \alpha_j^D + \phi_{bjt} + \varphi_{bit} + \varepsilon_{ijt},\end{aligned} \tag{3}$$

where $\mathbb{1}\{y_{ijt} = 1\}$ is the *active relationship* variable. I change the size bins for the firms using the trade values as the lagged of the total trade $\bar{x}_{t-1}$, rather than fixing the bins in the pre-shock period. The connection fixed effects φ_{bit} and ϕ_{bjt} are built in the same manner as for equation (2). I estimate equation (3) for both measures of *importer exposure* and report the results as in the previous section, using the measures for all relationships active one year before the first disruptions.

I estimate equation (3) separately for incumbent and entrant exporters, where entrant exporters are not selling to the US prior to October 2010 and incumbent exporters have already been serving the US market since then. I omit the connection fixed effects (φ_{bit}) for exporters when considering exporters that are not found in the pre-shock period. To relate the estimations is useful to refer to Table 2 that shows the average 'share of new relationships on all potential relationships', which is around 0.005. This statistic is estimated for the baseline of relationships formed in the periods before the shock.

Figure 16 shows the estimation results when considering only potential matches within firms that are already supplying the US market (the incumbent firms). I found that the probability of high exposed importers to form new matches decreases in the long term. This result could be consistent with Gigout and London (2021) and Bernard, Moxnes, and Ulltveit-Moe (2018b) who find that higher

Figure 15: Probability of ending relationships by importer's connectivity



Notes: The figure plots the β_l coefficients obtained from estimating equation (1), along with their respective 95% confidence intervals. The top panel displays the distribution for relationships exposed ($E_{j,0} = 1$) and non-exposed ($E_{j,0} = 0$) for the importer's distribution of connections. Meanwhile, the bottom panel showcases the results when using importers with a high-connectivity and low-connectivity. 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, initial connections, and cohort. The reported confidence intervals are estimated using standard errors clustered at the exporter level.

trade costs and lower efficiency can lead to a fall in the number of buyer-seller connections. Balboni et al. (2023) looks into long term responses, and use temporary flooding disruptions to domestic linkages. They find that these shocks can induce firms to undertake long-term adaptive changes to reduce their vulnerability to future flooding events. As a result of high exposure, importers may have to restructure their entire portfolio in the long run, which can lead to less relationships between Colombian suppliers to avoid over-reliance on these suppliers in the future.

Figure 17 shows the results for only potential matches among new firms that are new to the US market (entrant firms). The results show a higher probability of high exposed importers to form new linkages during the disruptions. As in Figure 13, having a high trade exposure seems to trigger a more persistent response from importers than having a high share of relationships exposed. This is also consistent with importers finding replacements during the COVID disruptions in Khanna et al. (2022).

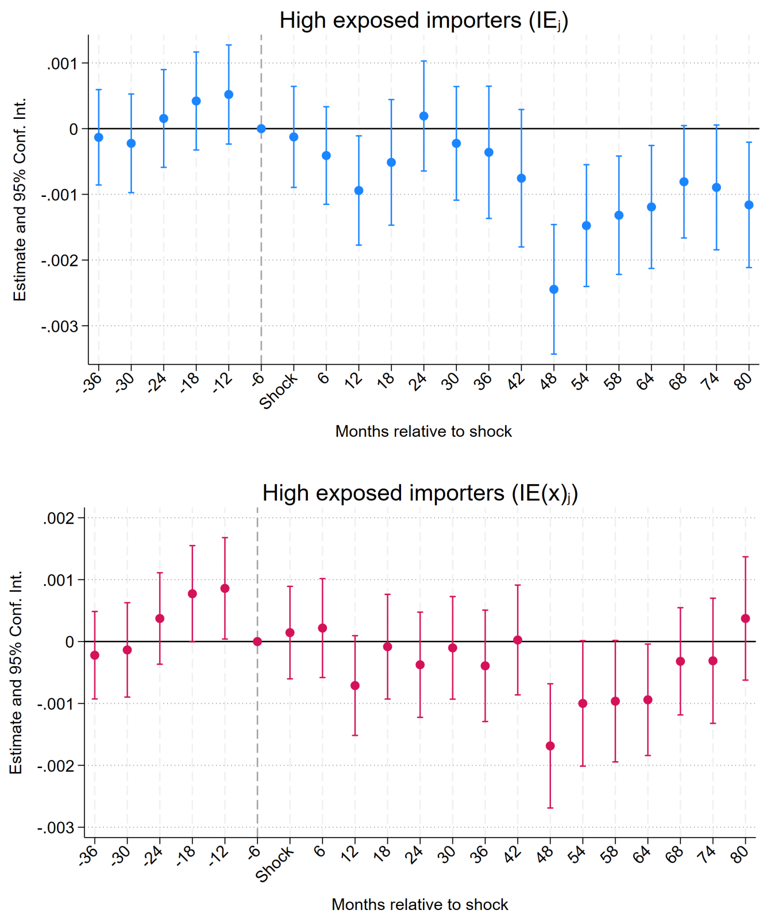
4.4 Beyond continuation of trade relationships

Buyer-seller transactions. I examine whether firms delay or fail to deliver their contracts due to road disruptions. I modify equation (1) so that the left-hand side is a binary variable if buyer-seller transactions occur at a given month, otherwise a zero. I measure the frequency of transactions taking place in a relationship during different lengths of time before disruptions and measure the frequency of transactions happening over these time windows. Based on how frequently transactions occur in a given window, I classify relationships into groups. To be more precise, I examine relationships that have low frequencies, e.g., transact less than once every year, and relationships with high frequencies, e.g., transact at least 10 months every year.

Figure 18 shows the results when looking at six, one, two, and three years of transaction histories, where relationships correspond to those who only transacted twice a year. The estimations show that transacting after a shock is less likely when using relationships that had transacted at least over a year and the effect is still negative when using relationships that transacted even three years before the shock. Furthermore, the effects persist throughout October, December, and February. Flowers are in high demand between Christmas and Valentine's Day.

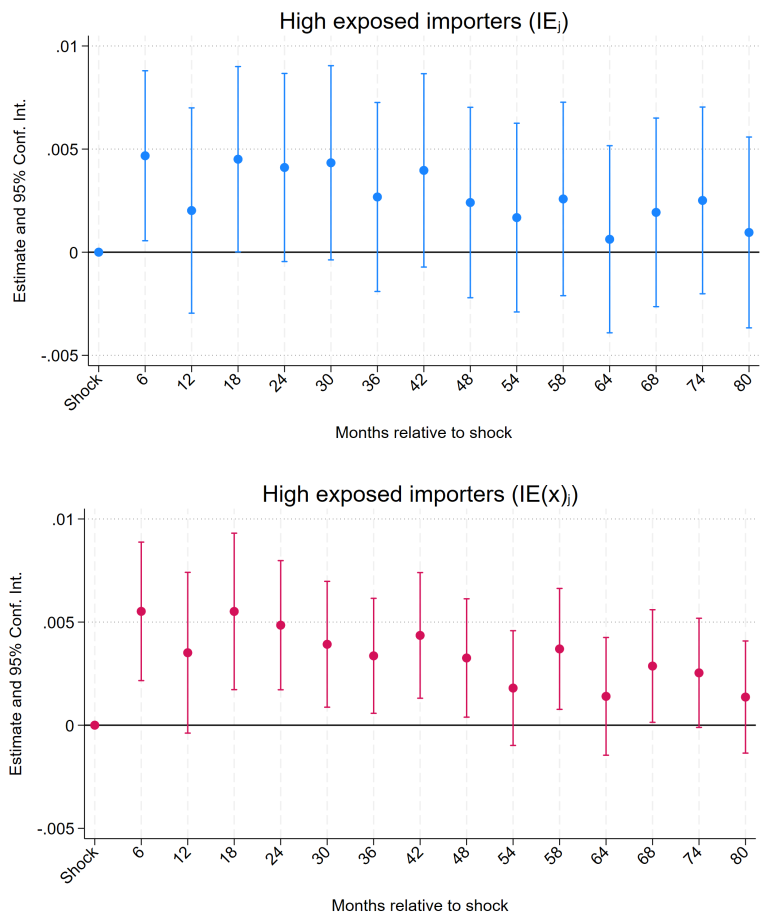
Figure 19 shows a different pattern. The number of transactions decreases when roads are closed in December when we track relationships that are frequently interacting just six months before the shock. Potentially, the decrease in transactions can be attributed to relationships that aren't old enough and that don't seem to be capable of delivering the contracts during the shock. The effect becomes less significant to none existent, the longer we establish the relationship frequency. That is, when focusing on relationships that have a constant interaction –reputation built over repetitive interactions– transactions are not affected when roads are disrupted. These analyses show that exposed relationships

Figure 16: Probability of creating a relationship with an incumbent exporter



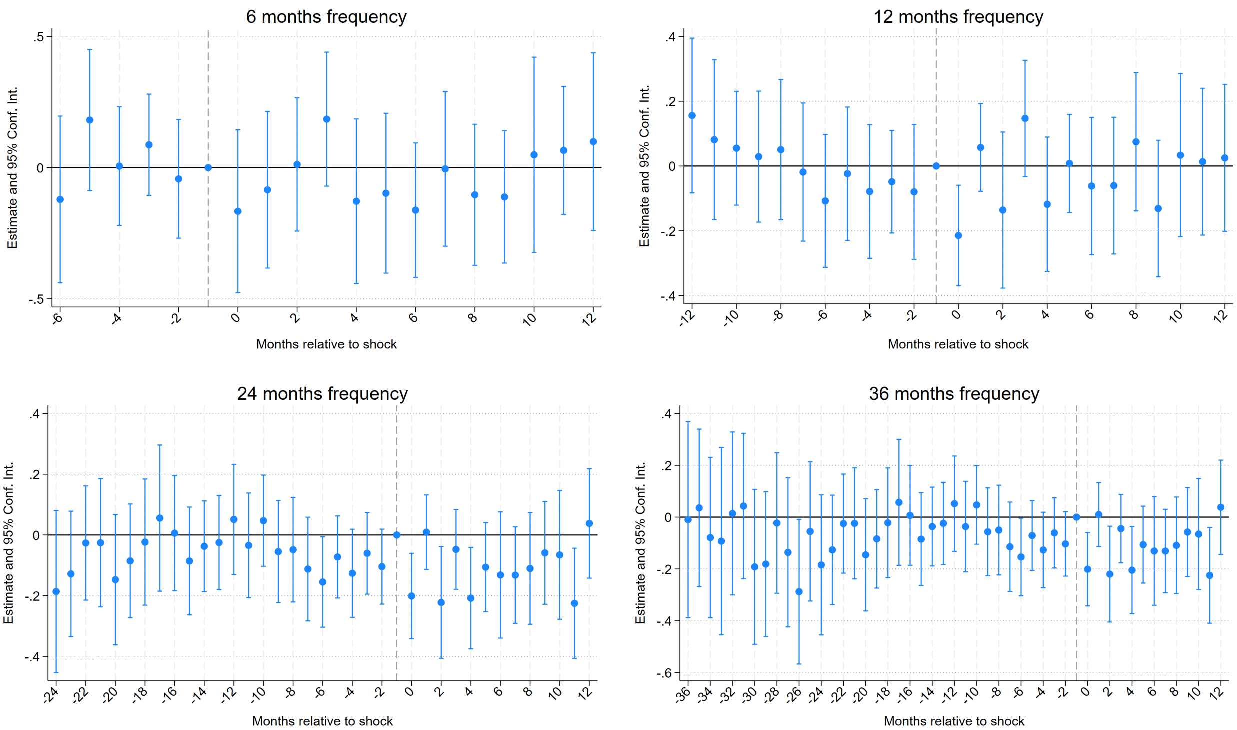
Notes: The figure plots the β_l coefficients obtained from estimating equation (3), along with their respective 95% confidence intervals. The top panel displays the results when $E_{j,0} = 1$ is based on the threshold derived from the distribution of the measure of *importer exposure through rel.* (IE_j). 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 sample consists of importer firms active at least two years before the disruptions, while exporter firms considered are already exporting to the US. All regressions include controls for firm fixed effects times firm size bin interactions, as well as fixed effects for importer, exporter, initial importer connections. The reported confidence intervals are estimated using standard errors clustered at the exporter level.

Figure 17: Probability of creating a relationship with an entrant exporter



Notes: The figure plots the β_l coefficients obtained from estimating equation (3), 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 sample consists of importer firms active at least two years before the disruptions, while exporter firms considered are only exporting to the US after the shock for the first time since 2007. All regressions include controls for firm fixed effects times firm size bin interactions, as well as fixed effects for importer, exporter, initial importer connections. The reported confidence intervals are estimated using standard errors clustered at the exporter level.

Figure 18: Probability of transacting for low-frequency relationships



Notes: The figure plots the β_l coefficients obtained from estimating equation (1) along with their respective 95% confidence intervals. I use as the left hand side variable the probability of a transaction in a given month. The lagged periods correspond to the months used to establish the frequency of the relationships. A low-frequency relationship has at most two transactions a year. The sample consists of relationships active at least six months (for the first graph) to a year (for the three remaining graphs) before the disruptions and uses all 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 variable *exposure to the shock* is restricted to only origin-cargo terminal combinations used 24 months before the shock. The reported confidence intervals are estimated using standard errors clustered at the exporter level.

without much repetitive interaction experience a decrease in transactions, and the decrease is during months with a high flower demand (in December, February following the closures in October).

4.5 Robustness

The first set of robustness estimations are to estimate results for the relationship level analysis in equation (1) using the alternative *exposure to the shock* (measures discussed in Section 3.4). I also present the results when changing the 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%. 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. The last set of results include the three measure of *exposure to the shock* using three-month periods. All these results can be found in Figures A.6, A.7 and A.8.

5 Theoretical framework

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 $t + 1$.[36]

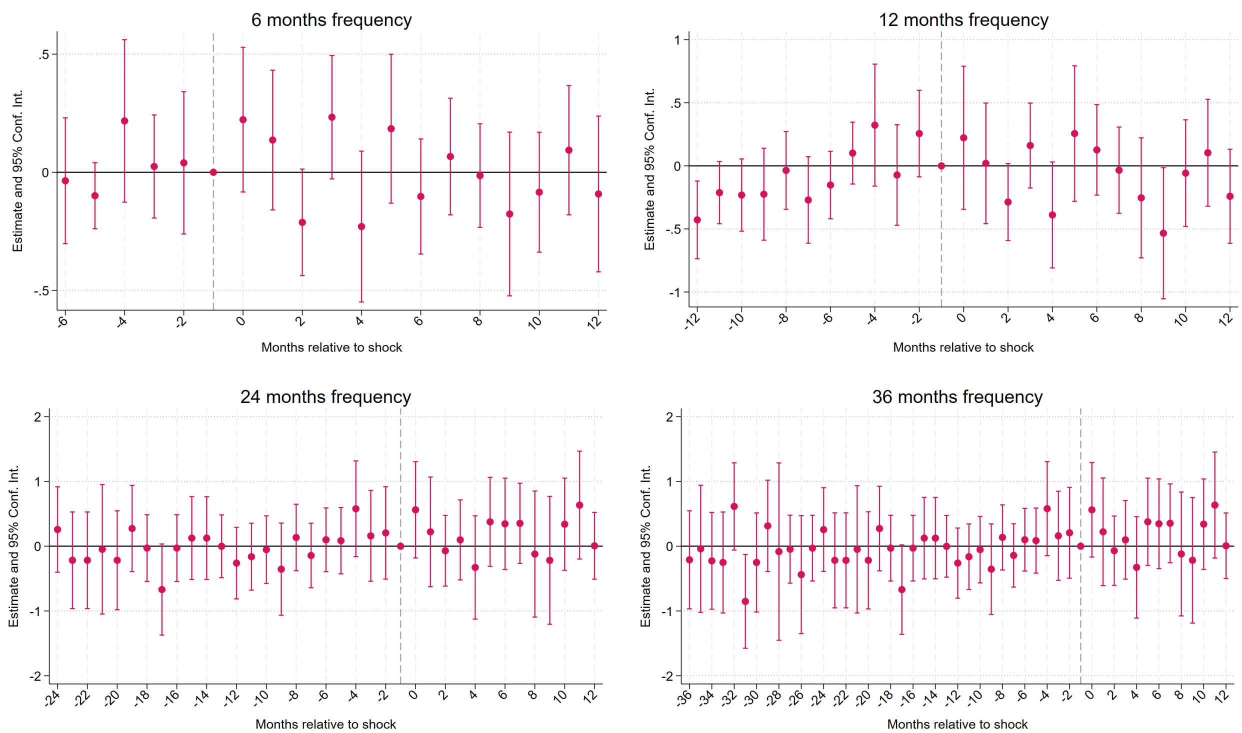
I assume that the discount factor is unity and so revenues and costs for both periods are known and constant, given that the final demand for each buyer is the same. For both importers and exporters I assume that revenue is a concave function in quantities, $R'(Q) > 0$ and $R''(Q) < 0$, and that the 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.[37] In other words, any transaction

[36]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.

[37]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.

Figure 19: Probability of transacting for high-frequency relationships



Notes: The figure plots the β_l coefficients obtained from estimating equation (1) along with their respective 95% confidence intervals. I use as the left hand side variable the probability of a transaction in a given month. The lagged periods correspond to the months used to establish the frequency of the relationships. A high-frequency relationship has at least ten transactions every year. The sample consists of relationships active at least six months (for the first graph) to a year (for the three remaining graphs) before the disruptions and uses all 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 variable *exposure to the shock* is restricted to only origin-cargo terminal combinations used 24 months before the shock. The reported confidence intervals are estimated using standard errors clustered at the exporter level.

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 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

$$\begin{aligned}\pi_t^j = \ & \mathbb{1}\{y_{ijt}=0\}\,\mathbb{1}\{m_{ijt}=0\}\left(R(S_{j,-i}+q_{ij}) - C(S_{j,-i}+q_{ij}) - N\alpha\lambda\right)\\ &+\mathbb{1}\{y_{ijt}=1\}\,\mathbb{1}\{m_{ijt}=1\}\left(R(S_{j,-i}) - C(S_{j,-i}) - (N-1)\alpha\lambda - \rho\right)\\ &+\mathbb{1}\{y_{ijt}=0\}\,\mathbb{1}\{m_{ijt}=1\}\left(R(S_{j,-i}+q_{ij}) - C(S_{j,-i}+q_{ji}) - N\alpha\lambda - \rho\right)\\ &+\mathbb{1}\{y_{ijt}=1\}\,\mathbb{1}\{m_{ijt}=0\}\left(R(S_{-j,-i}) - C(S_{j,-i}) - (N-1)\alpha\lambda\right),\end{aligned} \tag{4}$$

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.[38] $S_{j,-i}$ 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

$$\begin{aligned}\pi_{t+1}^j = \ & \mathbb{1}\{y_{ijt}=0\}\,\mathbb{1}\{m_{ijt}=0\}\left(R(S_{-ij}+q_{ij}) - C(S_{j,-i}+q_{ij})\right)\\ &+\mathbb{1}\{y_{ijt}=1\}\,\mathbb{1}\{m_{ijt}=1\}\left(R(S_{j,-i}+q_{jk}) - C(S_{j,-i}+q_{jk})\right)\\ &+\mathbb{1}\{y_{ijt}=0\}\,\mathbb{1}\{m_{ijt}=1\}\left(R(S_{j,-i}+\omega q_{ji}+(1-\omega)q_{jk}) - C(S_{j,-i}+\omega q_{ji}+(1-\omega)q_{jk})\right)\\ &+\mathbb{1}\{y_{ijt}=1\}\,\mathbb{1}\{m_{ijt}=0\}\left(R(S_{-j,-i}) - C(S_{j,-i})\right).\end{aligned} \tag{5}$$

Note that a firm that decides to keep the existing match and add a new one would only be able to sell

[38] 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 $q_{ij,t} = q_{ij,t+1}$

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 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

$$\begin{aligned}\Delta\pi_{ij} = \Delta(\pi_j) + \Delta(\pi_i) = \; & \left(R^j(S_{j,-i} + q_{ij}) - C_t^j(S_{j,-i} + q_{ij}) - R^j(S_{j,-i}) + C^j(S_{j,-i})\right) \\ & + \left(R^i(S_{i,-j} + q_{ij}) - C^i(S_{i,-j} + q_{ij}) - R^i(S_{i,-j}) + C^i(S_{i,-j})\right) \\ & - \lambda + \rho_j + \rho_i.\end{aligned} \tag{6}$$

To relate this result to how road disruptions change the relationship surplus, I consider a decrease in the quantities of flowers delivered (see Figure 18 and Figure 19). 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 $\lambda < \rho^j + \rho^i$.[39]

I refer to the channel as the *indirect* effect, where if the circumstances of the firm's portfolio worsen, i.e., failures on some contracted deliveries occur, firms can still obtain revenue from any relationship that delivers. In this case, importers have 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 $\lambda < \rho_i + \rho_j$.[40]

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.

From prediction to empirical results. In Figure 8 firms are more likely to maintain an existing relationship that is exposed to road disruptions. It is possible to rationalise these results if the *direct* effect is negative and the cost of establishing a new relationship is lower than the losses from from non-delivery and maintenance of the relationship. In this case, the *indirect* effect has to be larger than the *direct* effect, which means firms will be more likely to keep a relationship. Alternatively, the results can also be rationalised when the *direct* effect is positive and the cost of establishing a new relationship is higher than the losses from from non-delivery and maintenance. If this is the case, then the *direct* and *indirect* effects go in the same direction; and the final effect on the relationship surplus is unambiguously an increase.

Figure 13 from the second empirical results shows that relationships with high exposed importers are more likely to end preceding the shock. The results also show that these importers are more likely to form new relationships during and after the shock (see Figure 17). The model predictions can explain these findings when the *direct* effect is negative and larger than the *indirect* effect. The

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

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

relationship surplus is negative when the costs of establishing a new one are lower than the losses from non-delivery and maintenance. While these results consider importers who may be limited to sourcing from their current relationships, any positive effect from the *indirect* effect might not be enough to offset the negative effect of the *direct* effect.

Ultimately, the model illustrates how firms' decisions on how to maintain their specific relationships are based on their overall portfolio profits, as well as the cost associated with replacing them.

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. While importers with high exposure cannot source within their current portfolio during the crisis, they are more likely to find new relationships with entrant exporters, but the effects seem to be temporary. Additionally, these importers may be diverting away from Colombia in the long run due to the low probability of forming long-term relationships.

To conclude, I emphasise 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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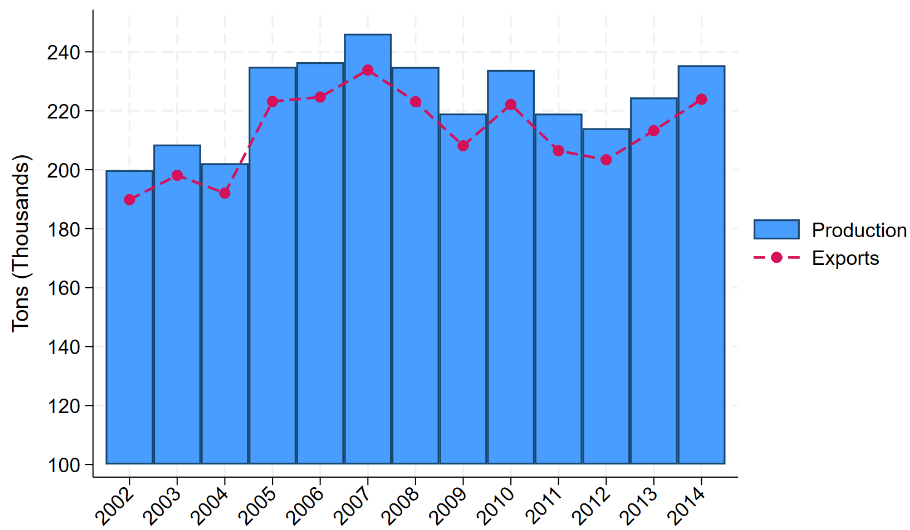
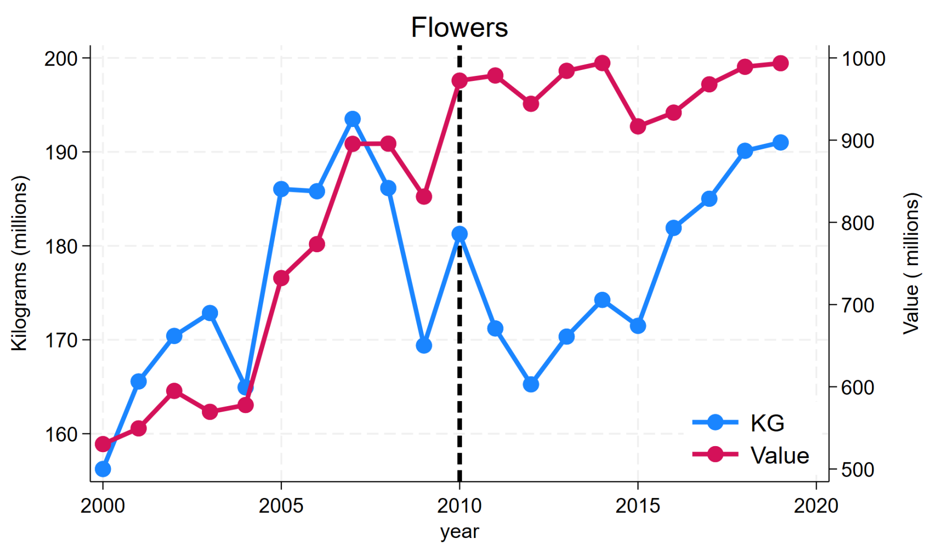
A Figures

Figure A.1: Production and exports of cut flowers



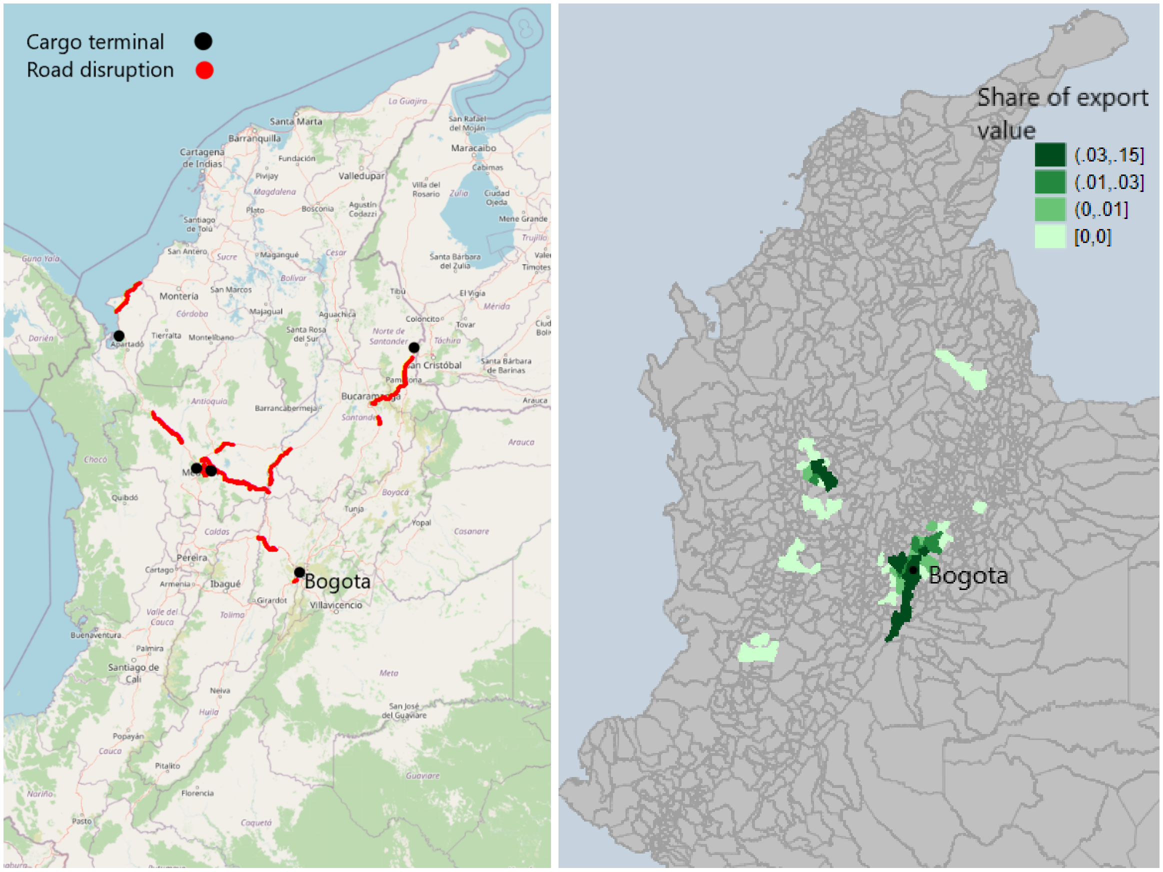
Source: MADR - ICA (2016).

Figure A.2: Cut flowers exported quantity and value



Notes: Estimates for the total quantities are based on net export data (excluding packaging). Value of exports reported in U.S. millions.

Figure A.3: Disrupted roads, cargo terminals and production of flowers

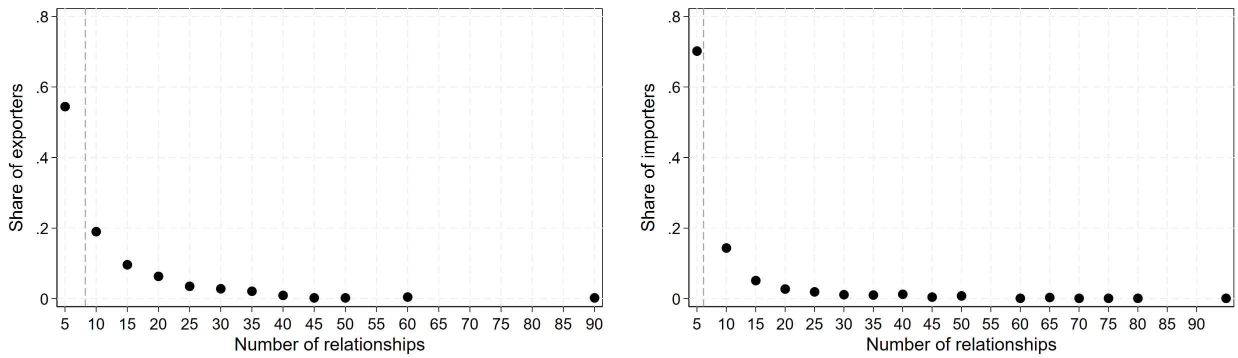


Notes: The figure on the left displays the roads disrupted between flower farms in red during La Niña 2010-11, and the cargo terminals used by flower exporters in black dots. Four out of the five cargo terminals are airports, while one (Apartado) in the North is a seaport. The figure on the right illustrates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

Figure A.4: Example of a reported road closure

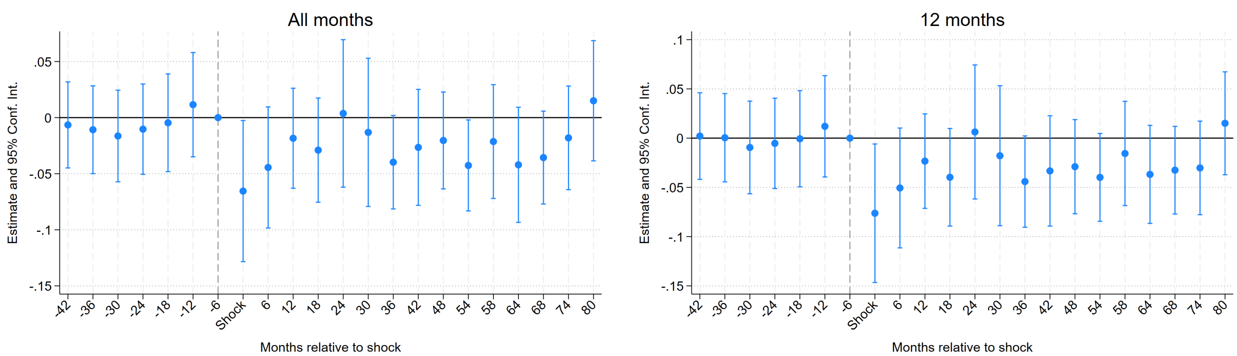
Notes: The figure illustrates an example of a road disruption. In the top panel, there's a photograph of the road shortly after the landslide, and in the bottom panel, there's a photograph of the same road after it was repaired.

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



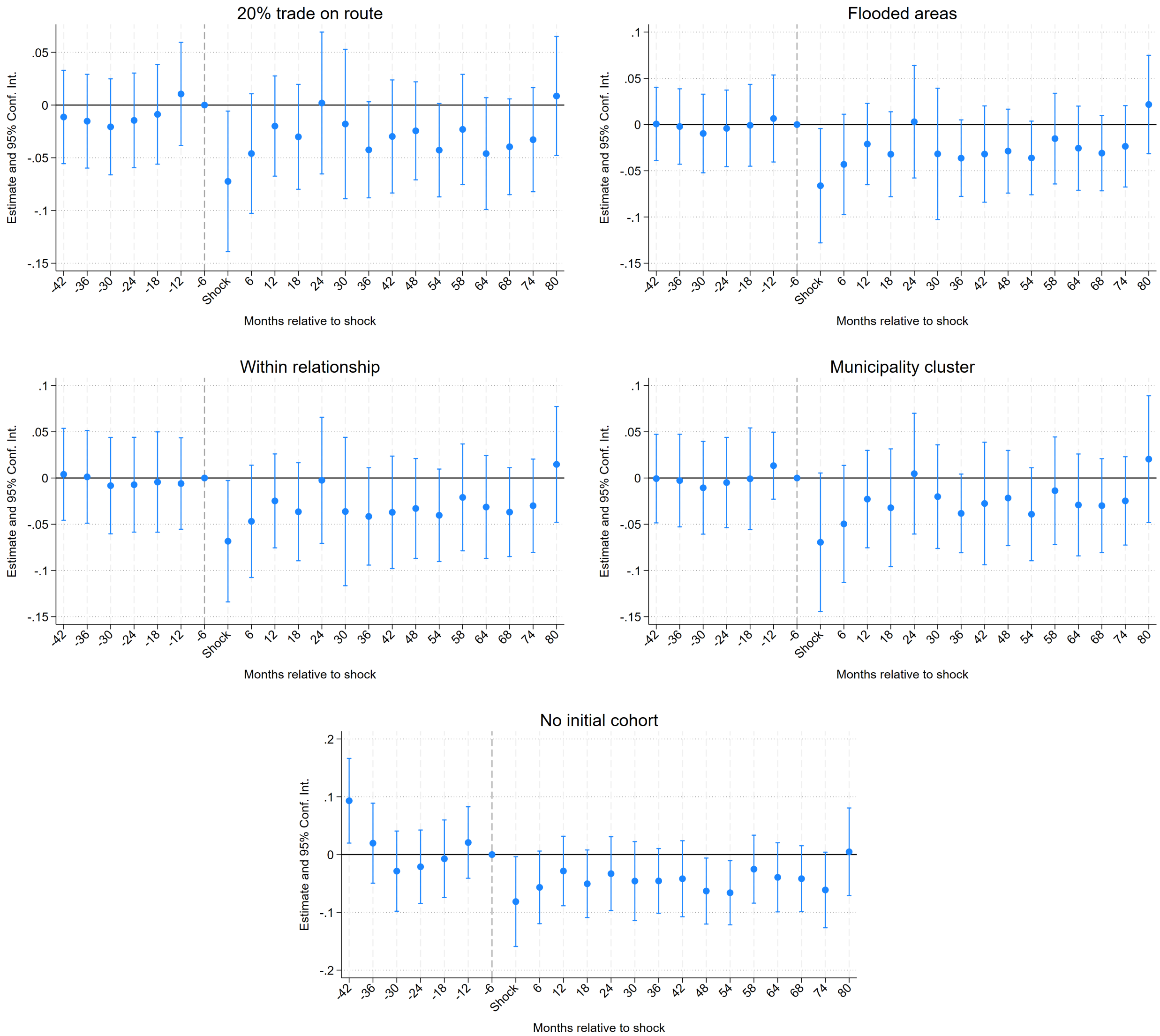
Notes: The figure shows the distribution of exporters and importers based on the number of relationships. The term "number of relationships" refers to the maximum total of active relationships a firm has within a specific six-month period. I group the number of relationships of all firms into bins of 5. The analysis covers seven six-month periods from April 2007 to September 2010. 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: Robustness 1. Effect of road disruptions on the probability of ending a relationship



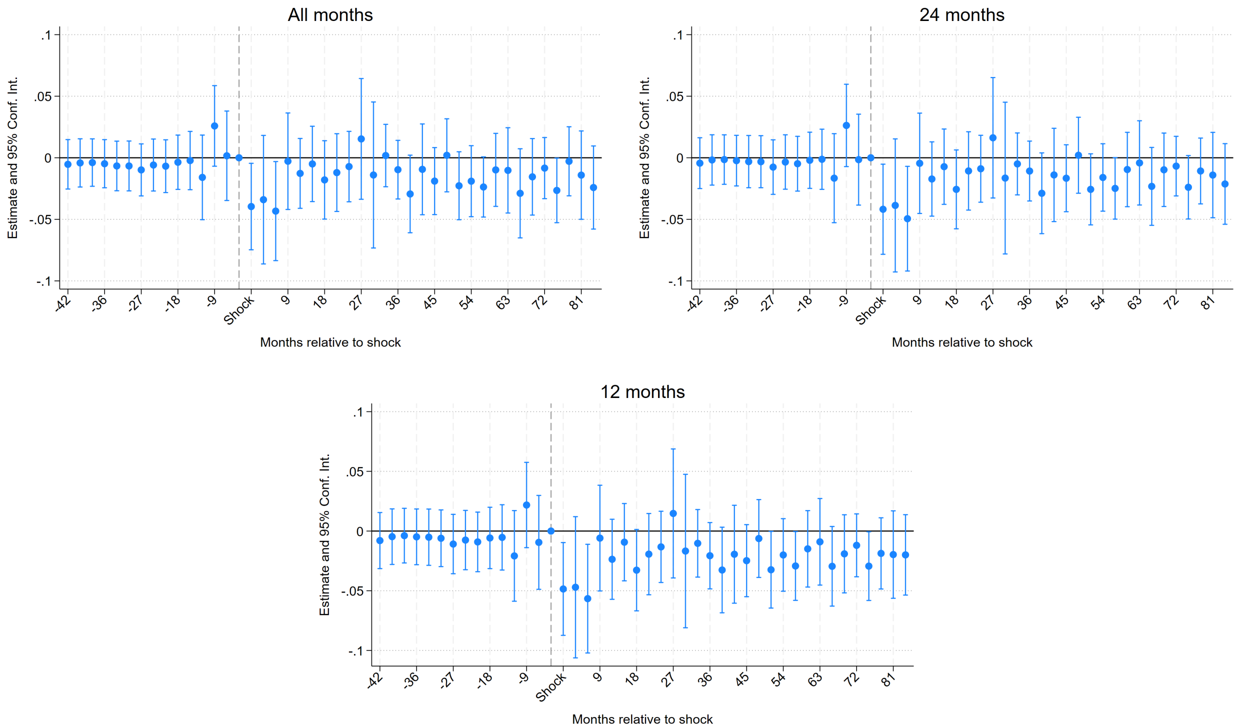
Notes: The figure plots the β_l coefficients from estimating equation (1) and the respective 95% confidence intervals. The top graphs use the different variable measures of *exposure to the shock*. In the left graph, all origin-cargo combinations are used, while in the right graph, only routes used 12 months before the shock are used. 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.7: Robustness 2. 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. In the top-left graph, I restrict the trade value to 20% in each route for estimating exposure to shock variables at the relationship level. My top-right graph includes all exporters in flood-prone areas. In the middle section, I add relationship fixed effects, and on the right, I estimate standard errors clustered by municipality. In the bottom graph, the first cohort is not included. The sample includes exporter and importer firms active one year before the disruptions and except for the last graph all regressions use all 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, excluding the middle-right estimations.

Figure A.8: Robustness 3: 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 graphs use the different variable measures of *exposure to the shock*. In the left graph, all origin-cargo combinations are used, while in the right graph I use the benchmark measures restricting to routes used 24 months before the shock are used. The bottom panel considers only routes used 12 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.

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

$$\Delta\pi_{ij} = \Delta(\pi^j) + \Delta(\pi^i) = -(\rho^j + \rho^i). \tag{7}$$

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

$$\Delta\pi_{ij} = \Delta(\pi^j) + \Delta(\pi^i) = -\lambda. \tag{8}$$

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

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

□