

Trade, Trucks, and Landslides: The Impact of Natural Disasters on Domestic Trade

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Abstract

Disruptions to transportation networks, such as natural disasters, can generate substantial economic costs and reshape trade activity. This paper combines data on more than 1,200 road landslides with seven years of weekly domestic trade flows in Colombia to estimate how transportation network disruptions affect trade and regional welfare. Using a structural gravity framework, we show that road blockages to bilateral transport links reduce trade by increasing transportation frictions. However, the welfare effects are heterogeneous because these shocks also reallocate trade across regions, creating both winners and losers. Consumption-oriented regions can benefit when their own trading links remain unaffected while disruptions occur elsewhere in the network, whereas regions lose when competing links remain operational and their relative market access deteriorates. These effects arise from the interaction between direct bilateral transportation shocks and indirect multilateral adjustments throughout the domestic trade network.

Keywords: Transportation disruptions; Natural disasters; Domestic trade

JEL codes: F14; F17; O18; Q54

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1. Introduction

Each year, natural disasters are responsible for billions of dollars of economic damages globally (Kousky, 2014).¹ These damages come both from the cost of mitigating and repairing the physical impacts and from the disruptions to economic activity that follow. The effects of these disruptions are particularly acute in low- and middle-income economies (Kellenberg and Mobarak, 2011), especially in countries whose geography puts them at elevated risk of weather-related disturbances such as landslides, floods, and other climate-driven events that undermine transportation infrastructure and impede commerce. The frequency and severity of such weather-related disruptions is expected to increase under climate change (Seneviratne et al., 2021), underscoring the importance of quantifying the economic damages caused by such events and bolstering the resilience of domestic transportation and trade infrastructure.

However, identifying the causal effects of network disruptions remains challenging for several reasons. Natural disasters rarely occur in isolation and often affect multiple dimensions of economic activity, making it difficult to distinguish the direct effects of disrupted links from broader indirect effects. Moreover, the granular data required to examine these effects across different contexts and network connections are scarce. Credible identification therefore requires detailed trade and network data combined with numerous localized and temporary shocks that affect different links across space and time.

The country of Colombia offers an ideal setting in which to investigate the economic impacts of natural disasters in trade links, for two main reasons. First, Colombia’s domestic trade network relies extensively on road infrastructure. Most traded goods are shipped by truck (Ministerio de Transporte, 2021) since the country lacks well-developed trade infrastructure in other modes such as rail and river transportation. Because natural disasters, and especially landslides, typically have the most severe impacts on road infrastructure, this makes the country’s domestic trade network especially susceptible to disaster-related

¹Estimates from the World Bank valued the global economic cost of natural disasters at \$92 billion in 2015 (Hallegatte et al., 2017).

disruptions. Second, Colombia’s hilly and mountainous topography leaves much of the country vulnerable to the frequent occurrence of landslides. Landslides occur year-round in different regions and commonly block key transportation linkages for extended periods of time, causing significant delays in shipments that hinder inter- and intraregional trade. Moreover, and as in most economies (both developing and developed), the value of Colombia’s intranational trade vastly exceeds the value of its international trade, highlighting the importance of evaluating the impacts of such disruptions on domestic commerce.

To shed light on a comparatively underexplored aspect of the economic impacts of natural disasters in trade, we investigate the question of how landslides affect domestic trade, and in turn, economic welfare. To do so, we use a detailed and novel dataset combining information on Colombia’s domestic trade (i.e., trade between and within Colombian regions), its road network, and the occurrence of landslides within the road network. We accomplish three interrelated objectives in our analysis. First, we measure the average effect of landslides on trade flows between regions. Second, we quantify the counterfactual impacts of landslides on domestic trade and welfare for all of Colombia, that is, how landslides disrupting one bilateral trade linkage impact all other trade linkages in the domestic trading network. Third, we pinpoint the regions and trade linkages for which landslides have caused the largest negative economic impacts, thereby identifying the locations towards which investments in transportation resilience would be likely to yield the greatest benefits. In doing so, we provide evidence on how natural disaster-related disruptions impede domestic trade within and between regions while accounting for the general equilibrium (multilateral) impacts of these disruptions on the entire Colombian domestic trade network. Our findings thus provide detailed and novel insights into the question of how short term disruptions affect domestic trade.

Our methodological approach relies on the widely used structural gravity framework and combines econometric and simulation-based counterfactual analyses. Using a generalized formulation of the gravity model and controlling for a host of unobserved factors via high-

dimensional fixed effects, we first estimate the relationship between weekly trade flows in agricultural products from source to destination regions and the occurrence of landslides at points along the routes that link these regions. We then use the parameter estimates from this analysis to calibrate the underlying structural model and conduct a set of simulation analyses. These counterfactual simulations allow us to quantify both the direct and indirect effects of landslides on Colombia’s domestic trade and welfare.

Our econometric estimates show that landslide disruptions to Colombia’s road network have pronounced negative effects on bilateral trade. In our preferred specification, a 1% increase in the number of landslides affecting routes between trading partners reduces weekly bilateral trade by an average of 0.059%. Building on this estimated relationship, our counterfactual simulations reveal substantial variation in the effects of landslides across regions and over time. Regions that depend heavily on external supplies experience the largest welfare losses. The general equilibrium framework also uncovers an additional margin by showing that landslides generate millions of dollars in both trade gains and losses in “bystander” regions through spillovers from disruptions elsewhere in the domestic trade network.

Our analysis shows that, although transportation network disruptions generally reduce trade, their effects on consumer welfare vary substantially across regions. This heterogeneity depends critically on whether a region is consumption-oriented or production-oriented. Consumption-oriented regions rely more heavily on imports because local production is insufficient to meet demand, whereas production-oriented regions generate a surplus that is shipped to other markets. Consumption-oriented regions tend to gain when the links they use to source goods remain available, since they can continue importing the quantities needed to satisfy local demand. However, their welfare decrease when links that connect other regions remain operational. Greater connectivity elsewhere in the network creates alternative trading opportunities and induces a reallocation of trade, which can divert shipments away from these importing regions and reduce the quantities they receive. Production-oriented regions respond differently. When their outbound trading links remain available, they can redirect a

larger share of their production toward other markets, increasing the volume shipped out of the region. These results show that welfare effects depend not only on whether a region is directly connected to an affected link, but also on how changes in connectivity elsewhere in the network reshape trade flows.

Our findings contribute to two distinct strands of literature. First, we build on work assessing how natural disasters affect trade and other economic activity. Related work with which our study aligns includes [Felbermayr and Gröschl \(2013\)](#), who examine the effects of natural disasters on economic growth via their impacts on trade, and [Hamano and Vermeulen \(2020\)](#), who analyze the way in which natural disasters cause traded products to be reallocated to different ports within a country. Other recent research examining how disasters affect domestic and international supply chains includes [Carvalho et al. \(2021\)](#) and [Hadachek et al. \(2024\)](#). Closely related to our study is that of [Ayala García et al. \(2023\)](#), who assess how local tax revenues are affected by natural disasters in Colombia through both direct and trade-mediated spillover effects. We extend this research by leveraging a dataset recorded at a higher level of spatial and temporal detail than used in existing work, which often relies on data recorded at an annual level and/or at a coarse geographical scale. Conducting our analysis at this level of detail is important in light of the short-run, geographically confined nature of most weather-caused disruptions to trade.

Second, our findings add to the literature on trade costs, that is, the broad set of factors which encourage or impede trade. We specifically build on the comparatively limited body of research focused on subnational trade costs in developing and emerging economies.^{2,3} Recent work includes [Atkin and Donaldson \(2015\)](#), who use micro-data on product-level spatial price gaps to quantify intranational trade costs in Ethiopia and Nigeria. Studies by [Donaldson and Hornbeck \(2016\)](#) and [Donaldson \(2018\)](#), who investigate how improvements in

²[Anderson and van Wincoop \(2004\)](#) and [Hummels \(2007\)](#) provide comprehensive surveys of trade costs, including their conceptual treatment and empirical determinants.

³Several recent studies analyze domestic trade costs in middle- and high-income economies. See, for example, [Duranton et al. \(2014\)](#) and [Jaworski et al. \(2023\)](#), both of which measure the effects of the U.S. interstate highway network, and [Agnosteva et al. \(2019\)](#), who assess interprovincial trade costs in Canada. [Xu and Fan \(2012\)](#) provide comparable evidence on trade costs between Chinese provinces.

transportation infrastructure in the historical United States and India, respectively, fostered improved market access within and between regions, also parallel our work. Most closely related to our study is that of [Allen et al. \(2024\)](#), who analyzes trade costs in the Colombian trucking sector in relation to features of the industry’s market structure. Though we do not measure trade costs directly in our analysis, we build on existing research in this area by quantifying how transportation disruptions caused by natural disasters, and the discrete changes in market access that these disasters give rise to, affect domestic trade and welfare. Again, our study improves on existing evidence by investigating these questions with more granular spatial and temporal precision compared to most of the existing work in this area.

The paper proceeds as follows. Section 2 provides contextual background on Colombia’s agricultural production and domestic trade, as well as detail on the Colombian road network and trade infrastructure. Section 3 outlines the components of our dataset and provides descriptive detail on its contents. Section 4 introduces the empirical methodology that we use for estimation and simulation. Section 5 presents the results of our empirical analysis. Lastly, section 6 provides concluding discussion.

2. Context

2.1 Production and Trade

Our empirical setting focuses on Colombia’s domestic trade in agricultural products. Colombia’s agricultural production is dominated by smallholders ([DANE, 2015](#); [Oxfam, 2016](#)), who sell their production at multiple points in cities, mainly in large wholesale markets in which produce is aggregated. These wholesale markets form the first stage of the country’s food supply chain ([FAO and FLAMA, 2024](#)), where buyers purchase products for distribution to supermarkets, restaurants, and other outlets ([DNP, 2015a,b](#); [FAO, 2020](#)).

Because of this structure, the system functions as a feeder network: numerous municipalities ship large volumes of production to wholesale markets, taking advantage of the scale economies afforded by shipping products to large, central markets. [Nino \(2026\)](#) shows that

these markets are located in population centers that together contain more than 80% of the country’s residents. Their centrality within the trade network makes these markets the most important source of food distribution in the country.

To reach wholesale markets, producers depend on trucking services. These services may transport goods in their own vehicles or, more commonly, hire intermediaries who arrange freight transport from municipalities to wholesale hubs. More than 90% of domestic freight is moved by road ([Ministerio de Transporte, 2021](#)). This is the case because Colombia, similar to many other emerging economies, lacks well-developed railroad and fluvial infrastructure ([Murcia, 1998](#)). This ensures that road freight transportation plays a critical role in Colombia’s supply chain and trade.

Even though the country’s mountainous topography and the effective lack of other types of transportation infrastructure act as an impediment to trade, especially for periphery areas with underdeveloped infrastructure ([Allen et al., 2024](#); [Herrera Dappe et al., 2024](#); [Nino, 2026](#)), most regions are involved in the country’s domestic trade network for agricultural products. The main reason for this relates to Colombia’s diverse climate and geography, which changes with altitude and temperature, which creates pronounced differences in agricultural production patterns across regions ([González-Orozco and Porcel, 2021](#)). The southern and eastern parts of Colombia are well suited for production of tree-grown commodities such as coffee and palm oil, high-altitude mountainous regions in the country’s interior provide ideal conditions for potatoes and horticultural products, and some regions in the plains are suitable for sugar cane and rice. The varied nature of interregional specialization results in a well-integrated trade system characterized by diverse comparative advantages primarily attributable to differences in agro-ecological conditions.

2.2 Natural Disasters

Colombia’s location along the Andean Cordillera, its mountainous geography, and its high precipitation rates make it one of the countries most affected by, and vulnerable to, landslides

(Grima et al., 2020). These catastrophic events can be triggered by various factors, including heavy rainfall, tectonic movements, natural erosion, and human activities (Sanderson and Sharma, 2016). However, the relationship between rainfall and landslides makes these events particularly prevalent in certain locations. Colombia’s situation in this regard is similar to other parts of the world with mountainous geography and high precipitation, such as Southeast Asia, Central America, and other South American countries (Nadim et al., 2006).

These high frequency events are among the most prominent natural threats on Earth, affecting infrastructure and causing billions of dollars in economic losses globally (Kjekstad and Highland, 2009). For example, landslides cause the highest annual property damage of any natural hazard in Turkey (Yalçın, 2011). In the European Alps—Italy, Austria, and Switzerland—landslides cause annual losses of roughly \$0.5 to \$5 billion (Kjekstad and Highland, 2009), while in Germany the annual average is about \$300 million (Klose et al., 2016).

Besides the direct effects associated with their physical damages, landslides have a range of indirect economic effects. For instance, landslides can reduce agricultural productivity, decrease asset values, and disrupt market activity (Kjekstad and Highland, 2009; García-Delgado et al., 2022; Winter et al., 2016). Evidence from Italy shows that hydrogeological events such as landslides decrease firms’ revenues by an average of 4.9% and employment by 2.2% (Clò et al., 2024). Evidence from British Columbia shows that closures caused by landslides and wildfires take comparably long to clear, and that closures in remote areas and those blocking a roadway entirely recover more slowly still (Rahman and Kim, 2024). In Colombia, landslides disconnect markets, creating a discrete change in affected regions’ ability to trade with other regions. This can lead to dramatic declines in interregional commerce and steep price increases that mainly affect vulnerable regions with limited road networks (Nino, 2026). Landslides also lower firms’ sales in affected areas and create imbalances in tax revenues (Ayala García et al., 2023). These events are of heightened relevance because the increasing frequency and severity of landslides driven by climate change poses significant

economic risks for many regions, both in Colombia and globally.

Despite extensive existing literature examining the link between natural disasters and trade integration or spatial price transmission in agricultural and other markets, few studies explicitly quantify the degree to which repeated natural disaster shocks affect trade flows beyond short windows of time. Most existing work either examines the short-run effects of a specific event, such as typhoons in Taiwan (Su et al., 2025) or floods in the Canadian province of British Columbia (Rahman and Kim, 2024), or relies on simulations of a few disruptions (Giedelmann Lasprilla et al., 2024; Reddy et al., 2016), rather than examining repeated observations of market transactions over multiple years and periods of exposure to different disruptions. Even studies that examine landslide-related variation tend to measure each landslide’s isolated, transitory impact on prices and other outcomes (Nino, 2026) and do not consider the cumulative economic impacts of the high-frequency occurrence of natural disasters over an extended interval of time. To our knowledge, our paper is the first to estimate the trade and welfare impacts of landslides by examining detailed market transactions at a granular spatial and temporal scale over a comparatively long period of time.

3. Data and Descriptive Statistics

3.1 Data

Our dataset combines three main sources of information. First, we construct a panel recording the monetary value of week-to-week inter- and intraregional domestic shipments of agricultural products traded throughout Colombia, combining information on goods’ prices with traded quantities. Our information on prices comes from weekly wholesale price series for 68 food products traded in the 20 largest Colombian markets between 2013 and 2020 published by the National Administrative Department of Statistics (*Departamento Administrativo Nacional de Estadística*, or DANE) through its price reporting platform, the *Sistema de Información de Precios* (SIPSA).⁴ These prices are merged with shipment records on traded quantities

⁴SIPSA collects and validates weekly price observations in the main wholesale markets, while DANE supervises the data collection process and quality control.

maintained by the Colombian Ministry of Agriculture. These records identify weekly trade flows within and between regions and contain information on the municipality of origin, the destination wholesale market, and the volume traded for every product.⁵ Details of the list of 68 products are provided in Appendix A.1.

Second, to identify the networks (roads and routes) that form the Colombian supply chain, we employ the Open Source Routing Machine (OSRM) algorithm of [Luxen and Vetter \(2011\)](#), a well-known routing algorithm from the transportation literature. This algorithm uses publicly available road data from the OpenStreetMap archives and has been validated in multiple contexts ([Randriamihaja et al., 2024](#); [Chen et al., 2024](#); [Olmos et al., 2020](#); [Dabiri et al., 2020](#); [Azadeh et al., 2022](#)), including the Colombian road network ([Nino, 2026](#)). We calculate the optimal route from all origin points (municipalities) to the final wholesale markets, producing more than 120,000 possible routes that detail the specific road segments used as well as the distance from origin to destination. This information is important for two reasons. First, it provides a precise measure of bilateral distance between trading regions that we employ in our empirical analysis. Second, it reveals the routes each supplier follows, allowing us to identify the exact road segments involved in the supply chain of every market affected by any landslide-caused disruption.

Third and finally, we compile information on landslides using reports maintained by the National Unit for Disaster Risk Management (*Unidad Nacional para la Gestión del Riesgo de Desastres*, or UNGRD), a Colombian government agency that documents natural disasters across the entire country.⁶ These records specify the disaster type, location, and

⁵Using the product composition observed in our data, we estimate that import-related goods account for approximately 1.6% of total trade value in the sample, while export-related goods account for approximately 3.6%. These estimates are based on product-level matches between the goods in our dataset and Colombia’s external trade data reported in WITS/UN Comtrade([World Bank, World Integrated Trade Solution \(WITS\), 2026](#)). Because our dataset captures domestic trade flows within Colombia rather than customs transactions, these figures should be interpreted as benchmark proxies rather than direct measures of imports or exports.

⁶UNGRD sends agents to validate the occurrence of natural disasters and provide details on the impacts of each event, though UNGRD is not the entity charged with fixing any resulting disruptions. Consequently, the records from UNGRD do not reveal the exact length of time needed to repair the impacts of a landslide. However, reports from Colombia’s *Instituto Nacional de Vías* ([INVÍAS, 2025](#)) indicate that 95% of these events are resolved within one to two weeks.

date of occurrence. For our 7-year study window we extract all landslides listed by UNGRD, corresponding to more than 1,200 events across the national territory, and merge them with the OSRM-generated network to determine which trade routes were affected by each blockage.

We aggregate our dataset at the region-week level, where each wholesale market is located in a different region. The origin points are natively defined at the municipality level, whereas destination regions (i.e., wholesale market) are defined at a more aggregate level roughly equivalent to departments (the highest administrative division in Colombia). To conform the spatial dimensions of the origin and destination regions, municipality-level origin regions are aggregated to department-level destination regions to match the twenty wholesale markets and thus define twenty exporting and importing regions. Bilateral distances in this new dataset are computed as the average across all origin-to-destination points for each market. Colombia is divided into 32 departments; we exclude from the analysis the island department of San Andrés and Providencia and five sparsely populated departments in the Amazon and Orinoco basins⁷ because the primary modes for shipping goods in these places are water and air transport. We combine the remaining seven departments with adjoining political entities to construct a balanced twenty-by-twenty trade matrix. The rule that we use for merging departments not containing a large wholesale market is to attach each such department to the trading department whose wholesale market is closest to the most populated areas of the department without its own market.⁸ This approach is grounded in the assumption that these departments host only small local markets and the bulk of traded products within these departments are sourced from the nearest large wholesale markets serving their population centers. More details on the data aggregation are provided in Appendix A.2.

⁷San Andrés and Providencia is a department in the Caribbean made up of small islands. The five Amazon and Orinoco departments are Vaupés, Guaviare, Guainía, Amazonas, and Vichada.

⁸Cundinamarca was merged with Bogotá, Chocó with Antioquia, La Guajira with Cesar, Caquetá with Huila, Arauca and Casanare with Boyacá, and Putumayo with Nariño.

3.2 Descriptive Statistics

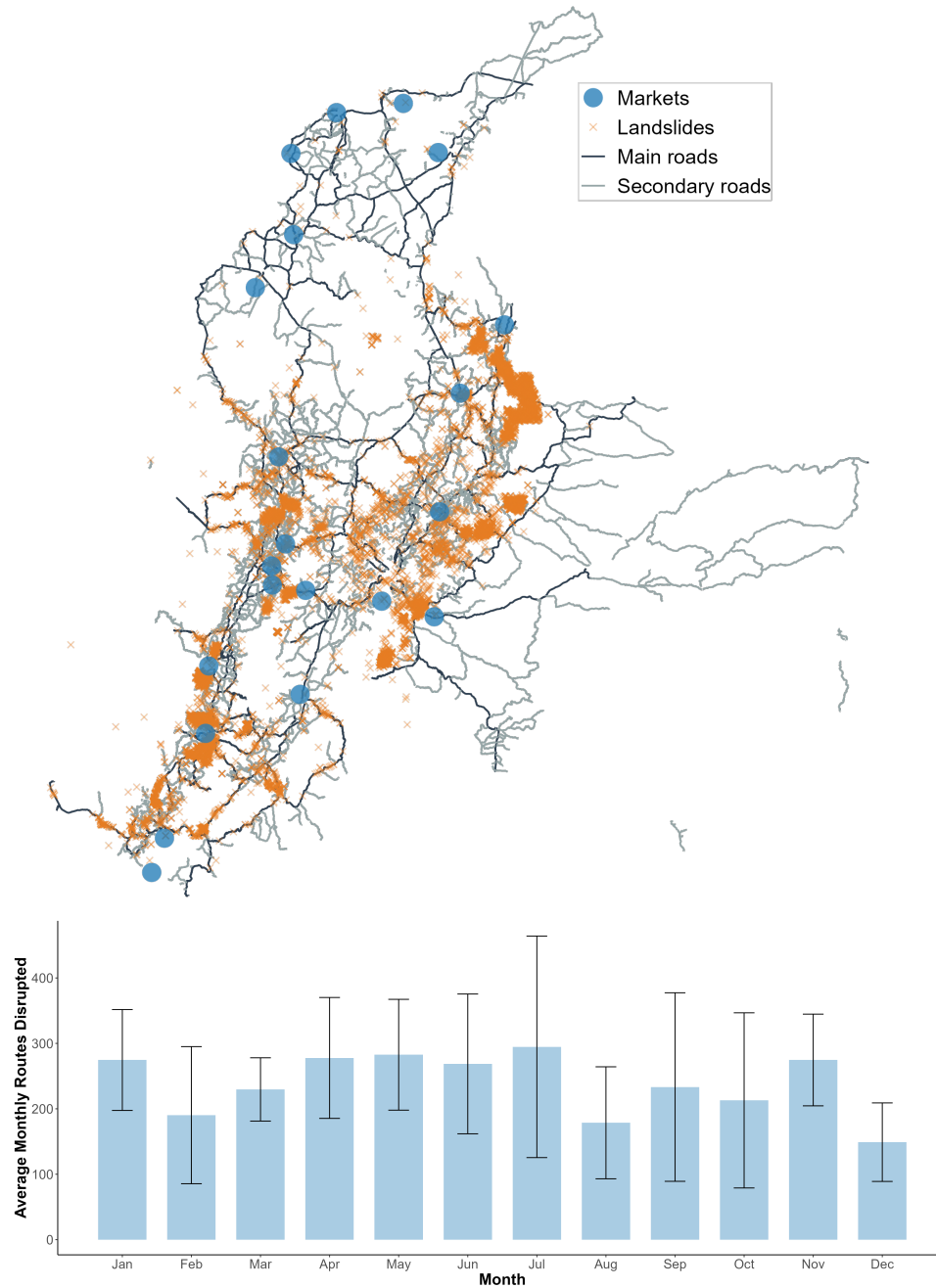
Figure 1 shows the location of the 20 regional markets that constitute our final dataset along with the road infrastructure that connects these markets, including both main highways and secondary routes. The locations of the landslides across the seven years in our dataset are depicted by orange crosses, illustrating the spatial distribution of these events over time. Landslides occur across many different parts of the country and are mainly concentrated in the middle of the country. This concentration is due to the mountainous geography of Colombia’s inland territory, particularly along the central Andean Cordillera, where steep slopes and high levels of precipitation increase susceptibility to landslides. In the bottom part of Figure 1, we present the average monthly number of routes affected by landslides for each month of the year along with 95% confidence intervals around these averages. Taken together, the two panels show that landslides are spatially concentrated along the Andean interior but dispersed over time. That is, no single time of the year visibly experiences a greater propensity to experience landslides, and the confidence intervals around the monthly averages overlap throughout the calendar year. The lack of a clear temporal pattern reveals that there is no inherent seasonality in the occurrence of landslides, the existence of which could allow for firms and trade intermediaries to prepare for such events in the short and medium run.

Table 1 reports descriptive statistics on production and trade calculated at the annual level. Columns are defined in the table notes; the consumption share is omitted for the national row, where it equals one by construction.⁹ The first row reports the yearly national average. National production of the products in our analysis amounts to \$6.9 billion each year, of which exports and imports each account for \$2.8 billion and own-demand accounts for \$4.1 billion.

The second row shows that the average region produces about \$344 million annually,

⁹The underlying data are recorded in Colombian pesos (COP); however, for ease of interpretation, we report monetary values in U.S. dollars (USD). To do this, we use the average exchange rate between COP-USD exchange over the seven-year sample period, which is equal to 2,694 COP/USD.

Figure 1. Markets, Landslides, and Road Routes, 2013 to 2019



Notes: The top panel shows the locations of wholesale markets (blue dots), landslides (orange crosses), main roads (dark blue lines), and secondary roads (grey lines) over the 2013 to 2019 sample period. The bottom panel displays the average monthly number of disrupted routes with 95% confidence intervals.

Table 1. Descriptive Statistics on Markets and Disruptions

Panel A: Characteristics of Trade					
	Total Production (1)	Exports (2)	Own-Demand (3)	Imports (4)	Share Consumption (5)
National Average	6,871 (2,111)	2,772 (773)	4,099 (1,353)	2,772 (773)	
Regional Average	344 (408)	139 (125)	205 (367)	139 (247)	0.76 (0.55)
Regional Max	1,325 (724)	158 (49)	1,167 (681)	1,016 (324)	1.67
Regional Min	16 (13)	8 (2)	8 (12)	17 (24)	1.42
Supply-Market-Week Observations	166,400	166,400	166,400	166,400	166,400
Supply-Market-Year Observations	3,200	3,200	3,200	3,200	3,200
Panel B: Characteristics of Regions Roles					
	Production Oriented ($\rho_i < 0.8$)		Consumption Oriented ($\rho_i \geq 0.8$)		
Mean consumption-to-production ratio	0.30 (0.24)		1.23 (0.32)		
Mean total demand	39.71 (30.96)		647.43 (746.02)		
Panel C: Characteristics of Transportation					
Average annual disrupted origin-week links per market	150 (21)				
Average Distance (km)	656 (131)				

Notes: Panel A summarizes annual regional trade metrics. Column (1) reports average annual production, column (2) reports exports, column (3) reports own-region demand, column (4) reports imports, and column (5) reports the consumption-to-production ratio ρ , which for consistency we compute over 2013–2019, the window of the counterfactual analysis, as set out in Appendix A.3. The first row reports statistics at the national level, while the second through fourth rows report the regional average, the region with the highest trade volume, and the region with the lowest trade volume, respectively. Panel B reports the consumption-to-production ratio and total demand for the two regional classifications, defined by ρ as reported in Appendix Table A1. Panel C reports the average number of weekly route disruptions throughout the year and the average distance from supply points to final destinations. Standard deviations are reported in parentheses.

with exports and imports each averaging \$139 million and own-region demand \$205 million. Cundinamarca has the largest trade volume: it produces \$1,325 million, exports \$158 million, imports \$1,016 million, and consumes \$1,167 million of its own production. Sucre has the smallest, at \$16 million produced, \$8 million exported, \$17 million imported, and \$8 million consumed locally. Appendix Table A2 reports these figures for every region. The last column gives consumption relative to production, where consumption includes goods sourced from other regions. Averaged across regions this ratio is 0.76; for Cundinamarca it reaches 1.67, indicating that such regions depend on production elsewhere to satisfy local demand.

We classify regions according to their ratio of consumption to production, as reported in Panel B. This distinction matters because a region’s position as a net seller or net buyer shapes the welfare effects of landslide-induced disruptions. We denote region i ’s ratio of total consumption to total production over the sample period by ρ_i . Using a cutoff of $\rho = 0.8$ divides the twenty regions into two equally sized groups. Ten regions are classified as

production-oriented ($\rho_i < 0.8$), while the remaining ten are classified as consumption-oriented ($\rho_i \geq 0.8$).¹⁰ Production-oriented regions have an average ratio of 0.30 and relatively low average demand of \$40 million. Consumption-oriented regions have an average ratio of 1.23 and average demand of \$647 million. Their local demand therefore exceeds local production, making them more dependent on inflows from other regions.

Table 1 also summarizes the characteristics of the supply chain. On average, landslides disrupt roughly 150 origin-week links serving each wholesale market per year, or 14.4% of the $20 \times 52 = 1,040$ origin-week links a market can have in a year. In addition, the table describes that goods must travel an average of 656 kilometers from their supply points by region to reach their destination wholesale markets. Table A3 in the appendix provides further description of the frequency of landslides in weekly bilateral disruptions. In 86% of observations of weekly bilateral trade, no landslides are present; in 7%, between 1 and 10 links are affected; and in the remaining 7%, more than 10 links are affected.

A visual representation of interregional production and trade is presented in Figure 2. The left panel shows the annual average value of demand, the middle panel shows the annual average share of consumption relative to production, and the right panel shows the trade balance. All maps are overlaid with the main road network. The first map shows that demand is concentrated in the central and western regions of Colombia. Antioquia, Valle del Cauca, and Cundinamarca account for approximately \$4.9 billion in trade value and together represent about 71% of national demand. A second tier of important demand centers is located in the northern and eastern parts of the country. These include Atlántico, with \$540 million; Norte de Santander, with \$398 million; Santander, with \$272 million; and Bolívar, with \$127 million. Together, these regions account for 19.4% of national demand.

The middle panel of Figure 2 shows the spatial distribution of regions according to their share of consumption relative to production. Regions with high consumption-to-production ratios are not spatially concentrated. These include Cundinamarca, Antioquia, Risaralda,

¹⁰Region-level values of ρ are reported in Appendix Table A1, while Appendix A.3 provides the definition.

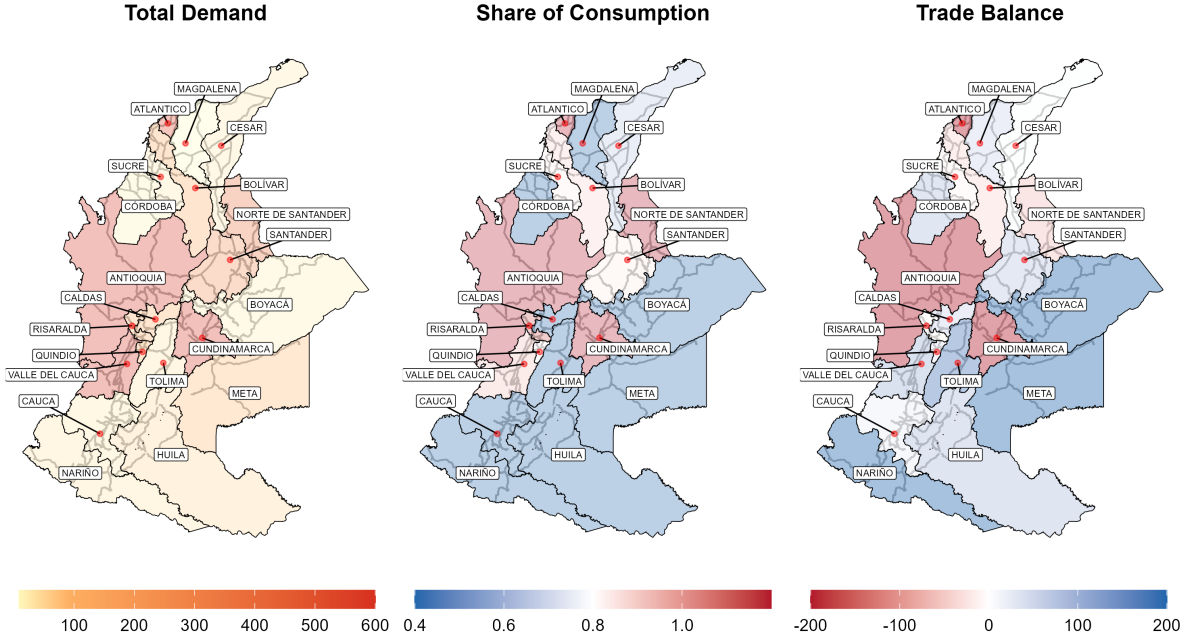
Atlántico, and Norte de Santander. As shown in the left panel, these regions also tend to have relatively high levels of demand, suggesting a spatial relationship between demand and the consumption-to-production ratio. Regions with low consumption-to-production ratios are located mainly in the south and east of the country, although some northern regions also exhibit relatively low shares. Regions whose ratio is close to one, such as Valle del Cauca and Santander, are found in the west and the northeast.

The right panel of Figure 2 shows the trade balance across the 20 markets. The region with the lowest trade balance is Cundinamarca, with a deficit of USD 858 million. This outcome is expected, as this region contains the largest share of Colombia’s population. The second largest trade deficit is observed in Antioquia, at USD 421 million, which hosts the country’s second-largest city. The third largest deficit corresponds to Atlántico, with a trade balance of USD –221 million. In contrast, the regions with the highest trade surpluses are located in the eastern and southeastern parts of the country. Boyacá records a surplus of USD 450 million, exporting approximately 97% of its production, followed by Meta with USD 310 million (84% exported), Nariño with USD 204 million (88% exported), and Tolima with USD 172 million (93% exported).¹¹

The three components of Figure 2 reveal important patterns in national production and features of the Colombian supply chain. Regions with the highest levels of consumption are generally those with the largest populations. However, local production is often insufficient to meet domestic demand, requiring these regions to rely on imports. Departments in the east and southwest support high-demand areas by exporting a large share of their production. Some northern departments also run trade surpluses, but their limited production capacity keeps their share of interregional trade small.

¹¹More details on the spatial concentration of exports and imports are presented in Figure A.2.

Figure 2. Yearly Average Demand, Consumption Share, and Trade Balance in Million USD



Notes: The left panel shows demand across regions on a log scale, with yellow indicating lower demand and red indicating higher demand. The middle panel presents the ratio of consumption-production, where blue represents lower shares and red represents higher shares. The right panel illustrates net exports, with red regions being net importers and blue regions being net exporters. The overlay in each subfigure represents the main Colombian road network.

4. Methods

Our empirical strategy proceeds in two steps that build on one another. We first fit a structural gravity model of Colombian domestic trade to weekly inter- and intraregional shipments recorded between 2013 and 2020. The coefficients recovered from that exercise then calibrate a counterfactual simulation, which lets us ask how the landslides observed over the sample period reshaped the country's internal trade patterns.

4.1 Gravity Model

The foundation for our empirical approach is the generalized version of the gravity equation (Anderson and van Wincoop, 2004; Fally, 2015) given by

$$X_{ijt} = \frac{Y_{it}}{\Pi_{it}^{-\theta}} \frac{E_{jt}}{P_{jt}^{-\theta}} \tau_{ijt}^{-\theta}, \quad (1)$$

where X_{ijt} is the monetary value of exports from exporter i to importer j in period t .

Three components govern this relationship. Two of them summarize market size: $Y_{it} = \sum_j X_{ijt}$ measures the supply available at the origin, while $E_{jt} = \sum_i X_{ijt}$ measures the demand faced at the destination. Since the two summations run over all destinations and all origins respectively, each encompasses intra-regional shipments, that is, the observations for which $i = j$. The third component, τ_{ijt} , gathers the bilateral frictions that make trading between two regions easier or harder. Accompanying these are Π_{it} and P_{jt} , the outward and inward multilateral resistance terms (MRTs) of the exporter and the importer, defined implicitly by

$$\Pi_{it}^{-\theta} = \sum_{j=1}^N \frac{E_{jt} \tau_{ijt}^{-\theta}}{P_{jt}^{-\theta}} \quad \text{and} \quad P_{jt}^{-\theta} = \sum_{i=1}^N \frac{Y_{it} \tau_{ijt}^{-\theta}}{\Pi_{it}^{-\theta}}. \quad (2)$$

Ever since Anderson and van Wincoop (2003) formalized them, the MRTs have been read as weighted averages of the barriers a region confronts across the whole set of its trading partners, with consumption shares serving as weights on the importing side and production shares on the exporting side (Anderson, 2011). Their role, however, is not confined to summarizing average frictions; they are also the channel through which localized shocks propagate. Should τ_{ijt} shift for one particular pair, that pair is affected directly, while every other pair in the system is affected indirectly as Π_{it} and P_{jt} adjust in response. A result we rely on heavily below is due to Fally (2015), who shows that quantities proportional to the MRTs can be backed out of estimated exporter-by-time and importer-by-time fixed effects; this property is what makes our counterfactual simulation feasible. The two remaining objects are the trade

elasticity $\theta > 0$, which dictates how responsive shipments are to movements in trade costs, and N , the number of trading regions.

Since the object of our econometric analysis is to isolate the role that landslide-induced disruptions play in trade between regions, we let τ_{ijt} depend on landslide incidence along the relevant bilateral linkage together with three geographic controls in common use:

$$\tau_{ijt}^{-\theta} = \exp\{\beta_1 \operatorname{arcsinh} L_{ijt} + \beta_2 \ln D_{ij} + \beta_3 C_{ij} + \beta_4 H_{ij}\}. \quad (3)$$

Note that (3) parameterizes $\tau_{ijt}^{-\theta}$, the object that enters (1) directly, rather than τ_{ijt} itself; a negative coefficient therefore indicates a covariate that raises trade costs and depresses bilateral flows. The variable of interest is L_{ijt} , the count of landslides recorded on the linkage joining regions i and j during week t , entered through the inverse hyperbolic sine so that the many zeros in the data are retained.¹² Its coefficient β_1 thus records how strongly bilateral shipments respond to the number of blockages along a given route. The three remaining regressors are conventional gravity covariates that we include to limit omitted variable bias. D_{ij} is the effective travel distance in kilometers separating i and j , computed with the OSRM routing procedure described above. C_{ij} turns on when the two regions are adjacent, absorbing domestic border effects, whereas H_{ij} turns on for intra-regional observations ($i = j$), absorbing home-market effects.¹³

¹²The transformation retains linkage-weeks without landslides, which make up 85.6% of our observations and would be dropped under a logarithm. Two qualifications follow. First, β_1 is not an elasticity across the whole sample: the elasticity implied by (3) equals $\beta_1 L_{ijt} / \sqrt{L_{ijt}^2 + 1}$, which is zero at $L_{ijt} = 0$ and approaches β_1 only as L_{ijt} grows (Bellemare and Wichman, 2020); we therefore restrict the elasticity reading to disrupted linkages and report discrete comparisons elsewhere. Second, the $\operatorname{arcsinh}$ transformation is in general sensitive to the scale of the variable it is applied to (Aihounton and Henningsen, 2021). This concern is muted here: because L_{ijt} aggregates blockages across the route segments joining each pair, its positive values are large enough that $\operatorname{arcsinh} L_{ijt}$ and $\ln L_{ijt} + \ln 2$ differ by less than 0.003 at and above the median positive count, so that among disrupted linkage-weeks the specification is empirically indistinguishable from a scale-invariant logarithmic one. The binary specification in column (2) of Table 2 is invariant to both concerns by construction. Its coefficient is not directly comparable to that of column (1), since the two multiply different regressors, but once placed on a common scale the two agree closely: column (2) implies a trade reduction of 17.6% on any disrupted linkage-week, while column (1) implies 16.7% at the median positive count and 15.5% averaged over all disrupted linkage-weeks. Appendix B reports further functional forms, including bins of the landslide count.

¹³Both effects are usually discussed in an international setting, yet the domestic evidence for them is well

Inserting (3) into (1) and appending a mean-zero disturbance ϵ_{ijt} delivers the equation we take to the data:

$$X_{ijt} = \exp \{ \beta_1 \operatorname{arcsinh} L_{ijt} + \beta_2 \ln D_{ij} + \beta_3 C_{ij} + \beta_4 H_{ij} + \gamma_{it} + \delta_{jt} \} + \epsilon_{ijt}. \quad (4)$$

Here the fixed effects $\gamma_{it} = \ln(Y_{it}) + \theta \ln(\Pi_{it})$ and $\delta_{jt} = \ln(E_{jt}) + \theta \ln(P_{jt})$ absorb the exporter and importer size terms jointly with the outward and inward MRTs. Because the MRTs transmit trade-cost movements originating anywhere in the network, specification (4) recovers the direct bilateral consequences of landslides through $\beta_1 \operatorname{arcsinh} L_{ijt}$ and their system-wide consequences through γ_{it} and δ_{jt} . The two sets of fixed effects additionally sweep out unobserved origin- and destination-specific determinants of trading behavior that may correlate with landslide exposure, among them persistent geographic frictions, established trading relationships, the state of local infrastructure, market structure, and regional institutional capacity.

Estimation is by Poisson pseudo-maximum likelihood (PPML), the approach advocated by Santos Silva and Tenreyro (2006) and since adopted as the default in this literature. Two properties recommend it over an OLS regression on the log-linearized gravity equation: observations with zero trade are retained rather than discarded, and the estimator stays unbiased and consistent when the disturbances are heteroskedastic. We report standard errors clustered by bilateral pair, which leaves ϵ_{ijt} free to be arbitrarily correlated within a given trading relationship.

4.2 Simulation Analysis

Having estimated (4), we use its coefficients to calibrate a counterfactual simulation. The question the exercise addresses is how shipments across the Colombian network would have

established. The “border puzzle” documented for interstate shipments in the United States and interprovincial shipments in Canada by McCallum (1995) and Anderson and van Wincoop (2003) points to the extra trade sustained between neighboring jurisdictions, while Wolf (2000) shows that buyers within a region source disproportionately from producers located inside it.

been reallocated had the landslides recorded in our data not blocked the road system. Because landslide incidence varies from one week to the next, we run the simulation separately for every week in the sample and report the resulting changes both over time and in the aggregate; the time subscript t is therefore retained throughout.¹⁴

The exercise begins with baseline flows, that is, the bilateral values implied by the trade costs that were actually observed, before any hypothetical change in landslide incidence. We recover them from the constrained regression

$$X_{ijt} = \exp\left\{\widehat{\beta}_1 \operatorname{arcsinh} L_{ijt}^B + \widehat{\beta}_2 \ln D_{ij} + \widehat{\beta}_3 C_{ij} + \widehat{\beta}_4 H_{ij} + \gamma_{it} + \delta_{jt}\right\} + \varepsilon_{ijt}, \quad (5)$$

in which L_{ijt}^B records the landslides actually observed and the slope coefficients $\widehat{\beta}_1$ through $\widehat{\beta}_4$ are held fixed at the values estimated from (4), leaving only the two sets of fixed effects to be determined.

Fitting (5) returns baseline exporter and importer fixed effects, $\widehat{\gamma}_{it}^B$ and $\widehat{\delta}_{jt}^B$, which by the argument of [Fally \(2015\)](#) are proportional to the structural MRTs prevailing under observed trade costs. Baseline flows $\widehat{X}_{ijt}^B$ then follow as the fitted values of that regression:

$$\widehat{X}_{ijt}^B = \exp\left\{\widehat{\beta}_1 \operatorname{arcsinh} L_{ijt}^B + \widehat{\beta}_2 \ln D_{ij} + \widehat{\beta}_3 C_{ij} + \widehat{\beta}_4 H_{ij} + \widehat{\gamma}_{it}^B + \widehat{\delta}_{jt}^B\right\}. \quad (6)$$

Counterfactual flows are constructed in exactly the same manner, the sole difference being the landslide input. We set $L_{ijt}^C = 0$ on the affected linkages, so that the counterfactual portrays a road network on which the blockage never materializes, either because the landslide does not occur or because it is perfectly prevented in advance. Two versions of this intervention are implemented: a nationwide one, in which every landslide in the country is removed at once, and a regional one, in which only the events recorded on linkages involving a single region are removed, region by region. Appendix C relaxes the assumption of complete removal

¹⁴The gravity estimation uses the full 2013–2020 sample; the counterfactual covers 2013–2019. Coverage of the second half of 2020 is incomplete owing to the COVID-19 disruption, and we drop the year as a whole so that annual aggregates remain comparable.

and reports scenarios in which landslide incidence instead falls by intermediate percentages. Throughout, our interest lies in trade between regions, so intra-regional trade costs are left at their observed values.

Re-estimating (5) with L_{ijt}^C in place of L_{ijt}^B delivers the counterfactual fixed effects $\hat{\gamma}_{it}^C$ and $\hat{\delta}_{jt}^C$, which capture how the MRTs adjust once the disruptions are lifted. Counterfactual flows follow from the same functional form:

$$\hat{X}_{ijt}^C = \exp\left\{\hat{\beta}_1 \operatorname{arcsinh} L_{ijt}^C + \hat{\beta}_2 \ln D_{ij} + \hat{\beta}_3 C_{ij} + \hat{\beta}_4 H_{ij} + \hat{\gamma}_{it}^C + \hat{\delta}_{jt}^C\right\}. \quad (7)$$

The gap between the two sets of predicted values, $\Delta\hat{X}_{ijt} = \hat{X}_{ijt}^C - \hat{X}_{ijt}^B$, is what we report in the results that follow. Because the fixed effects are re-estimated under the counterfactual landslide distribution, this difference embeds the direct effect on the disrupted linkage together with the reallocation induced across every other pair in the network as the MRTs adjust. Aggregating $\Delta\hat{X}_{ijt}$ over destinations, over origins, or over both yields the regional export, regional import, and national trade changes discussed below.

5. Results

5.1 Econometric Estimates

Table 2 presents our main estimation results across four model specifications.¹⁵ Column (1) reports our preferred specification, which includes the inverse hyperbolic sine transformation of landslide frequency ($\operatorname{arcsinh} L_{ijt}$), geographical distance ($\ln D_{ij}$), an indicator variables for contiguity (C_{ij}) and within-region trade (H_{ij}). Columns (2) through (4) present alternative specifications to assess the robustness of our findings. Our preferred specification in column (1) reveals that landslides significantly reduce bilateral trade flows. The coefficient on $\operatorname{arcsinh} L_{ijt}$ (β_1 from equation (4)) is equal to -0.059 and statistically significant. Among linkages that

¹⁵The size of the estimation sample in each specification (107,504) differs from the total size of our sample (166,400 as reported in Table 1) due to the exclusion of separated observations from the estimation. Separated observations are generally those for which trade flows are perfectly predicted by one or more of the fixed effects (see [Correia et al., 2020](#)).

Table 2. Regression Results

	(1)	(2)	(3)	(4)
$\text{arcsinh } L_{ijt}$	-0.059^{***} (0.017)		-0.093^{***} (0.023)	
L'_{ijt}		-0.193^{***} (0.074)		-0.403^{***} (0.096)
$\ln D_{ij}$	-1.334^{***} (0.220)	-1.332^{***} (0.220)		
C_{ij}	-0.053 (0.187)	-0.053 (0.187)	0.588^{***} (0.220)	0.587^{***} (0.220)
H_{ij}	1.309^{***} (0.263)	1.314^{***} (0.263)	3.156^{***} (0.140)	3.157^{***} (0.140)
Observations	107,504	107,504	107,504	107,504
Exporter–Time FE	✓	✓	✓	✓
Importer–Time FE	✓	✓	✓	✓

Notes: Dependent variable is the value of weekly bilateral exports from source regions to destination regions. Estimation method is PPML. Standard errors clustered by bilateral pair in parentheses. L_{ijt} measures the count of landslide occurrences between i and j in period t . L'_{ijt} is a binary indicator for the occurrence of landslides along a trading linkage. Intercept is estimated in each specification but not reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

actually experience disruption, this implies that a 1% increase in landslide frequency is associated with a 0.059% decrease in trade value. Geographical distance exhibits the expected negative effect, with a coefficient of -1.334, consistent with other estimates on this variable from the literature.¹⁶ The within-region indicator (H_{ij}) shows a strong positive coefficient of 1.309, reflecting a significant home-market effect even after conditioning on distance. The contiguity indicator (C_{ij}) is statistically insignificant when distance is controlled for, suggesting that adjacency between trading regions does not confer additional trade advantages beyond proximity.

To verify the stability of our core findings, we examine alternative specifications. Column (2) replaces the continuous landslide measure with a binary indicator (L'_{ijt}) equal to one if any landslide occurred on the route between region i and j and zero otherwise. The coefficient of -0.193 indicates that landslide occurrence per se reduces trade by approximately 17.6 percent.

¹⁶In a meta-analysis, [Disdier and Head \(2008\)](#) report a mean estimate for the distance effect of around -0.9.

Columns (3) and (4) omit the distance variable. Omitting distance changes the estimates substantially: when distance is excluded, the coefficient on $\text{arcsinh } L_{ijt}$ increases to -0.093 (column 3), representing a 58% increase in magnitude. The landslide effect remains statistically significant, but the change in coefficient size shows that distance must be controlled for.

The necessity of including distance controls becomes apparent when comparing coefficients across specifications. The contiguity indicator coefficient reverses sign from -0.053 in columns (1) and (2), where it is insignificant, to 0.588 and 0.587 (highly significant) in columns (3) and (4), respectively. Similarly, the within-region indicator coefficient more than doubles from 1.309 to 3.156 when distance is omitted. These shifts are consistent with omitted variable bias: discrete geographic indicators do not substitute for distance.

We also estimate the specification reported in Table B1 in the appendix, which replaces the continuous measure with four bin dummies covering 1–10, 11–25, 26–50, and more than 50 affected links, leaving the no-landslide category as the omitted group. Each bin enters negatively relative to that category, significantly so at the 1% level for the 11–25 bin and at the 10% level for the remaining three. However, the coefficients do not increase with intensity. They range from -0.165 to -0.324 with no monotonic pattern, and the differences between bins are not statistically distinguishable. The cost of disruption therefore appears to operate largely at the extensive margin, through whether a linkage is blocked at all rather than through how many blockages it carries.

Moreover, a potential concern is that agents may anticipate landslide events or adjust behavior after roads are restored, which could bias our estimates. Additionally, unobserved confounding factors unrelated to landslides may also affect trade. To address these concerns, we conduct several robustness checks. First, we estimate a specification including leads and lags of the landslide variable (Figure B.1) to assess whether the effects are driven by pre-trends or anticipation. The results show no significant effects in the periods prior to the event, suggesting the absence of anticipation effects. Furthermore, the impact is concentrated in the contemporaneous period (period 0) and dissipates afterward, with no evidence of

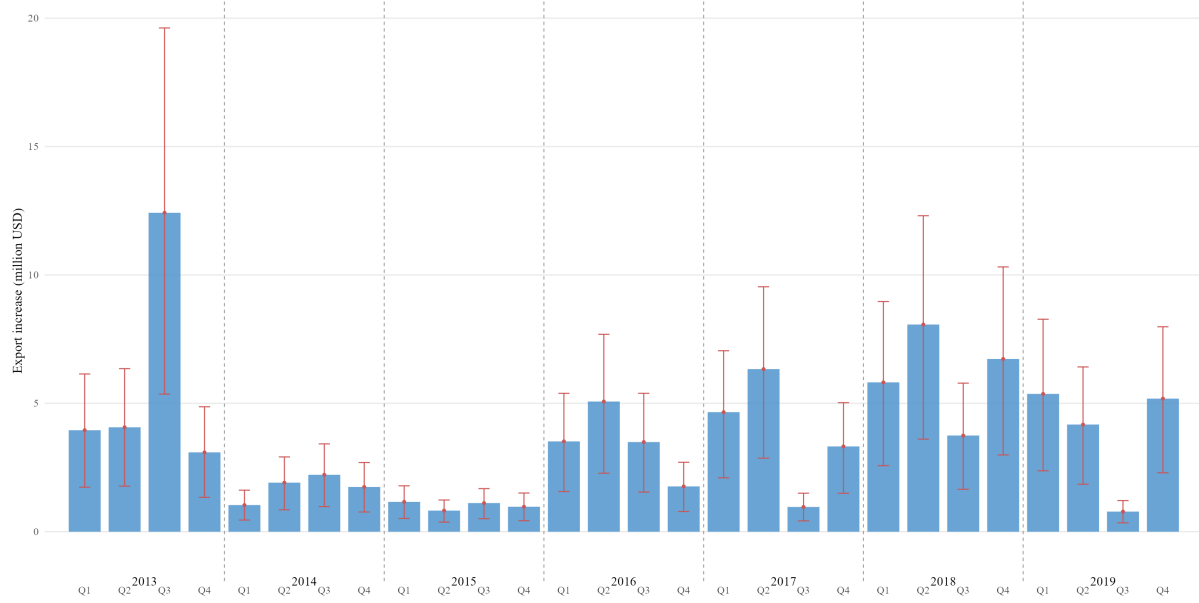
compensatory increases in trade in subsequent periods. Overall, the evidence indicates that the effect is short-lived and confined to the timing of the shock, as expected.

Second, in Table B2, we extend the baseline estimates presented in Table 2 by incorporating additional specifications that include origin-destination (pair) fixed effects and precipitation controls at both the origin and destination. These controls account for potential confounding factors, such as rainfall, which may simultaneously affect the likelihood of landslides and agricultural production (supply). We also control for precipitation at the destination, as rainfall may influence local demand conditions. Adding precipitation controls to our preferred specification leaves the estimates essentially unchanged: the coefficient on $\text{arcsinh } L_{ijt}$ remains -0.059 and that on L'_{ijt} remains -0.192 (columns (3) and (4) of Table B2), which indicates that rainfall at the origin or the destination does not account for the estimated effect. In the four specifications that additionally absorb pair fixed effects, the coefficient declines but remains significant, while the binary indicator becomes not significant.

5.2 Counterfactual Simulation Estimates

Our counterfactual scenario assumes the absence of all landslides in Colombia. We conduct this analysis at the weekly level across all Colombian regions. In this scenario, producers can freely allocate their output without landslide constraints. Figure 3 presents the export impacts of this counterfactual over time. The counterfactual gains are positive in every quarter. The single largest quarter is the third quarter of 2013, at USD 12.4 MM, which reflects an exceptional disruption episode. Annual gains fall to USD 6.9 MM in 2014 and USD 4.1 MM in 2015 before recovering, and reach their maximum of USD 24.4 MM in 2018. In 2017 through 2019, Q3 records the smallest export increase of the four quarters.

Figure 3. Export Changes after Avoiding Landslides



Notes: Export increases are reported in million USD. Q1–Q4 denote the quarters within each year. The bars show the counterfactual evaluated at $\hat{\beta}_1$; the vertical lines are 95% intervals obtained by re-running the counterfactual at $\hat{\beta}_1 \pm 1.96 \text{ s.e.}(\hat{\beta}_1)$, the coefficient on $\text{arcsinh } L_{ijt}$ in column (1) of Table 2.

As specified previously, total additional exports in the country would be around USD 103.5 MM, representing approximately 3.73% of annual exports. Figure 4 shows the cumulative trade change if landslides were averted over the seven-year period from 2013 to 2019 across different regions of Colombia. The left map reflects the total trade gain in millions of dollars, measured through exports.

The map shows that most of the trade gains from avoiding landslides are concentrated in the western part of the country. The most benefited region is Antioquia, with USD 30.8 MM in additional trade, followed by Valle del Cauca with USD 25.7 MM and Cundinamarca with USD 12.3 MM. Together, these three regions account for 66.4% of the total. Other regions in the east, such as Norte de Santander (USD 9 MM), Santander (USD 6.4 MM), and Meta (USD 3.3 MM), represent a second tier of export increases, jointly accounting for 18% of the additional trade. In contrast, the northern part of the country would not experience significant increases in trade if landslides were avoided.

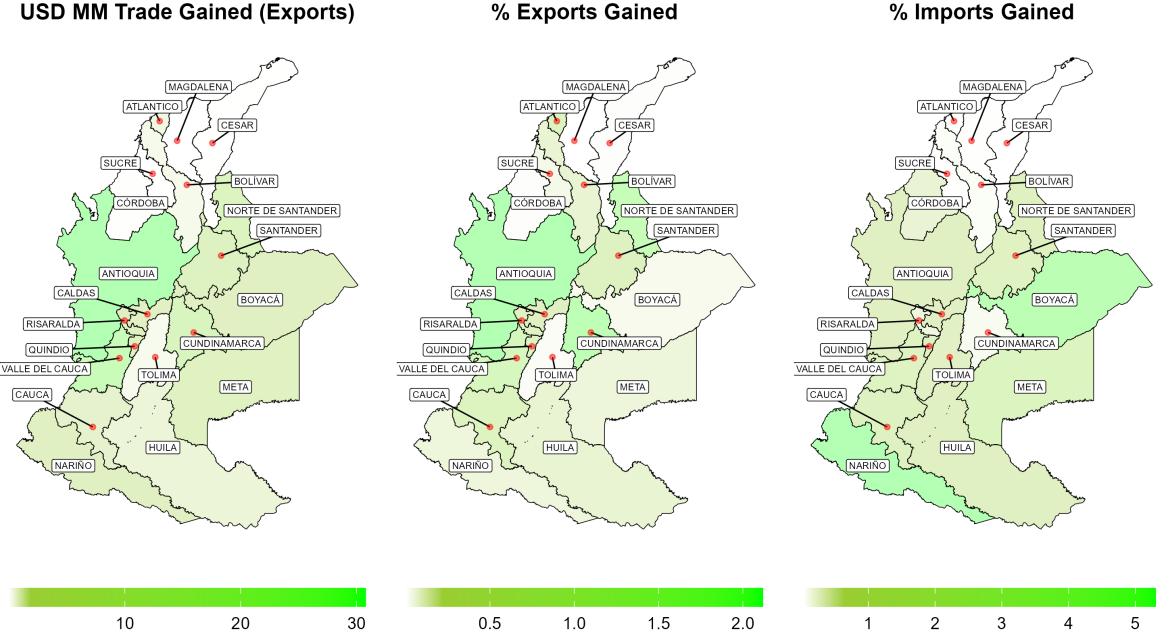
To assess the effect relative to each region's market size, the middle and right maps in Figure 4 show percentage changes in exports and imports relative to their baseline levels.

Consistent with the level effects, the west of the country experiences the largest percentage increase in exports, followed by the centre. Antioquia raises its exports by 2.12% and Cundinamarca by 2.02%. The third-largest percentage increase, 1.78% in Norte de Santander, does not follow the ranking of the level effects. Other sizable increases occur in Valle del Cauca (1.10%), Atlántico (0.59%), Cauca (0.57%), and Quindio (0.56%).

Regions experiencing increases in imports when landslides are avoided are distributed throughout the country, although two regions account for the largest import responses: Nariño, with a 5.36% increase, and Boyacá, with a 5.14% increase. Other notable regions include Meta (1.93%), Valle del Cauca (1.45%), and Cauca (1.31%). Regions that experience the largest increases in imports generally exhibit positive trade balances, exporting close to 90% or more of their production.

We examine multiple counterfactual scenarios by evaluating gains from trade under full (100%) and partial reductions of landslides (75%, 50%, and 25%). Results are presented in Figure C.2 in the Appendix. The figure shows consistent patterns across scenarios. Export gains arise over similar periods, are already observable under partial reductions, and become more persistent as disruptions are further reduced.

Figure 4. Aggregated Benefits of Avoiding Landslide Disruptions



Notes: The left map reports trade gains in USD millions resulting from the counterfactual scenario in which all landslide disruptions in Colombia are eliminated. White indicates zero effect, while darker shades of green correspond to larger gains. The middle map shows percentage changes in exports relative to baseline levels under the same counterfactual scenario, and the right map presents percentage changes in imports. All maps display Colombian regions with internal trade linkages and include regional labels.

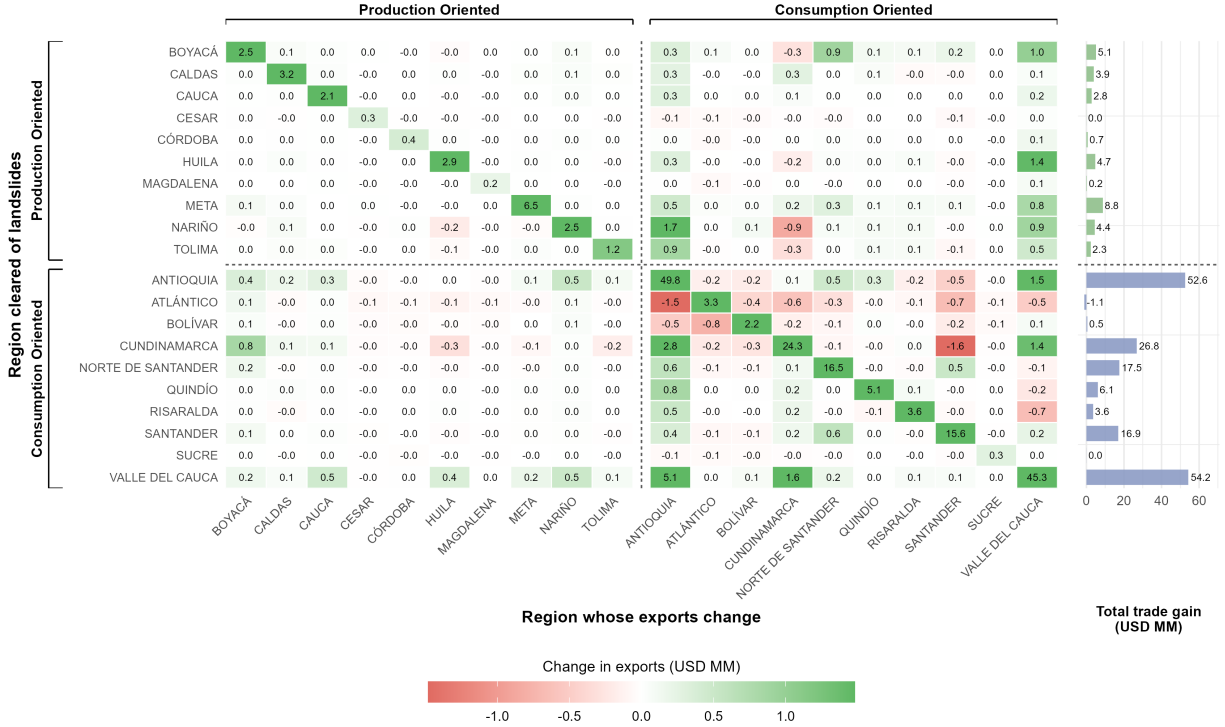
One important advantage of our analysis is that it allows us to identify the most vulnerable places in terms of their effects on aggregate trade at the national level. In particular, we can assess what would happen if landslides were eliminated in a specific region and how this localized change would affect trade flows throughout the entire country.

To identify the regions whose disruptions matter most for national trade, beyond the initial counterfactual scenario of eliminating all landslides in Colombia, we now run counterfactual simulations in which landslide disruptions are eliminated one region at a time and measure the resulting change in total trade at the country level. Figure 5 presents aggregated gains in trade (exports) from avoiding landslide disruptions in the trucking network over the full period. Details on the effects for each specific week and region are provided in Appendix C.

The heat-map matrix reports, on the vertical axis, the region in which landslides are eliminated, and on the horizontal axis, the region whose trade is affected. The figure also includes a bar graph summarizing the total trade gains associated with eliminating landslides

in each region as well as the classification of the region based on the consumption-production ratio presented in the previous sections. A geographical representation in aggregated terms is presented in Figure C.1 in Appendix C.

Figure 5. Regional Trade Gains from Eliminating Landslides



Notes: The heat map reports counterfactual results from eliminating landslides in each specific region, shown on the vertical axis, and the corresponding regions affected by this intervention on the horizontal axis. Cell values report changes in trade in USD millions, highlighted in red for negative effects and in green for positive effects. The figure also includes a side bar chart showing the cumulative trade gains from eliminating landslides in each region, obtained by summing trade changes across all affected exporter regions.

The heat map reveals that eliminating landslides in Antioquia and Valle del Cauca generates the largest increases in national trade. Avoiding landslides only in Valle del Cauca would increase total exports by approximately USD 54 MM nationwide, while eliminating disruptions in Antioquia would increase exports by about USD 52.6 MM. Other regions with substantial contributions to national trade gains include Cundinamarca (USD 26.8 MM), Norte de Santander (USD 17.53 MM), Santander (USD 16.9 MM), and Meta (USD 8.76 MM). In contrast, avoiding landslides in northern regions such as Magdalena, Cesar, Sucre, and Bolívar would generate virtually no changes in aggregate trade patterns, while for Atlántico national exports would decline slightly, by USD 1.1 MM. The ability to disentangle network

effects is an important contribution of our analysis, since disruptions reach both the region where the disaster occurs and other regions that rely on the affected transportation network. For instance, eliminating landslides in Antioquia would increase trade in Valle del Cauca by USD 1.5 MM, in Nariño by USD 0.5 MM, and in Norte de Santander by USD 0.5 MM.

Several patterns emerge from the heat-map matrix. First, the largest gains for each region arise from eliminating landslides within its own territory. For example, of the USD 52.6 million increase in trade generated by eliminating landslides in Antioquia, USD 49.8 million, or 95%, originates within Antioquia itself, with the remaining gains accruing to other regions. Second, the regions that benefit the most from eliminating landslides elsewhere are consumption-oriented ones; Antioquia and Valle del Cauca are the clearest cases. Finally, clearing landslides in other regions does little for production-oriented regions.

Because these region-by-region interventions are evaluated one at a time, their gains do not add up to the gain from removing all landslides at once. When only one region's routes are cleared, that region captures trade that would otherwise have been diverted elsewhere, whereas under the nationwide counterfactual every region's frictions fall simultaneously and the multilateral resistance terms adjust so that regions compete for the same reallocated flows. This general equilibrium substitution is why the sum of the region-specific gains exceeds the USD 103.5 MM obtained under the nationwide scenario, and why each region's own gain is larger when it is cleared in isolation.

Overall, the results show that preventing transportation disruptions in the largest demanding regions, particularly Antioquia, Valle del Cauca, and Cundinamarca, would generate the highest trade returns at the national level. These gains arise both from increased trade within the affected producing regions and from spillover effects on trade with other regions.

5.3 Welfare Estimates

Finally, we analyze welfare changes across our counterfactual scenarios. Welfare here refers to the sufficient statistics proposed by [Yotov et al. \(2016\)](#), represented as the ratio of real

consumption.¹⁷ This sufficient welfare statistic is theoretically identical to the welfare measure demonstrated by [Arkolakis et al. \(2012\)](#), expressed as a combination of the change in home goods trade as a share of total expenditure (in this case, intra-regional trade) and trade elasticity. It should be noted, however, that while these prior studies consider all goods under general equilibrium by definition, our analysis is restricted to the agricultural sector at domestic trade, from which international trade is excluded. As such, the welfare measure obtained here may be interpreted as a subset of the broader general equilibrium welfare gains considered in the literature.

Furthermore, in estimating the fixed effects (equivalently, MRTs) during the simulation process, not all fixed effects can be estimated; at least one fixed effect must be excluded from the estimation (see [Yotov et al., 2016](#) for further detail). Consequently, one region becomes the reference region, and all welfare changes are expressed as relative changes with respect to the reference region. In our subsequent welfare analysis results, the reference region is Atlántico, as it experiences very few landslides (see Figure 1), is connected to other landslide-prone regions, and represents one of the largest markets.¹⁸

We compute the average welfare change across all counterfactual scenarios in which regions were cleared of landslides between 2018 and 2019, using this period as a reference for recent years.¹⁹ Using a sufficient-statistics approach based on the welfare estimates from these counterfactual scenarios, we examine which types of regions benefit the most from improved network connectivity. In particular, we distinguish between the effects of clearing a region’s own trading routes and clearing links elsewhere in the network that the region does not directly use, while also accounting for whether the region is a net buyer or a net seller in the domestic trade network.

For each region, we define ρ_i as the ratio of total purchases to total sales, reported in

¹⁷Sufficient welfare statistics are expressed as $\hat{W}_i = W_i^C / W_i^B$, where $W_i = E_i / P_i$ (defined as real consumption) and superscripts C and B denote values in the counterfactual and baseline scenario, respectively.

¹⁸Therefore, in the subsequent welfare analyses (in particular, Figure D.1), the welfare change of Atlántico is normalized to zero.

¹⁹Appendix D reports the welfare change of each region under every region-specific counterfactual in Figure D.1, together with the underlying weekly welfare ratios.

Appendix Table A1, and divide the twenty regions into two equal groups using $\rho = 0.8$ as the cutoff. Regions with higher values of ρ_i are relatively more consumption-oriented, while those with lower values are relatively more production-oriented. The dependent variable is the log welfare change, $\widehat{W}_{jkt} = \ln W_{jkt}^C - \ln W_{jkt}^B$, for region j in week t when the routes associated with region k are cleared. All specifications include clearing-region and week fixed effects, with standard errors clustered at the recipient-region level.

Table 3 presents the results of this specification. The first column reports the change in welfare when links used by the same region are cleared, distinguishing between consumption-oriented and production-oriented regions. The estimates show that consumption-oriented regions experience a 1.22% increase in welfare, which is statistically significant, whereas production-oriented regions experience a 0.14% decline that is not statistically significant. When the routes associated with another region are cleared, both groups experience welfare losses of 0.09% and 0.13%, respectively, with both estimates statistically significant at the 1% level.²⁰

One possible mechanism, also suggested by the patterns in Figure 5, is that when the routes of a production-oriented region reopen, the region ships a larger share of its output to other markets and retains less for local consumption. Consumption-oriented regions experience the opposite adjustment, as improved connectivity facilitates inflows from other regions and lowers their local price index. This mechanism helps explain why removing a transport friction does not necessarily increase welfare everywhere and why the largest gains accrue to regions that buy more than they sell. We examine this hypothesis more directly in the following section.

A potential concern when interpreting heterogeneity by region type is that ρ_{it} may be systematically correlated with landslide exposure. Regions with greater trade activity may appear more exposed because their goods travel through a larger road network. Conversely, regions with limited trade may be more vulnerable if low infrastructure use weakens govern-

²⁰Table D1 reports the pooled regression estimates of the relationships between regional welfare, ρ , and landslide exposure. Both estimated relationships are positive, and the coefficient on ρ is statistically significant.

ment incentives to invest in road maintenance. To examine this concern, we estimate two auxiliary regressions. First, we regress the log of ρ_{it} on the inverse hyperbolic sine of the number of landslides affecting region i , including region and year fixed effects. We find no statistically significant relationship between the two variables. We then repeat the analysis using landslides that occurred in the previous year. The estimated coefficient changes little and remains statistically insignificant. These results provide no evidence that a region's position as a producer or consumer is systematically related to its exposure to landslides. Details of these specifications are reported in Table D2.

5.4 Trade Movement

We test the mechanism of trade reallocation by type of region in Figure 6. The figure illustrates the change of exports when landslide disruptions are removed by the type of region. As discussed above, we classify regions into two groups, *production-oriented* and *consumption-oriented*. We then aggregate export flows by the classification of the origin and the destination and by the group in which the disruption occurs.

The left panel shows changes in exports when landslide-related disruptions are removed from routes connected to production-oriented regions. Green indicates an increase in exports, while red indicates a decrease. Once these routes reopen, trade is reorganized across the network, with both types of regions increasing shipments to other markets and reducing the share of output retained for local consumption. However, this reallocation is considerably stronger among production-oriented regions, which increase exports to consumption-oriented regions by a larger magnitude than the corresponding adjustment in exports from consumption-oriented regions. The asymmetry is sizeable: clearing these routes raises trade in production-oriented regions by USD 22.5 MM, against USD 10.5 MM in consumption-oriented regions, so the reallocation is concentrated among the regions whose own routes reopen.

Interestingly, a different pattern emerges when links connected to consumption-oriented regions are cleared. As in the previous case, both types of regions increase exports to

Table 3. Welfare change by trade orientation and whose routes were cleared

	Region whose routes are cleared	
	Region j itself	Another region
Demand-oriented ($\rho_j \geq 0.8$)	0.0122*** (0.0014) [0.0004]	-0.0009*** (0.0001) [0.0002]
Production-oriented ($\rho_j < 0.8$)	-0.0014 (0.0050) [0.8043]	-0.0013*** (0.0002) [0.0023]
Clearing-region FE	Yes	Yes
Week FE	Yes	Yes
Observations	97,560	

Notes. All four entries are coefficients from a single regression. The sample is partitioned into four mutually exclusive cells by whether region j is demand- or production-oriented and whether the counterfactual clears j 's own routes or another region's; the four cell indicators are entered together with clearing-region and week fixed effects and no constant, the same fixed-effect specification as Table D1, where the fixed effects are normalized to have zero mean over the estimation sample, therefore the cell coefficients are adjusted means. Regions are split at a cutoff of $\rho = 0.8$, which gives ten regions on each side.

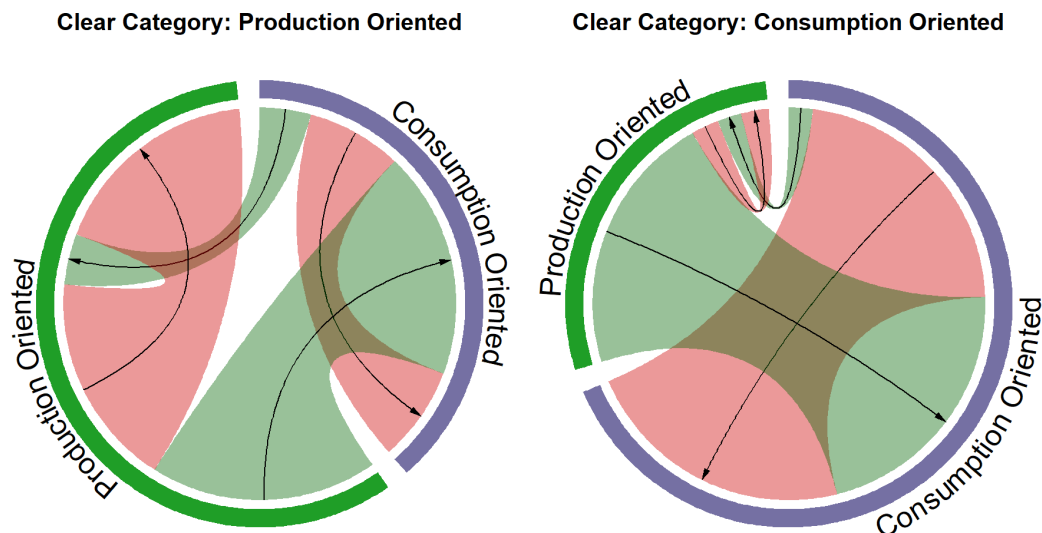
Standard errors clustered by region ($G = 20$) are in parentheses; restricted wild-cluster-bootstrap p -values (Webb weights, 9,999 replications) are in brackets, and significance is based on them.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (wild-cluster-bootstrap p).

other markets. However, the main adjustment occurs through a substantial decline in self-consumption in consumption-oriented regions, which is offset by larger inflows from production-oriented regions. This reallocation draws goods away from producing regions and increases local prices, reducing consumer welfare in net-exporting regions such as Boyacá, Nariño, and Meta even as their exports increase; Figure D.1 in Appendix D reports the change for every region.

This mechanism also helps explain why removing disruptions in other regions can reduce local welfare. Improved connectivity elsewhere induces a reallocation of trade across the network, which can divert goods away from some regions. It also explains why consumption-oriented regions tend to experience welfare gains when disruptions are removed from the links they use, as improved access allows them to receive substantially more goods from other regions.

Figure 6. Trade Movement When Landslides are Prevented



Notes: The chord diagram represents changes in export flows between two groups of regions: *production-oriented* ($\rho_j < 0.8$) and *consumption-oriented* ($\rho_j \geq 0.8$). The left panel shows the changes when landslides are cleared in production-oriented regions and the right panel when they are cleared in consumption-oriented regions. Arrows indicate the direction of the flow. Green indicates an increase in exports along that link, while red indicates a reduction that compensates for those increases. Values are in USD millions over the 2013–2019 period.

6. Conclusion

Our econometric analysis reveals that landslides impose significant frictions on bilateral trade flows. Among linkages that actually experience disruption, a 1% increase in landslide

frequency is associated with approximately a 0.059% decrease in trade value. The binary specification further indicates that the mere occurrence of a landslide along a trade route reduces trade by around 17.6 percent. Robustness checks across alternative specifications consistently support these findings.

Simulating the complete elimination of landslides across Colombia over the 2013-2019 period suggests total additional exports of approximately USD 103.5 million, equivalent to roughly 3.73% of annual exports. The gains are geographically concentrated, with Antioquia, Valle del Cauca, and Cundinamarca together accounting for 66% of the total. Region-specific simulations further highlight the network dimension of these disruptions: clearing the routes of Valle del Cauca alone raises national exports by USD 54 million, and clearing those of Antioquia by USD 52.6 million, with part of each gain accruing to other regions that depend on the same roads.

Our analysis also reveals that the welfare effects of landslides are not uniformly negative across regions. Production-oriented regions, where output exceeds local demand and exports are relatively important, may experience a decline in consumer welfare when landslide disruptions are removed. Reopening affected routes redirects goods toward more profitable destination markets, reducing local availability and raising prices in exporting regions; in Boyacá and Nariño this effect is strong enough that welfare falls even when it is their own landslides that are cleared. By contrast, consumption-oriented regions, which rely on inflows from elsewhere to meet local demand, experience the largest welfare gains when disruptions are removed from the routes through which they source goods. Clearing a region's own routes raises welfare by 1.22% in the consumption-oriented half of the sample, against a statistically insignificant decline of 0.14% in the production-oriented half. When another region's routes are cleared instead, both groups lose, by 0.09% and 0.13% respectively, and both estimates are significant at the 1% level.

This asymmetry matters for where transport resilience is worth strengthening. The two regions whose disruptions cost the country the most trade, Valle del Cauca and Antioquia,

are not the ones that gain most in welfare when their own routes are cleared; Valle del Cauca ranks first on the former and sixteenth of nineteen on the latter. Nor do the spillovers share a sign: clearing some regions raises welfare across most of the network while clearing others lowers it. Since the gains from clearing regions one at a time do not add up to the gain from clearing them together, the ranking of candidate investments depends on whether the objective is national trade volume or regional welfare.

Our analysis has several limitations. It covers domestic trade in agricultural products and excludes international trade, so the welfare measure reported here should be read as a component of the broader general equilibrium gains studied in the literature. The UNGRD records do not report when each event was cleared, which leads us to measure exposure by the count of disruptions rather than by their duration. Aggregating municipalities into twenty regions also leaves variation within regions unobserved. Subject to these qualifications, the paper adds to the literature on the economic consequences of natural disasters and to work on subnational trade costs in developing economies. It measures the cumulative effect of recurrent localized disruptions on domestic trade and welfare at a weekly frequency, and it quantifies how those effects reach regions that are not themselves disrupted.

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Appendix

A. Detail of Data

This appendix provides more detail on how we aggregated the data for the analysis as well as a detailed list of products traded in our analysis.

A.1 List of Products

Vegetable oil	Avocado (common)	Avocado (paper variety)
Pumpkin	Garlic	Celery
Rice	Green peas	Tuna
Rolled oats	Refined sugar	Local banana
Bocachico fish	Broccoli	Ground coffee
Pork	Beef	Chicken
White onion	Green onion	Corn on the cob
Cilantro	Cauliflower	Passion fruit
Spinach	Strawberry	Crackers
Sweet granadilla	Soursop	Guava (pear variety)
Green beans	Rice flour	Corn flour
Wheat flour	Eggs	Powdered milk
Batavia lettuce	Lentils	Common lime
Tahiti lime	Lulo	White corn
Mango	Apple	Purple passion fruit
Margarine	Mayonnaise	Melon
Blackberry	Orange	Potato
Papaya	Pasta	Watermelon
Cucumber	Pear	Bell pepper
Pineapple	Green plantain	Coastal cheese
Beetroot	White cabbage	Iodized salt
Tomato Sauce	Sardines	Tomato
Tree tomato	Grapes	Carrot

A.2 Aggregation of Data

We follow several steps to aggregate the data, as our raw dataset contains prices and quantities traded in the 20 main wholesale markets, with shipments originating from more than 1,000 municipalities. Because the gravity model requires a balanced trade specification, we aggregate these municipalities into a 20×20 trade flow matrix. The steps are as follows:

1. We aggregate municipalities into regions based on their geographic location.
 - Trade is aggregated as $\sum P_{ip} \times Q_{ip} = \tau_i$, where P_{ip} and Q_{ip} denote the price and quantity of product p in region i .
 - Distance is aggregated as $\frac{\sum \text{Dist}_{ij}}{N_i}$, where we average all distances from municipalities in region i to wholesale market j .
 - Landslide disruptions are aggregated as $\sum \text{Landslides}_{ijr} = L_{ij}$, where Landslides_{ijr} indicates a landslide on road segment r connecting municipality i to wholesale market j .
2. Departments that do not contain one of the twenty wholesale markets are attached to the market region whose wholesale market is closest to their main population centres. Specifically, Cundinamarca and Bogotá are treated as a single region; Chocó is merged with Antioquia; La Guajira with Cesar; Caquetá with Huila; Arauca and Casanare with Boyacá; and Putumayo with Nariño.
3. Some regions lack road connectivity and are therefore excluded from the analysis. These include the departments of the Amazon and Orinoco basins and the northern island territories of the country.

A.3 Rho Value per Region

Table A1 reports ρ for every region. For region i , let Y_i denote production, the total value of goods sold by i across all destinations, and let E_i denote consumption, the total value

of goods purchased in i across all origins. Both sums include i 's trade with itself, so that ρ_i is the ratio of the column sum to the row sum of the bilateral trade matrix inclusive of its diagonal. We then define $\rho_i = E_i/Y_i$. A region with $\rho_i = 1$ purchases exactly as much as it sells; when $\rho_i < 1$ production exceeds consumption and the region is export-oriented, and when $\rho_i > 1$ the region is import-oriented.²¹ We compute a single ρ_i per region over 2013–2019.

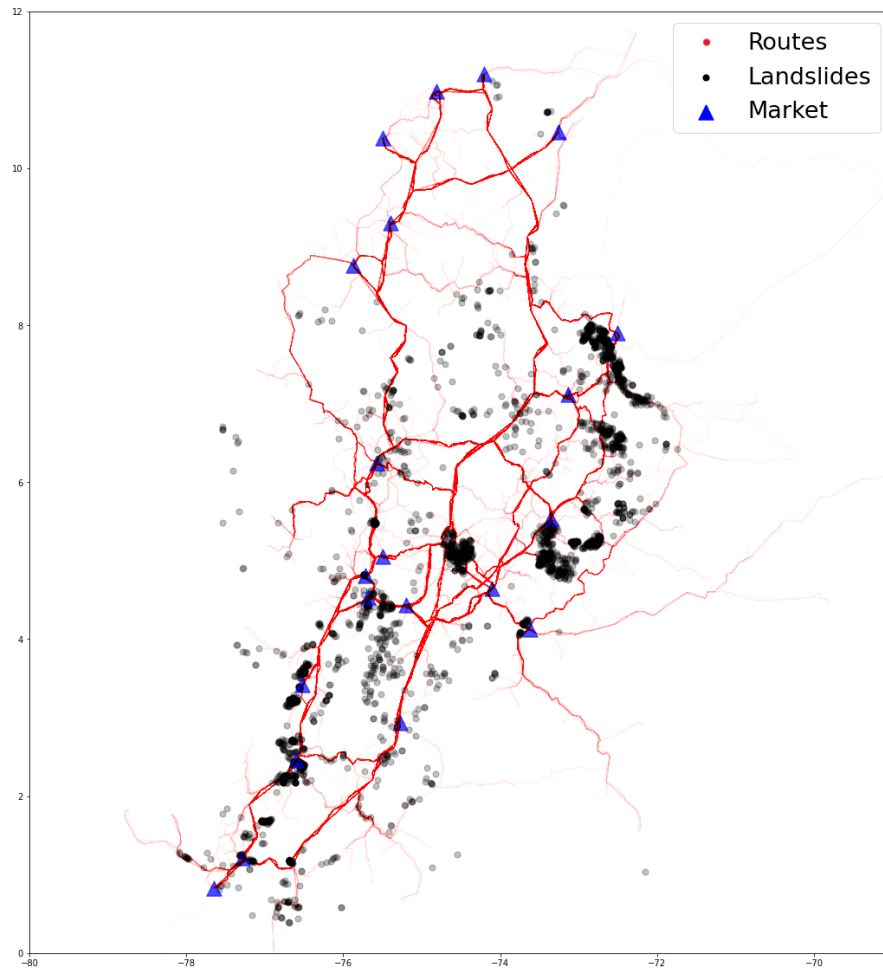
Table A1. Rho per region

Region	Rho
Atlantico	1.696078
Cundinamarca	1.668496
Sucre	1.415209
Antioquia	1.343075
Bolivar	1.305547
Norte de Santander	1.207912
Risaralda	1.124869
Valle del Cauca	0.928923
Quindio	0.801711
Santander	0.800749
Cesar	0.708463
Caldas	0.565917
Cauca	0.563787
Huila	0.373168
Meta	0.213123
Magdalena	0.132624
Cordoba	0.129522
Narino	0.120878
Tolima	0.118676
Boyaca	0.037175
Average (simple)	0.762795

²¹ ρ_j measures trade imbalance and is the empirical counterpart of the exogenous expenditure-output ratio for region in [Allen et al. \(2020\)](#), rather than the trade openness expressed as the domestic trade share in [Donaldson \(2018\)](#).

A.4 Routing Algorithm

This appendix provides more detail on the routing algorithm as well as the intersection with landslides and market location. Map A.1 shows the graphical representation of all the routes calculated to reach the wholesale markets in red, as well as the location of landslides in black and the location of the wholesale markets in a blue triangle.

Figure A.1. Routing Algorithm with Origin and Destination Points

Notes: Red lines represent the routes generated by the algorithmic routing approach of [Luxen and Vetter \(2011\)](#). Black dots indicate the locations where landslides occurred over the sample period, and blue triangles denote the locations of the 21 wholesale markets recorded in the routing data, which are aggregated to twenty regions in the analysis.

A.5 Additional Descriptive Statistics

This appendix provides detail on total production, exports, own demand, imports and trade balance by region.

Table A2. Detailed Descriptive Statistics on Markets

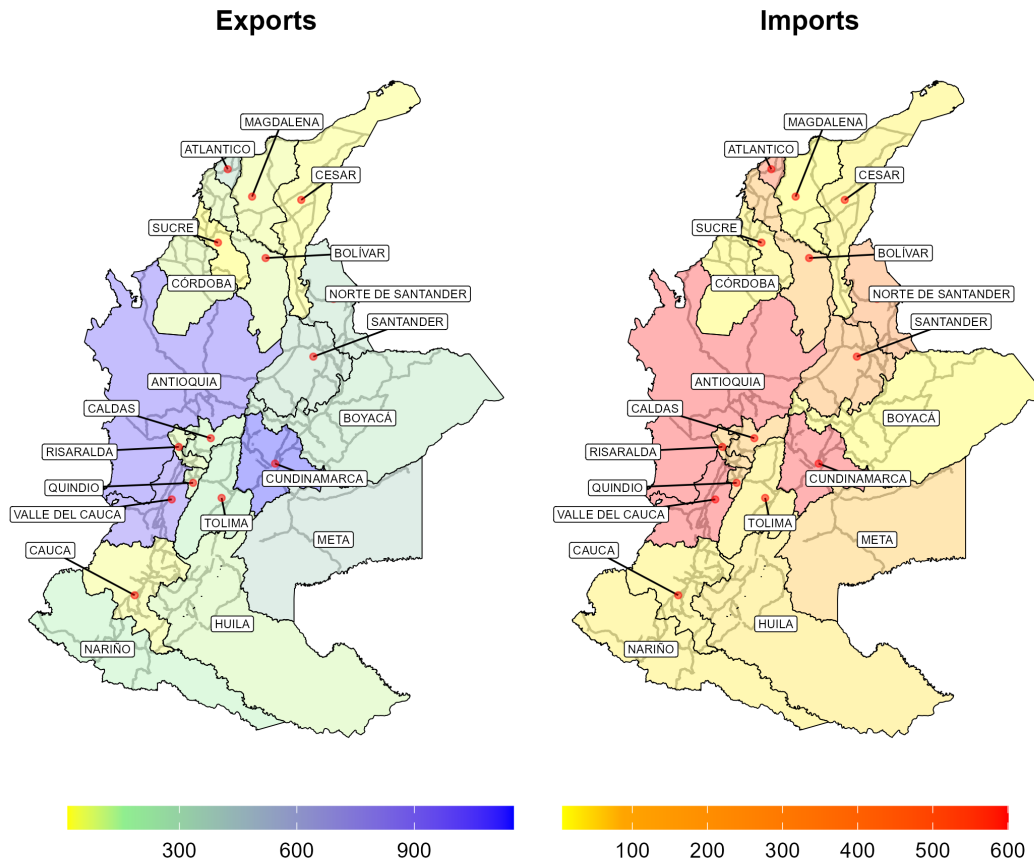
Markets	Total Production (1)	Total Demand (2)	Own Consumption (3)	Trade Balance (4)
National Avg.	343.57 (407.67)	343.57 (601.06)	204.97 (366.69)	0.00 (268.39)
ANTIOQUIA	1236.49 (240.13)	1656.99 (256.94)	1129.64 (176.11)	-420.50 (50.64)
ATLANTICO	319.44 (81.02)	540.69 (154.55)	229.34 (42.55)	-221.25 (91.61)
CUNDINAMARCA	1325.01 (723.93)	2183.28 (999.21)	1167.43 (680.84)	-858.28 (281.97)
BOLIVAR	90.76 (58.42)	126.56 (137.21)	53.99 (59.74)	-35.80 (79.49)
BOYACA	469.79 (151.33)	19.67 (17.38)	14.96 (13.21)	450.12 (134.32)
CALDAS	154.73 (134.75)	102.86 (145.68)	85.03 (120.10)	51.87 (16.28)
CAUCA	50.49 (43.21)	29.38 (47.99)	24.20 (43.05)	21.11 (11.06)
CESAR	28.70 (7.84)	24.85 (34.43)	1.36 (1.94)	3.85 (27.04)
CORDOBA	93.09 (42.84)	15.02 (20.84)	8.38 (11.60)	78.07 (22.79)
HUILA	125.40 (24.22)	46.70 (10.51)	16.13 (2.69)	78.71 (14.48)
MAGDALENA	56.38 (31.75)	8.83 (12.30)	2.88 (4.06)	47.54 (20.75)
META	396.44 (89.66)	86.29 (24.07)	64.06 (16.76)	310.16 (72.62)
NARINO	234.51 (29.56)	30.79 (24.79)	29.18 (23.31)	203.72 (15.18)
NORTE DE SANTANDER	342.20 (290.99)	397.66 (306.40)	250.57 (258.67)	-55.47 (21.59)
QUINDIO	133.49 (45.81)	106.42 (47.67)	65.11 (44.65)	27.07 (19.37)
RISARALDA	98.92 (21.26)	104.76 (20.20)	42.47 (10.19)	-5.84 (29.93)
SANTANDER	340.40 (102.09)	272.35 (52.26)	114.56 (26.44)	68.05 (77.70)
SUCRE	15.98 (13.51)	25.07 (35.92)	8.15 (12.22)	-9.09 (22.75)
TOLIMA	204.55 (55.29)	32.75 (45.81)	14.14 (20.12)	171.79 (29.67)
VALLE DEL CAUCA	1154.65 (151.76)	1060.50 (102.65)	777.85 (78.61)	94.15 (119.54)
Market-Week-Records	166,400	166,400	166,400	166,400
Market-Year-Records	3,200	3,200	3,200	3,200

Notes: Columns (1) through (4) report average yearly total production, total demand, own-region consumption, and the trade balance (exports minus imports), respectively, in millions of USD. The first row reports the national average; the remaining rows report regional yearly averages. Standard deviations across years are reported in parentheses.

Table A3. Distribution of Landslide Disruptions by Bin

Bin	Freq.	Percent	Cum.
0	142,464	85.62	85.62
1–10	11,745	7.06	92.67
11–25	5,601	3.37	96.04
26–50	4,019	2.42	98.45
51+	2,571	1.55	100.00
Total	166,400	100.00	

Notes: Distribution of weekly bilateral route-level landslide disruption counts across all region pairs and periods. Bin 0 indicates no landslide disruptions on a given route in a given week.

Figure A.2. Yearly Average Exports and Imports in Million USD

Notes: The left panel shows exports across regions, with yellow indicating lower exports and blue indicating higher exports. The right panel presents imports, where yellow represents lower imports and red represents higher imports. The overlay in each subfigure represents the main Colombian road network.

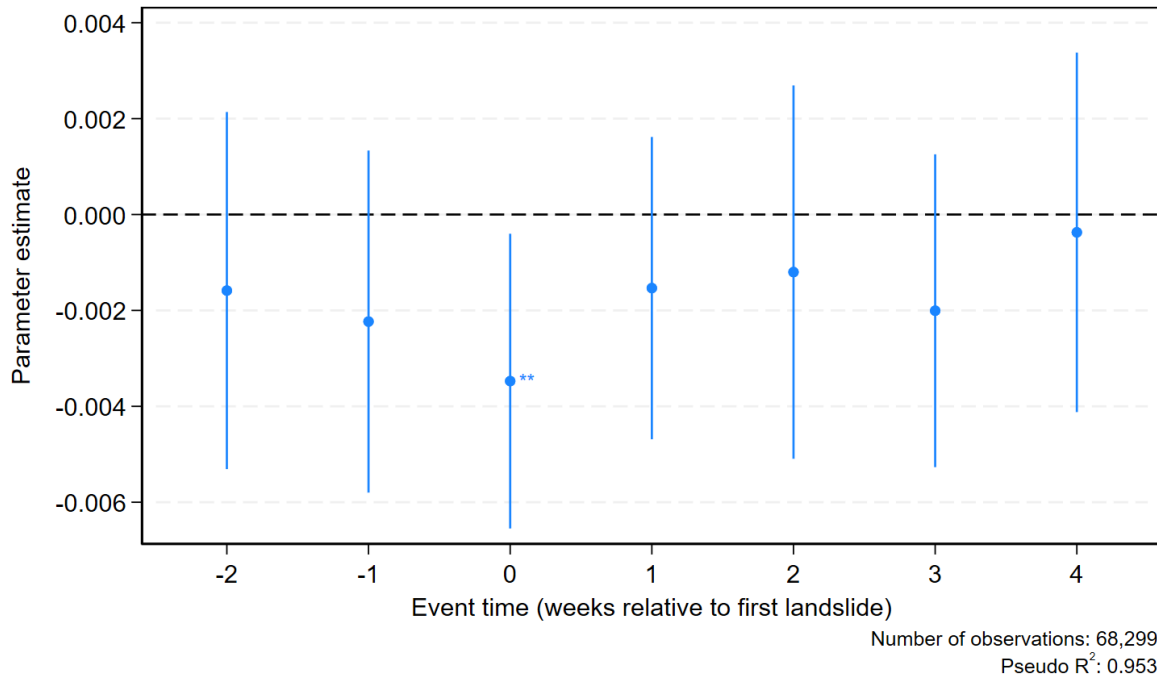
B. Main Specification Robustness Tests

This appendix provides results for robustness checks for the main specification.

Table B1. Robustness Check: Binned Landslide Intensity

	(1)
Bin 1–10	−0.165* (0.087)
Bin 11–25	−0.324*** (0.108)
Bin 26–50	−0.188* (0.101)
Bin 51+	−0.172* (0.099)
$\ln D_{ij}$	−1.331*** (0.220)
C_{ij}	−0.050 (0.187)
H_{ij}	1.315*** (0.262)
Observations	107,504
Exporter–Time FE	✓
Importer–Time FE	✓

Notes: Dependent variable is the value of weekly bilateral exports from source regions to destination regions. Estimation method is PPML. Standard errors clustered by bilateral pair in parentheses. The reference category is zero landslide disruptions (Bin 0). Intercept is estimated but not reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure B.1. Event Study

Notes: The graph shows point estimates and their confidence intervals from a modified version of equation (4), in which leads and lags of disruptions are included in the regression. Confidence intervals at the 95% level are shown as lines. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B2. Robustness Check with Pair Fixed Effects and Rainfall Controls

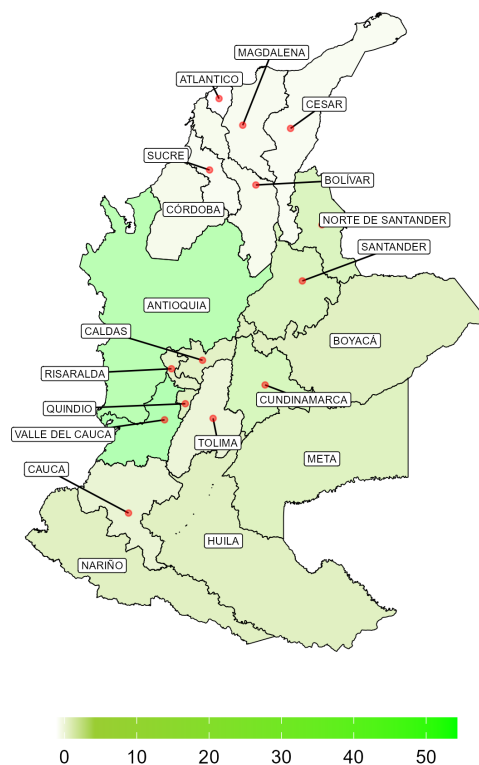
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{arcsinh } L_{ijt}$	−0.012* (0.006)		−0.059*** (0.017)		−0.012* (0.006)		−0.093*** (0.023)	
L'_{ijt}		−0.038 (0.025)		−0.192*** (0.074)		−0.038 (0.025)		−0.403*** (0.096)
$\ln D_{ij}$			−1.334*** (0.220)	−1.332*** (0.220)				
C_{ij}			−0.054 (0.187)	−0.053 (0.187)			0.588*** (0.220)	0.586*** (0.220)
H_{ij}			1.308*** (0.263)	1.313*** (0.263)			3.156*** (0.140)	3.156*** (0.140)
Constant	23.358*** (0.002)	23.359*** (0.003)	38.882*** (2.875)	38.865*** (2.875)	23.361*** (0.004)	23.362*** (0.004)	21.167*** (0.163)	21.194*** (0.164)
Observations	104,171	104,171	107,504	107,504	104,171	104,171	107,504	107,504
Exporter-Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Importer-Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Pair FE	✓	✓			✓	✓		
Precipitation Control			✓	✓	✓	✓	✓	✓

Notes: Dependent variable is the value of weekly bilateral exports from source regions to destination regions. Estimation method is PPML. Standard errors clustered by bilateral pair in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. L'_{ijt} is a binary indicator for whether a landslide occurred or not, while $\text{arcsinh } L_{ijt}$ is the inverse hyperbolic sine of the count of landslide occurrences. The intercept is reported in this table but suppressed in Table 2.

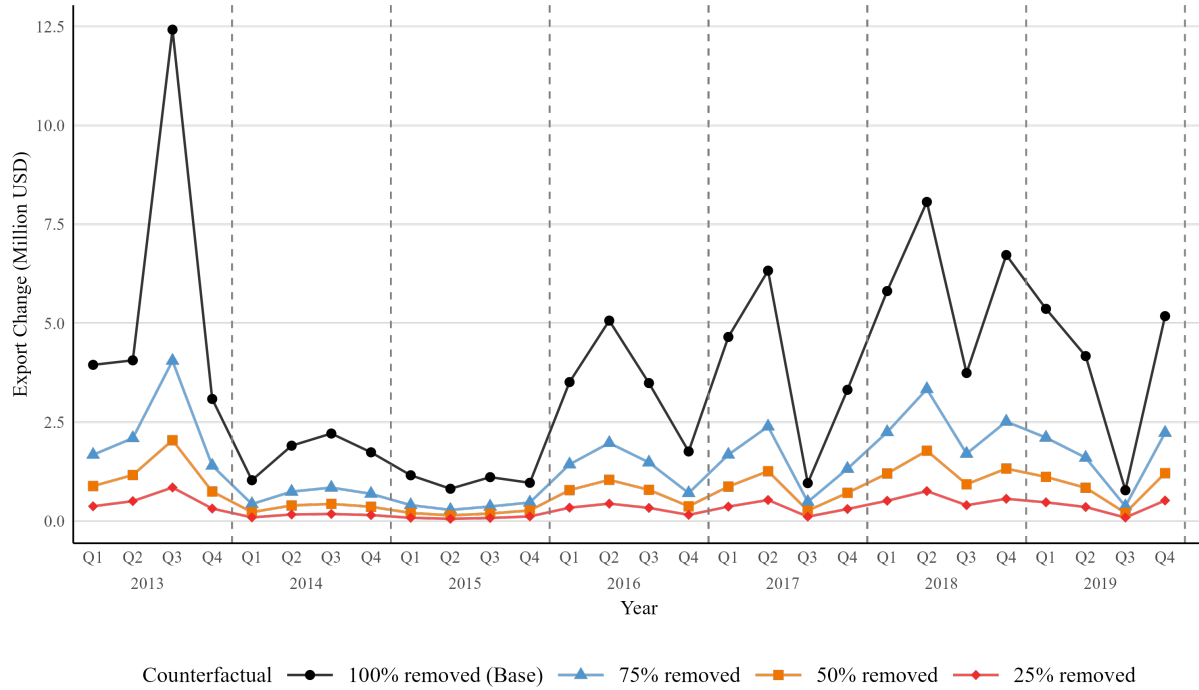
C. Additional Export Estimates

This appendix provides additional details on estimates of export changes.

Figure C.1. Trade Gains when getting rid of landslides in Specific Regions



Notes: The map reports trade gains in USD millions from the counterfactual scenario in which each region eliminates landslides, along with the corresponding impact on total national trade. White indicates no effect, while darker shades of green represent larger gains. The map displays Colombian regions, including internal trade linkages and regional labels.

Figure C.2. Change of Total Export Change under Different Clear Percentage

Notes: Export increases are reported in million USD. Q1-Q4 denote the quarters within each year. The black line reports the same estimates as in Figure 3, while the blue, orange, and red lines report export gains corresponding to 75%, 50%, and 25% reductions, respectively.

D. Additional Welfare Estimates

This appendix provides additional details on estimates of welfare changes.

D.1 Welfare by clearing region

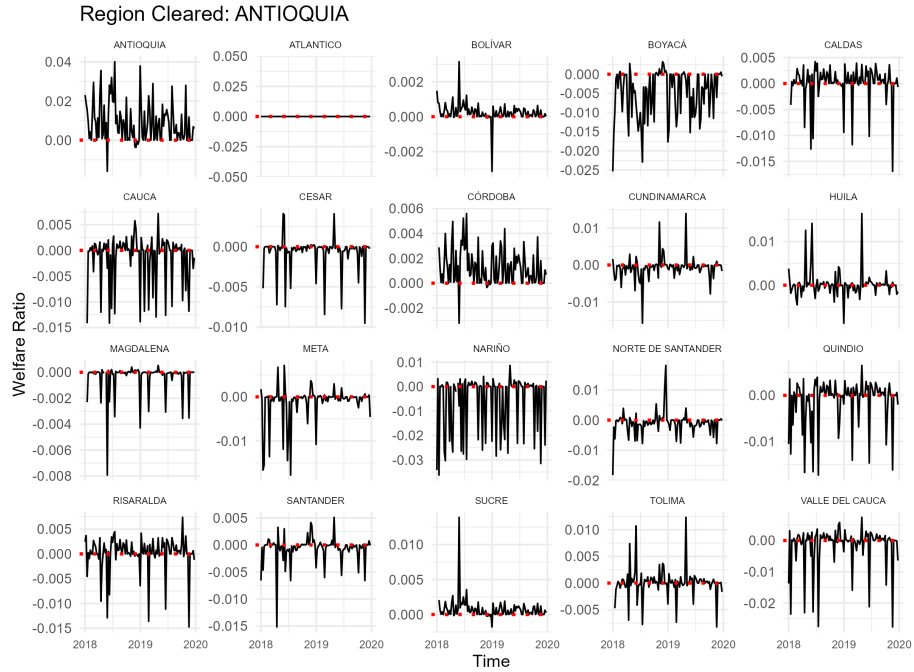
Figure D.1 reports the welfare change of every region under each region-specific counterfactual, averaged over 2018–2019. The vertical axis represents the region in which landslides are cleared and the horizontal axis the region whose welfare changes. The matrix indicates that, for most regions, clearing landslide disruptions in a given region increases welfare within that same region: the diagonal entries are positive for seventeen of the nineteen regions shown, with Boyacá and Nariño the two exceptions. Atlántico does not appear as a cleared region: it records very few landslides, which is why we use it as the reference region, and its welfare change is therefore zero by construction.

The regions that gain the most from clearing their own landslides, in percentage terms, are Norte de Santander (1.59%), Cundinamarca (1.54%), and Cesar (1.28%), followed closely by Risaralda (1.21%). In contrast, some regions experience welfare losses when landslides are cleared. For instance, when landslides in Boyacá are removed, most markets experience welfare losses; a similar pattern emerges when landslides in Nariño are cleared. Moreover, in these cases, the affected regions also experience a decline in consumer welfare within their own boundaries. More broadly, many regions face reductions in welfare when landslides are removed in key regions. When other regions are cleared, production-oriented regions lose the most welfare. The pattern is stronger when consumption-oriented regions clear their routes than when production-oriented regions do.

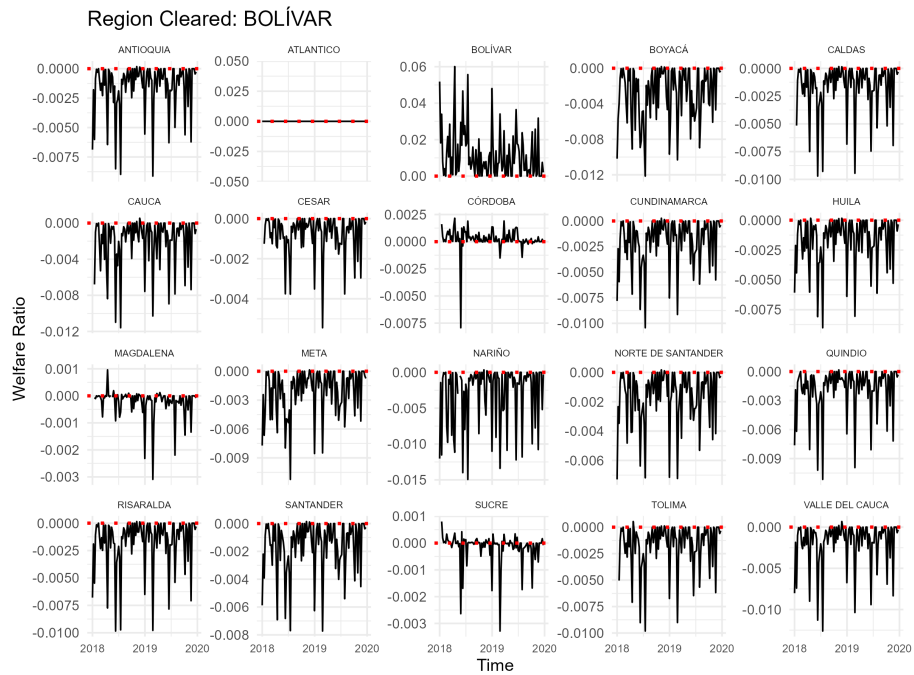
Figure D.1. Welfare change from Eliminating Landslides



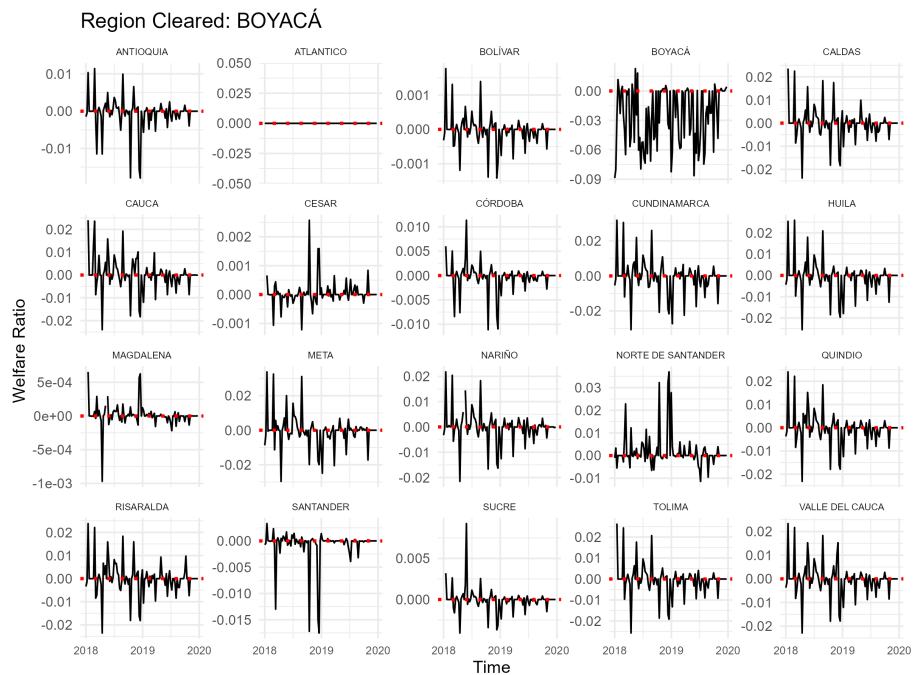
Notes: The heat map reports the counterfactual simulation results from eliminating landslides in each specific region. The vertical axis represents the cleared region, while the horizontal axis represents the region where changes in welfare occur. Cell values indicate the average percentage welfare change over 2018–2019, with negative effects shown in red and positive effects shown in green. Atlántico is the reference region and its welfare change is normalized to zero.

*D.2 Timeline of Welfare***Figure D.2.** Effect of Welfare when Antioquia is Cleared

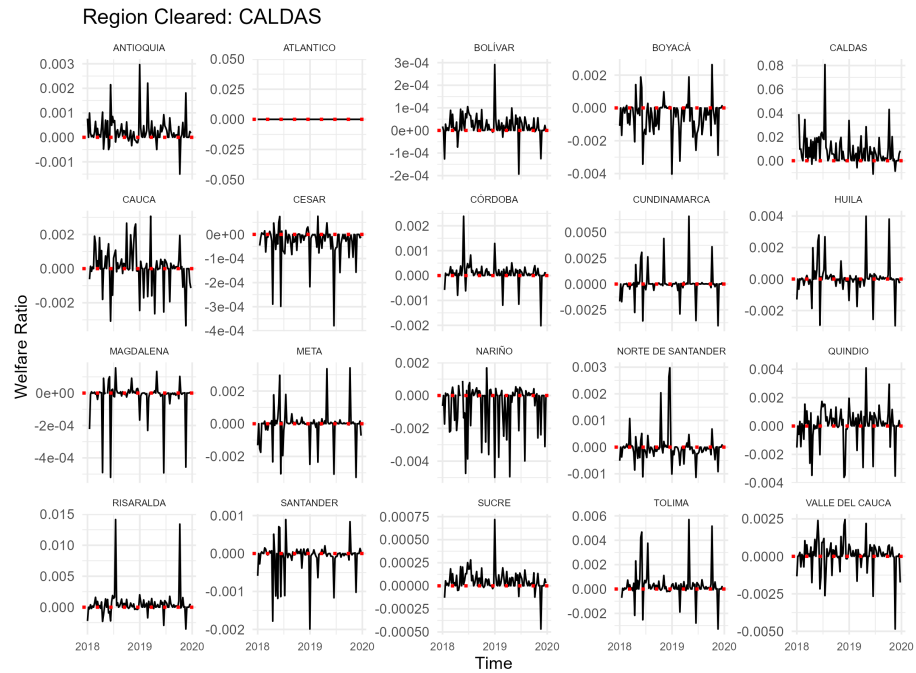
Notes: Plots show the weekly welfare ratio when the assigned region is cleared across different regions. We use the [Yotov et al. \(2016\)](#) approach to calculate welfare.

Figure D.3. Effect of Welfare when Bolívar is Cleared

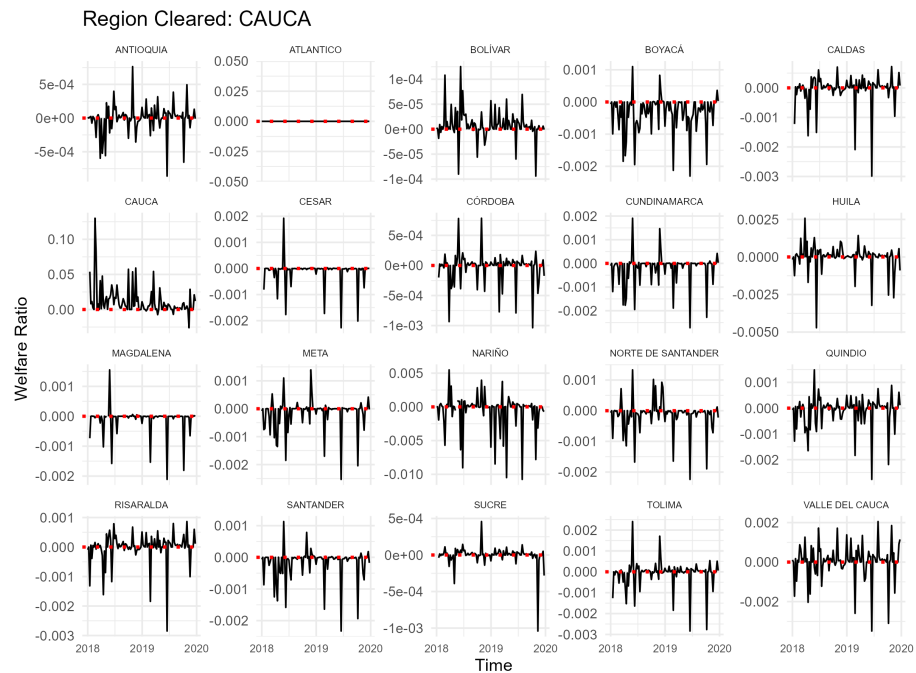
Notes: Plots show the weekly welfare ratio when the assigned region is cleared across different regions. We use the [Yotov et al. \(2016\)](#) approach to calculate welfare.

Figure D.4. Effect of Welfare when Boyacá is Cleared

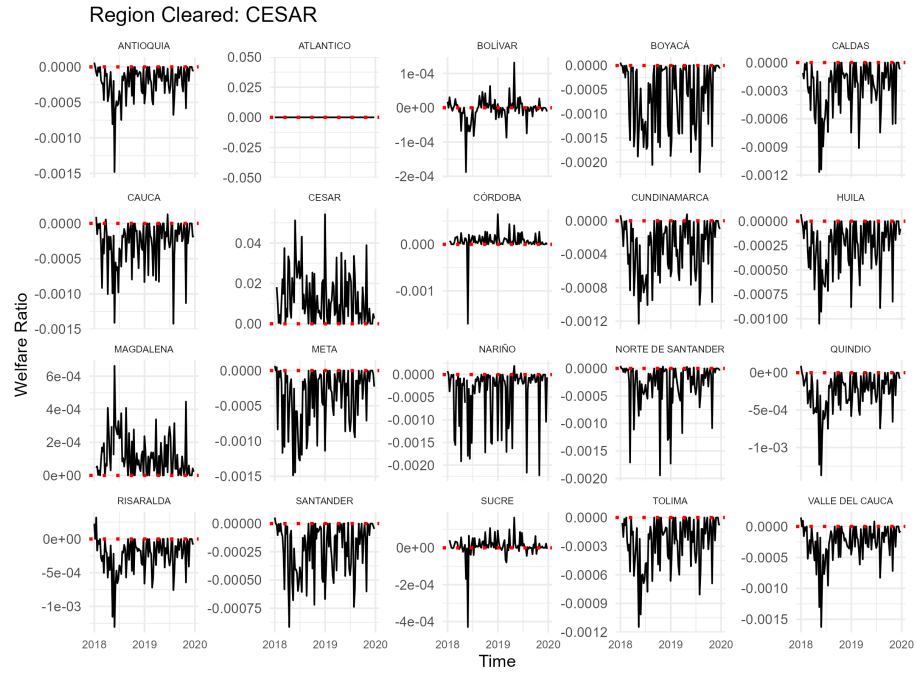
Notes: Plots show the weekly welfare ratio when the assigned region is cleared across different regions. We use the [Yotov et al. \(2016\)](#) approach to calculate welfare.

Figure D.5. Effect of Welfare when Caldas is Cleared

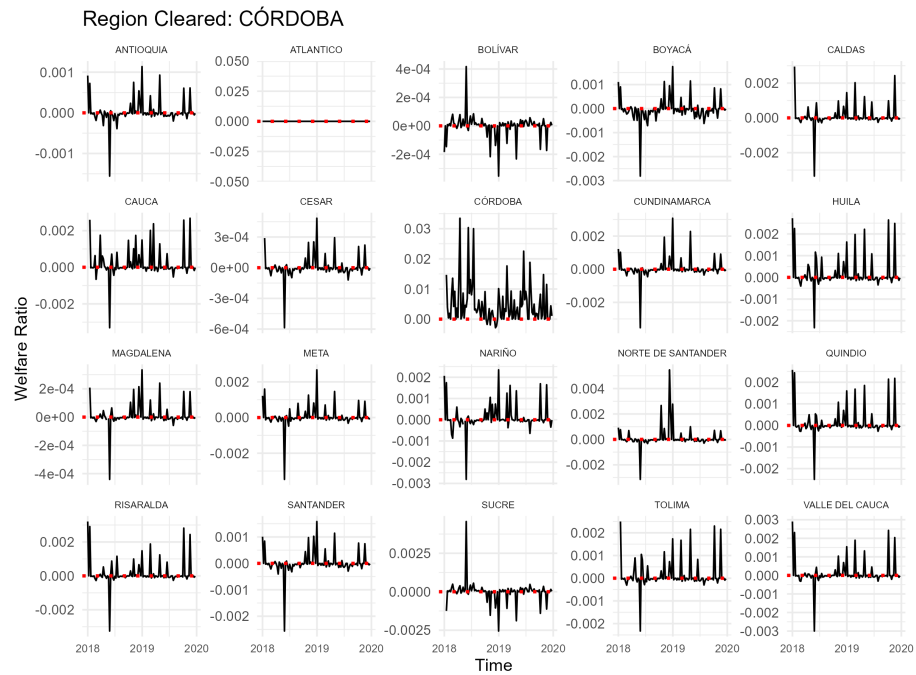
Notes: Plots show the weekly welfare ratio when the assigned region is cleared across different regions. We use the [Yotov et al. \(2016\)](#) approach to calculate welfare.

Figure D.6. Effect of Welfare when Cauca is Cleared

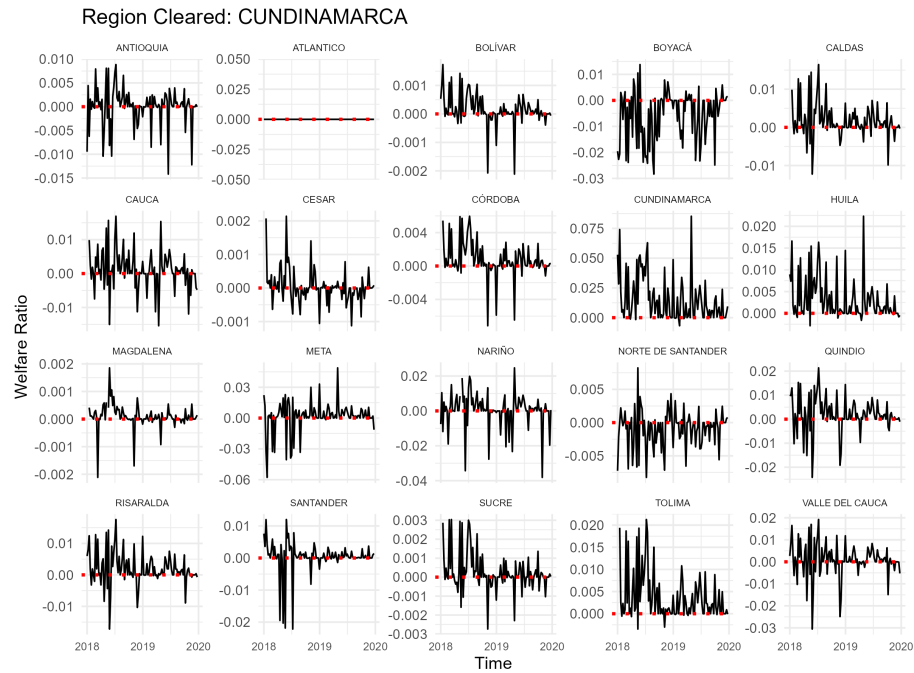
Notes: Plots show the weekly welfare ratio when the assigned region is cleared across different regions. We use the [Yotov et al. \(2016\)](#) approach to calculate welfare.

Figure D.7. Effect of Welfare when Cesar is Cleared

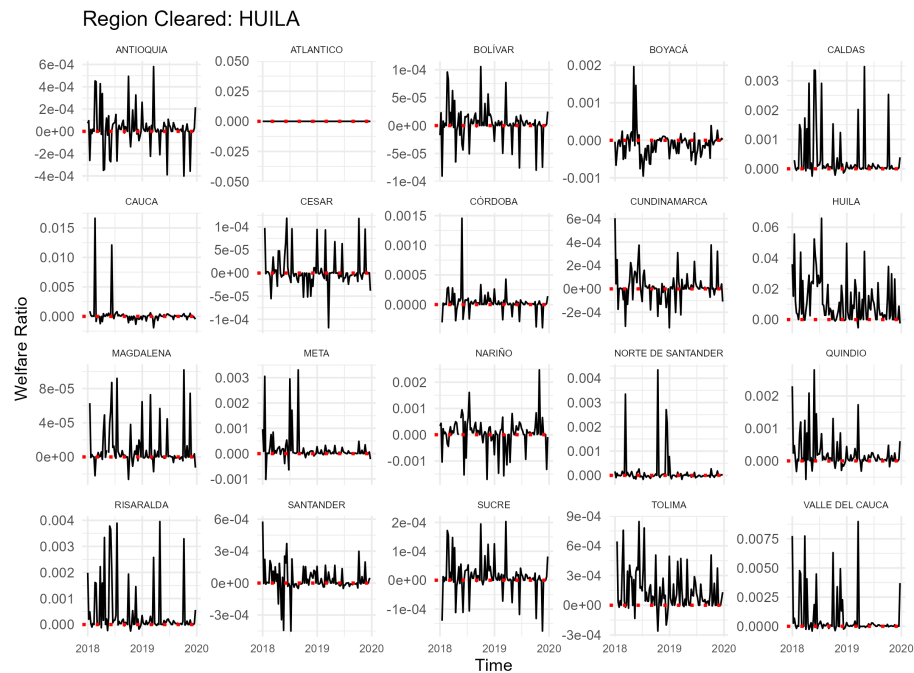
Notes: Plots show the weekly welfare ratio when the assigned region is cleared across different regions. We use the [Yotov et al. \(2016\)](#) approach to calculate welfare.

Figure D.8. Effect of Welfare when Córdoba is Cleared

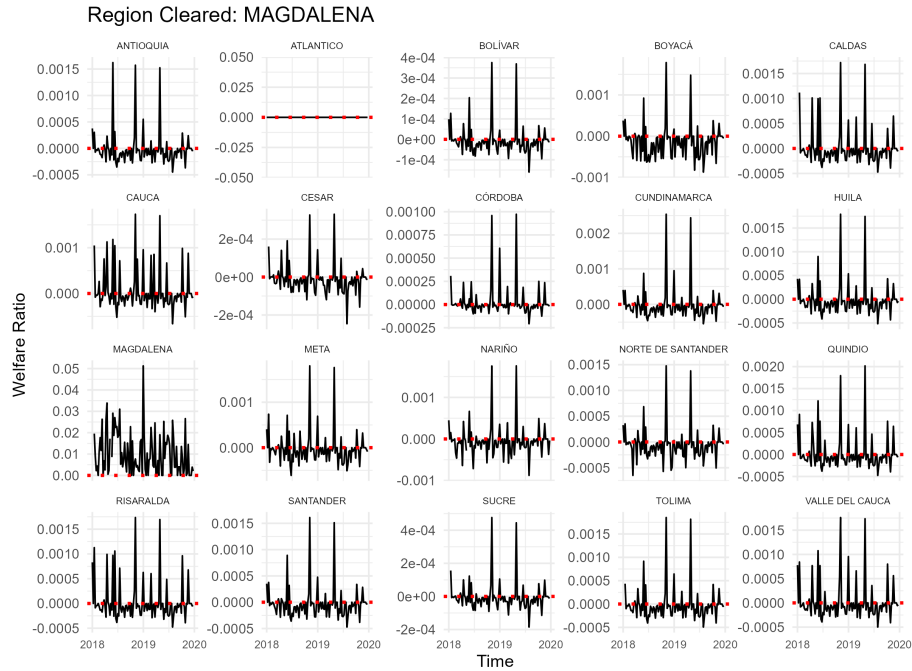
Notes: Plots show the weekly welfare ratio when the assigned region is cleared across different regions. We use the [Yotov et al. \(2016\)](#) approach to calculate welfare.

Figure D.9. Effect of Welfare when Cundinamarca is Cleared

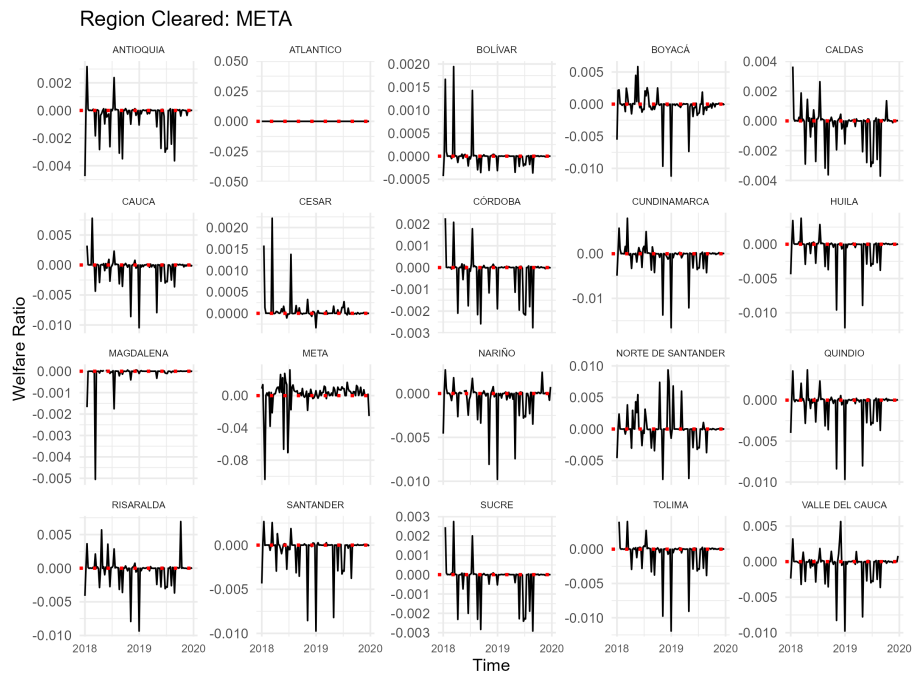
Notes: Plots show the weekly welfare ratio when the assigned region is cleared across different regions. We use the [Yotov et al. \(2016\)](#) approach to calculate welfare.

Figure D.10. Effect of Welfare when Huila is Cleared

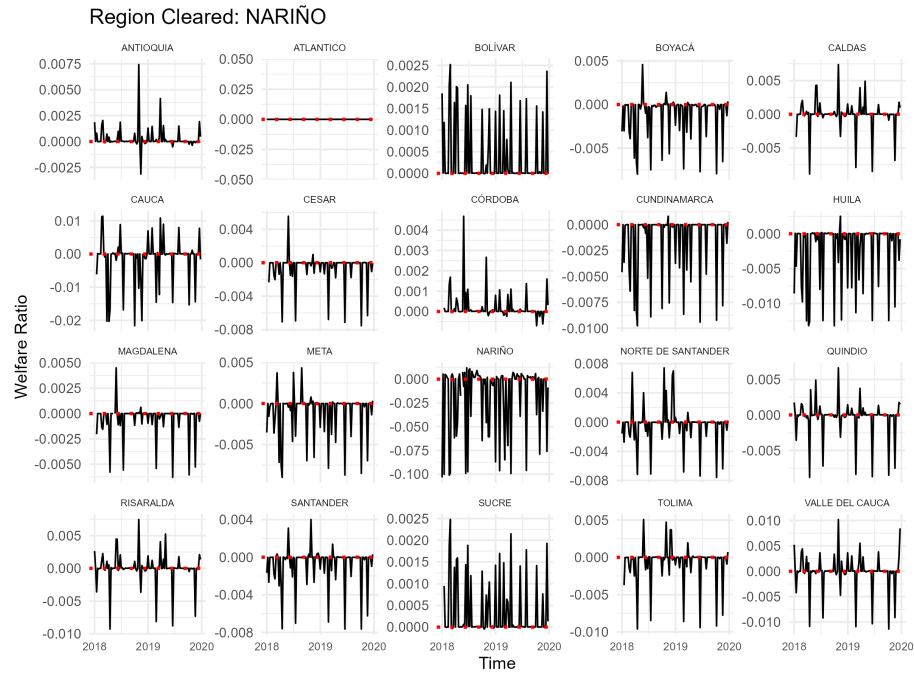
Notes: Plots show the weekly welfare ratio when the assigned region is cleared across different regions. We use the [Yotov et al. \(2016\)](#) approach to calculate welfare.

Figure D.11. Effect of Welfare when Magdalena is Cleared

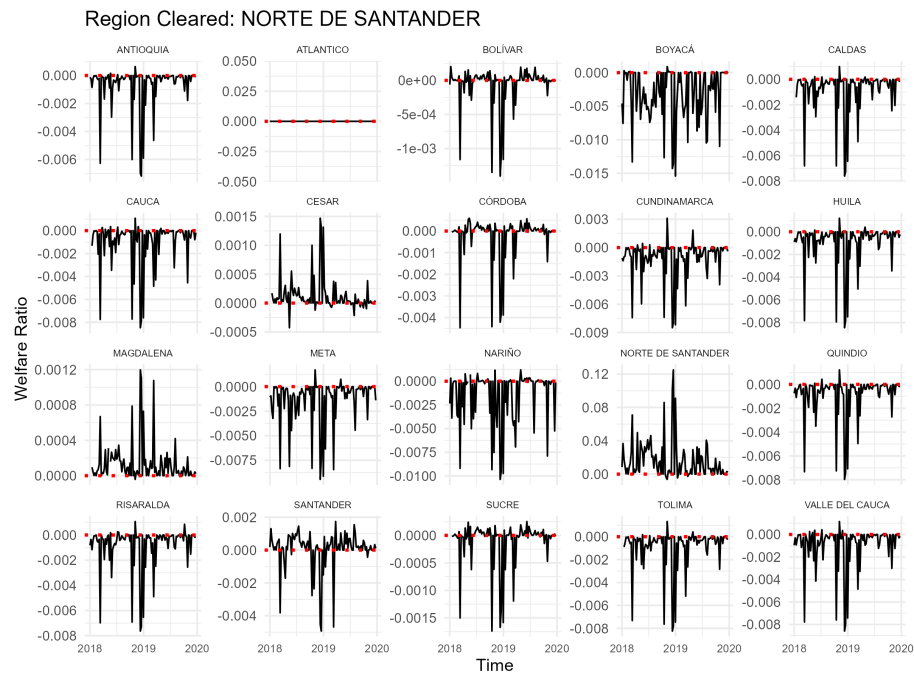
Notes: Plots show the weekly welfare ratio when the assigned region is cleared across different regions. We use the [Yotov et al. \(2016\)](#) approach to calculate welfare.

Figure D.12. Effect of Welfare when Meta is Cleared

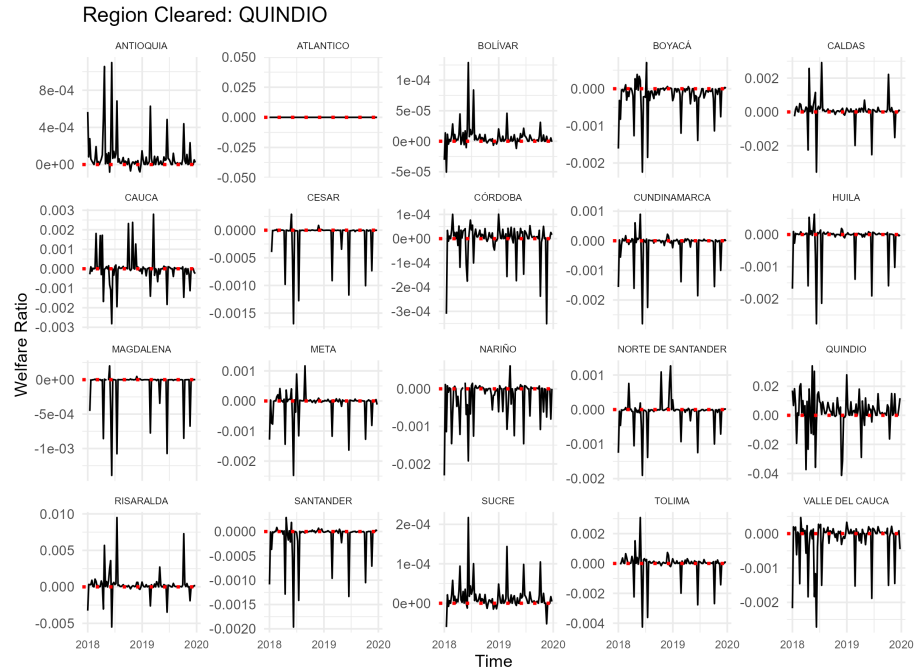
Notes: Plots show the weekly welfare ratio when the assigned region is cleared across different regions. We use the [Yotov et al. \(2016\)](#) approach to calculate welfare.

Figure D.13. Effect of Welfare when Nariño is Cleared

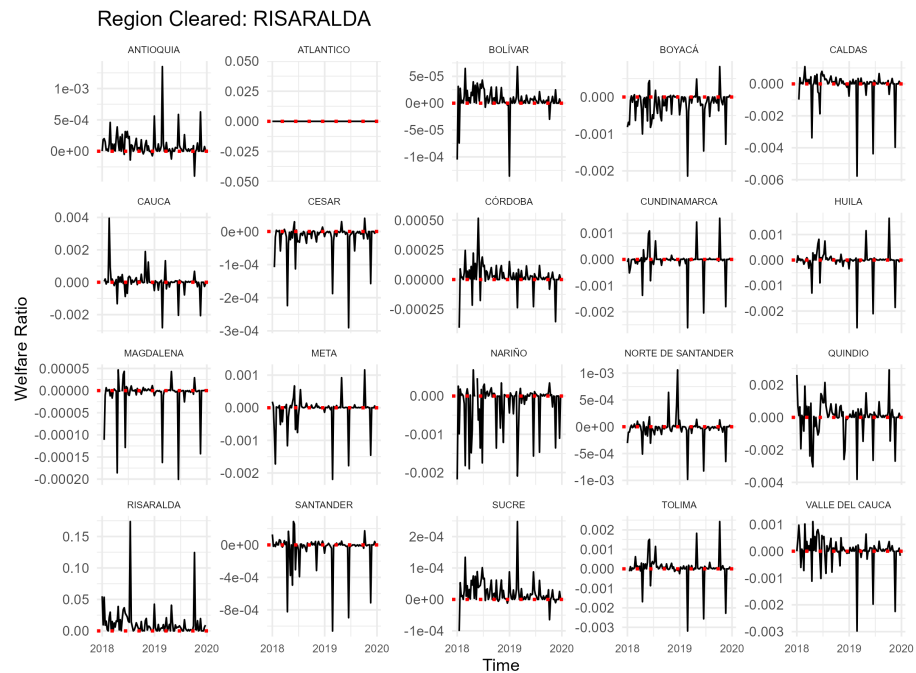
Notes: Plots show the weekly welfare ratio when the assigned region is cleared across different regions. We use the [Yotov et al. \(2016\)](#) approach to calculate welfare.

Figure D.14. Effect of Welfare when Norte de Santander is Cleared

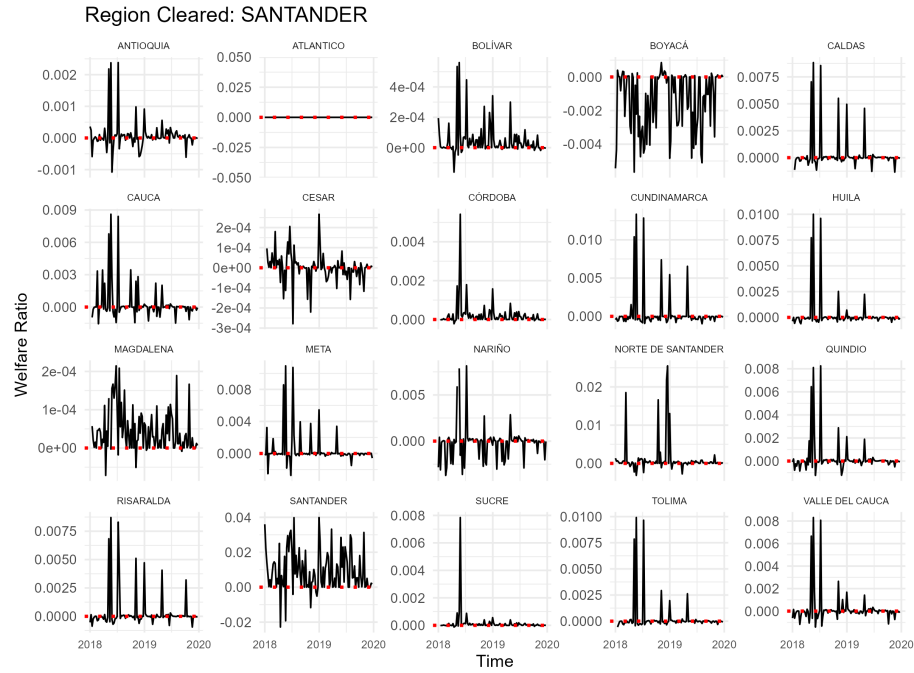
Notes: Plots show the weekly welfare ratio when the assigned region is cleared across different regions. We use the [Yotov et al. \(2016\)](#) approach to calculate welfare.

Figure D.15. Effect of Welfare when Quindio is Cleared

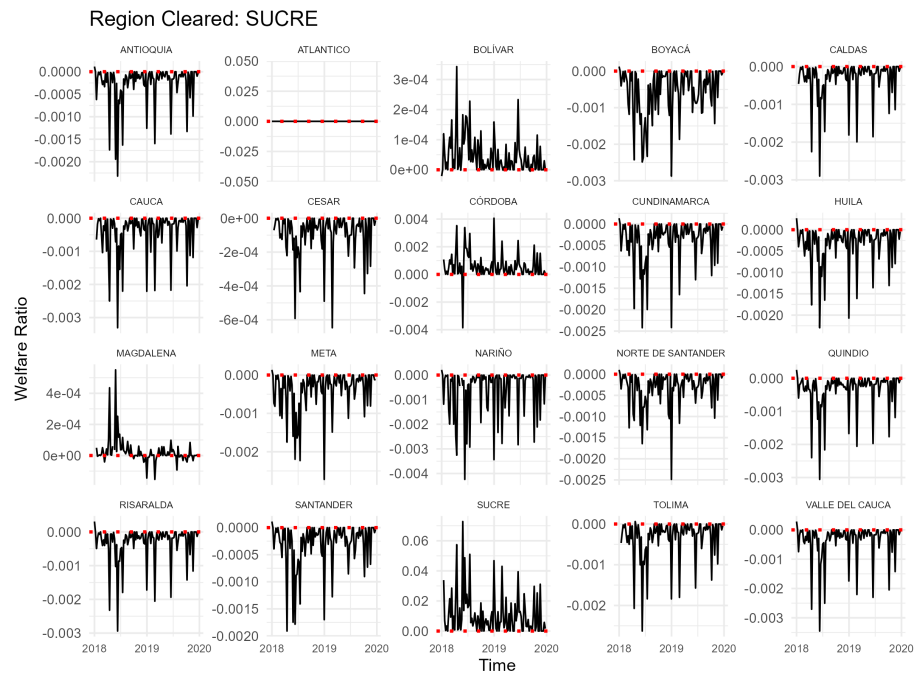
Notes: Plots show the weekly welfare ratio when the assigned region is cleared across different regions. We use the [Yotov et al. \(2016\)](#) approach to calculate welfare.

Figure D.16. Effect of Welfare when Risaralda is Cleared

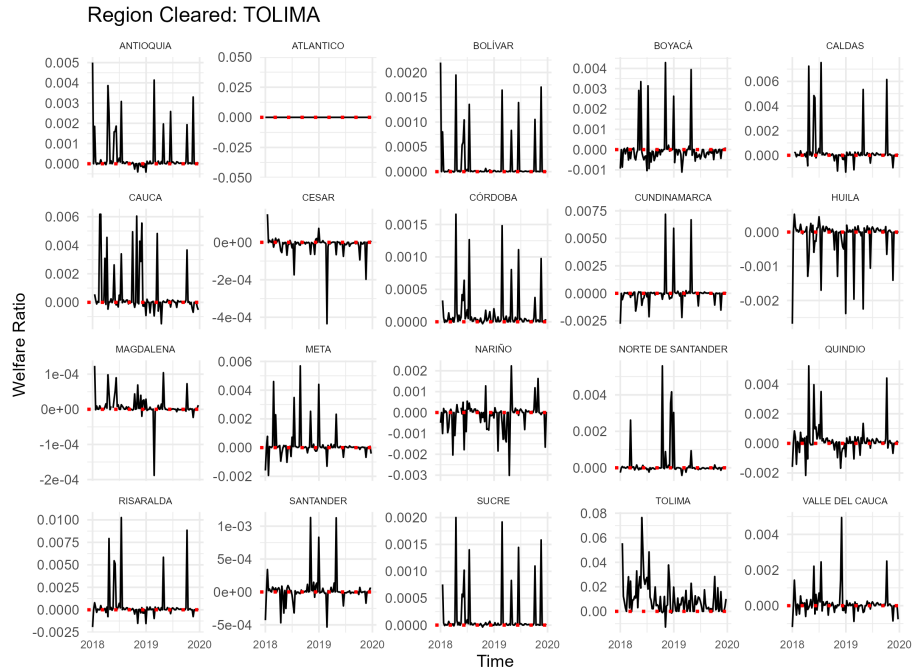
Notes: Plots show the weekly welfare ratio when the assigned region is cleared across different regions. We use the [Yotov et al. \(2016\)](#) approach to calculate welfare.

Figure D.17. Effect of Welfare when Santander is Cleared

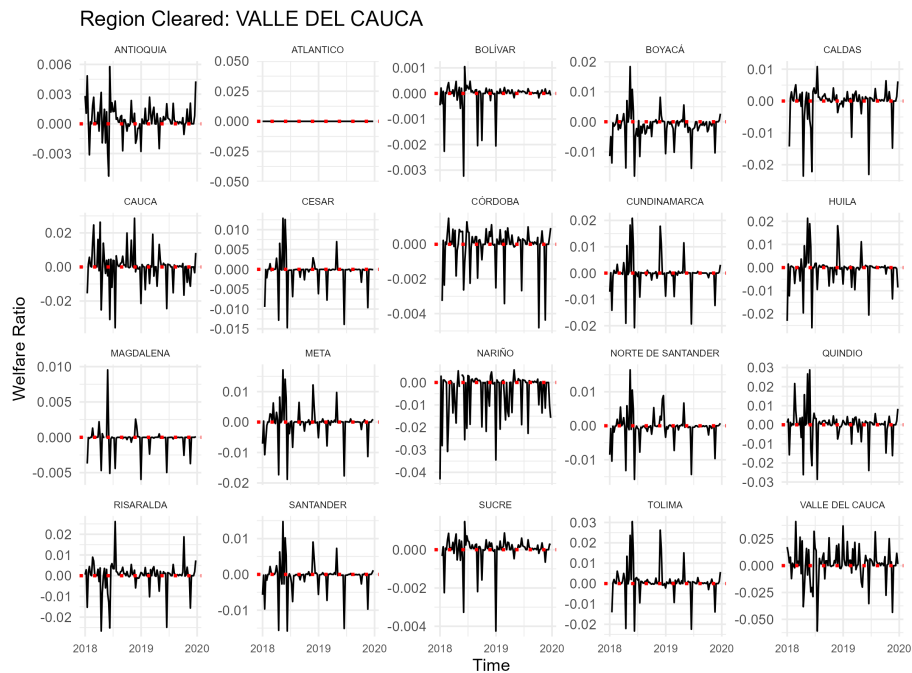
Notes: Plots show the weekly welfare ratio when the assigned region is cleared across different regions. We use the [Yotov et al. \(2016\)](#) approach to calculate welfare.

Figure D.18. Effect of Welfare when Sucre is Cleared

Notes: Plots show the weekly welfare ratio when the assigned region is cleared across different regions. We use the [Yotov et al. \(2016\)](#) approach to calculate welfare.

Figure D.19. Effect of Welfare when Tolima is Cleared

Notes: Plots show the weekly welfare ratio when the assigned region is cleared across different regions. We use the [Yotov et al. \(2016\)](#) approach to calculate welfare.

Figure D.20. Effect of Welfare when Valle del Cauca is Cleared

Notes: Plots show the weekly welfare ratio when the assigned region is cleared across different regions. We use the [Yotov et al. \(2016\)](#) approach to calculate welfare.

D.3 Rho and landslides relation

A natural concern is that chronic landslide exposure has itself shaped regional production structure, in which case ρ would be an outcome of the disruptions we study rather than a predetermined characteristic. Table D2 addresses this directly. We rebuild ρ year by year from the underlying trade data and regress its log on annual landslide exposure with region and year fixed effects. The contemporaneous coefficient is -0.082 ($p = 0.37$) and the one-year lag is -0.016 ($p = 0.85$); neither is distinguishable from zero. The R^2 of 0.97 indicates that nearly all of the variation in ρ is cross-sectional rather than within-region over time, which supports treating it as a fixed regional characteristic.

The 0.8 cutoff splits the sample into two equal halves and has no other claim on our attention. Quindío (0.802) and Santander (0.801) sit just above it and Cesar (0.708) just below, so the partition is sensitive to where the line is drawn. For that reason we also report column (1) of Table D1, in which ρ_j enters linearly and no threshold is imposed; the sign and the significance of the relationship are unchanged.

Table D1 reports the first set of estimates. The coefficient on ρ_j is 0.0010 with a wild-cluster-bootstrap p -value of 0.025: the higher a region's ratio of purchases to sales, the better it fares when landslides are removed somewhere in the network. Column (2) splits the exposure term by whether the cleared region is j itself. The own-clearing slope is 0.0031 ($p = 0.063$) while the bystander slope is 0.0002 and indistinguishable from zero ($p = 0.841$). A region gains when its own routes are cleared; clearing another region's routes does essentially nothing for it.

Table D1. Welfare effects of clearing landslides: pooled versus own/bystander exposure

	(1) Pooled exposure	(2) Own vs. bystander
ρ_j	0.0010** (0.0004) [0.0247]	0.0010** (0.0004) [0.0250]
$\text{asinh}(\text{Landslide}_{jt})$	0.0003 (0.0004) [0.6457]	
$\text{asinh}(\text{Landslide}_{jt}) \times \mathbf{1}[j = k]$ (own clearing)		0.0031* (0.0014) [0.0634]
$\text{asinh}(\text{Landslide}_{jt}) \times \mathbf{1}[j \neq k]$ (bystander clearing)		0.0002 (0.0004) [0.8413]
Clearing-region FE (all n dummies)	Yes	Yes
Week FE	Yes	Yes
Constant	No	No
Observations	97,560	97,560
R^2	0.2242	0.2964

Notes. The dependent variable is the sufficient statistic $\widehat{W}_{jkt} = \ln W_{jkt}^{\text{CDL}} - \ln W_{jkt}^{\text{BLN}}$, the log welfare change of region j in week t under the counterfactual that removes the landslides per region. $\text{asinh}(\text{Landslide}_{jt})$ is the inverse hyperbolic sine of the number of landslide-disrupted routes serving region j in week t ; ρ_j is region j 's ratio of consumption to production. Column (2) splits the exposure term by whether the cleared region is j itself. Standard errors, clustered by recipient region ($G = 20$), are in parentheses. Restricted wild-cluster-bootstrap p -values (Webb weights, 9,999 replications) are reported in brackets, and significance is based on them.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (wild-cluster-bootstrap p).

Table D2. Is ρ itself responsive to landslide exposure?

	(1) Contemporaneous	(2) + One-year lag
$\text{asinh}(\text{Landslide}_{it})$	−0.0821 (0.0892) [0.3672]	−0.0801 (0.0850) [0.3101]
$\text{asinh}(\text{Landslide}_{i,t-1})$		−0.0164 (0.0891) [0.8543]
Region FE	Yes	Yes
Year FE	Yes	Yes
Observations	96	86
R^2	0.9734	0.9748

Notes. The dependent variable is $\ln \rho_{it}$, the log of region i 's ratio of consumption to production in year t , rebuilt annually from the underlying trade data using the same definition as the seven-year aggregate ρ_j used elsewhere in the paper. Landslide_{it} is the annual count of landslide-disrupted routes involving region i . Standard errors clustered by region ($G = 20$) are in parentheses; restricted wild-cluster-bootstrap p -values (Webb weights, 9,999 replications) are in brackets.

The estimation sample comprises 96 of the 140 region-year pairs. Each region enters the sample from the first year in which it records trade.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (wild-cluster-bootstrap p).