Unpacking Global Shocks*

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Abstract

Economy-wide shocks affect demand, supply, and intermediary sectors simultaneously. We dissect the impact of the Covid-19 pandemic on international trade by combining information from customs records, smartphone-based human mobility, and container ship port calls. We find that local disruptions to domestic demand reduced import quantities, while local disruptions to foreign supply and at seaports increased import prices and reduced quantities. On net, local disruptions during the pandemic were a negative supply shock, and the residual structural factors were a positive demand shock. The resulting excess import demand contributed to the rise in domestic inflation.

Keywords: International trade, local disruptions, human mobility, shipping costs, COVID-19 pandemic, inflation.

JEL codes: F10, F14, F16, I12, I18, R41.

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1 Introduction

In economy-wide shocks such as pandemics, wars, and financial crises, an economy's demand-side, supply-side, and intermediary sectors experience disruptions simultaneously. The Covid-19 pandemic is the most recent example. On the supply side, production capacities were compromised by containment efforts, illness, and shifts in workers' preferences. The transportation sector was hit by similar issues and also suffered from potential congestion: ports with reduced capacity due to lockdown encountered substantial reorganization of the international trade networks. On the demand side, demand for goods and services was likely affected by changes in present and future expected income, work modalities, and shifts in consumers' preferences. Unpacking the role of shocks in different margins of the economy is crucial to characterizing the anatomy of global shocks and, thus, informing policymaking when challenging times arrive.

Economists usually compare aggregate trends in the data and those that are informed by macro models with different types of disruptions to tease out the role of demand-side, supply-side, and intermediary-side shocks.[1] In this paper, we propose a more direct approach, using a rich set of data at a highly granular level and exploiting the economic geography of the demand, transportation, and supply sides. Colombian imports are our measure of economic activity, and we directly measure local disruptions in the supply, demand, and transportation sectors. We characterize the direct impact of these disruptions and differentiate it from other indirect and general equilibrium changes that occurred simultaneously.

We find that local disruptions at both the importer and exporter locations led to a decline in the trade quantities, whereas disruptions at exporter locations were the main driver of price increases in the first months of the pandemic. Moreover, the transportation sector experienced negative productivity shocks due to local disruptions at seaports and congestion, leading to freight cost and import price increases in the second year of the pandemic. Overall, from a small open economy perspective like Colombia, the direct impact of the pandemic via local disruptions was a net negative supply shock. Other structural factors not directly associated with local shocks constituted a net positive demand shock. The underlying excess import demand contributed to the increase in domestic inflation.

Colombia offers a unique opportunity to characterize the impact of local trade disruptions during the pandemic. First, it is a relatively small economy in world trade.[2] Therefore, changes in local mobility in foreign cities are not likely to be impacted by the demand and supply of goods in Colombia. Thus, it is reasonable to assume that foreign mobility

[1] See, for example, Kilian 2009; Benguria and Taylor 2020; Novy and Taylor 2020.

[2] In 2019, the total value of Colombian imports was 70 billion dollars, and it ranked 39 in world GDP, 53 in total imports, and 61 in total exports. Data source: `https://data.worldbank.org/`.

shocks were exogenous to Colombian imports. In addition, changes in Colombian demand are unlikely to generate shipping congestion in foreign ports for the same reason. Second, Colombia is integrated into international supply chains, with an average import penetration in manufacturing sectors of about 60% before the pandemic.

Our paper uses highly granular data on trade flows, maritime transportation, and human mobility. Our trade outcomes are from Colombian customs records, which allow us to identify foreign exports and Colombian imports at the sub-national level (city or city-equivalent level). We aggregate Colombian imports to the monthly, product (6-digit HS categories), exporter city, and importer city level, including detailed information on quantities, import prices, export prices, and freight and insurance costs. On the transportation side, we employ the universe of port calls made by container ships in exporting countries from January 2018 to October 2021 to measure port performance. We observe the number of port calls, total ship capacities served at the ports, and the number of hours each ship spends at the ports, which we use to measure port efficiency.

We use changes in within-city human mobility relative to the pre-pandemic baseline to measure local shocks to exporters, importers, and ports. The monthly changes in mobility of cities in Colombia and its 27 major trading partner countries/regions are obtained from Facebook and Baidu. We interpret mobility declines during the pandemic as generated by government restrictions, sickness, voluntary containment efforts, and business closures. In foreign exporter cities and the transportation sector, we interpret mobility declines as capturing negative productivity and labor supply shocks to both exporters and seaports. On the demand side among Colombian municipalities, we interpret mobility declines as a combination of (a) negative income effects due to a loss in current and future income for firms and households, (b) substitution effects due to an increase in prices of domestic goods from disruptions to domestic producers, and (c) potential changes in preferences.

We exploit variations in local pandemic outbreaks as captured by human mobility reductions in different regions across the world over time to identify the impact of local disruptions. In our preferred specification, we find that a 10% decline in mobility at the Colombian importer location led to a 4.1% decline in quantity and no impact on prices. A 10% decline in mobility at the foreign exporter location led to a 3.5% decline in trade quantity and a 1% increase in prices.[3]

We then use the human mobility changes in port cities, optimal shipping routes, and changes in freight costs to investigate the impact of the pandemic on sea shipping. We

[3]Fajgelbaum et al. (2020) finds that the tariff hikes due to the U.S.-China trade war reduced imports and exports in the short run, mainly through quantities. In our setting, both quantities and prices reacted due to the nature of the shock—our shock captures not only changes in trade wedges, such as transport costs, but also shifts in the supply and demand curves.

find that an average change in mobility in port cities induced a 2.2% increase in the hours in port in the exporting country. Furthermore, this change in mobility in the exporting country's ports also implied a 4% increase in freight costs. In addition, we show that, in 2021, ships spent a larger number of hours in ports, and freight costs were higher than in 2020, even after controlling for port disruptions. This is likely to reflect the accumulated effect of the pandemic through the reconfiguration of trade patterns across the world due to the multiplicity of disruptions and changes in consumer demand during the pandemic.

Combining a stylized trade model and empirical estimates, we conduct four exercises designed to shed light on the margins of the pandemic trade impact. First, using the impact of exporter location mobility changes on quantity and prices, we back out the product-level elasticity of substitution across exporter cities—a key parameter to characterize supply chain resilience. There are two distinctive key features in this parameter compared to estimates in the literature: (1) product varieties are defined at the sub-national level instead of the national level, and (2) the monthly data frequency allows us to estimate a short-run elasticity instead of a long-run one. We find a short-run elasticity of substitution between sub-national level exporters of 3.4.[4,5] Moreover, the elasticity of substitution for importer city products with a pre-pandemic number of suppliers above the median is twice as large as those below the median. This suggests that the pre-shock foreign supplier portfolio is an important determinant of supply chain resilience.

Second, we conduct the over-time decomposition of the pandemic impact into a supply-side, demand-side, and transportation margin. At the onset of the pandemic, 67% of the total impact on import quantities was explained by disruptions on the importer side, 26% by disruptions on the exporter side, and the remaining 7% by disruptions at ports. The initial increase in import prices was explained entirely by disruptions on the exporter side. Towards the end of our sample, October 2021, most of the decrease in import quantities and the increase in import prices was explained by a linear increase in transport prices not directly related to port disruptions.

Third, we distinguish the direct impact of the pandemic due to local disruptions from an indirect effect likely caused by general equilibrium effects and other non-local structural changes. We find that the local shocks constituted a net negative supply shock throughout the pandemic. In contrast, the other structural factors started as a mild net positive supply

[4]If we interpret our model as a product-sub-national version of an Armington model, our elasticity of substitution can be interpreted as the trade elasticity. Anderson and Yotov (2020) find that the short-run trade elasticity is one-quarter of the long-term and Boehm et al. (2023) find it is about one-third. In our case, our estimates are short-run but between sub-national locations, which are likely to be more substitutable than between countries. Overall, these two forces seem to offset each other.

[5]We also estimate elasticities of substitution at the two-digit HS level. The range of significant estimates is $(0.7, 4.2)$.

shock but developed into a net positive demand shock as the pandemic progressed into 2021.

Finally, we explore the impact of the pandemic on domestic inflation through international trade. We find that local disruptions to foreign suppliers were related to the increase in domestic prices of tradable consumer goods, resulting in a short-run reduced-form pass-through from import to consumer prices of about 60%. In addition, we show that the pass-through from other systematic determinants of import prices—e.g. general equilibrium effects—was about 1%. These two results suggest that the pandemic generated excess import demand that was resolved by an increase in consumer prices.

The main contribution of our paper is to combine microdata and microstructure to characterize the locality of global shocks. This makes our paper closely related to the literature on the impact of local shocks on trade. Researchers have documented the impact of natural disasters on firm outcomes and how the effects propagate along supply linkages, domestically (Barrot and Sauvagnat, 2016; Carvalho et al., 2021) or internationally (Volpe Martincus and Blyde, 2013; Boehm et al., 2019).[6] Our main difference with the literature is that, while we measure shocks at the local level, we position these local shocks as part of a global shock and, consequently, can characterize the relative importance of the different margins affected.[7] Thus, we also add to the literature on the impact of economy-wide shocks, including pandemics, wars, and financial crises (Benguria and Taylor, 2020; Novy and Taylor, 2020; Jordà et al., 2022). Our key contribution to this literature is that instead of relying on macro models and aggregate time-series data, we use real-time local-level data to directly measure shocks on the demand side, supply side, and transportation sector and empirically identify the causal impact of each of these shocks.[8]

We contribute to the literature on the role of transportation in trade, especially new literature on maritime shipping. In two recent papers, by Heiland et al. (2019) and Ganapati et al. (2021), the authors use container ship port call data to measure the global maritime shipping network and estimate the impact of changes in certain nodes in the network on global trade and welfare. We contribute to the literature in three ways. First, we focus on a different type of shock to maritime shipping: disruptions in port cities associated with declining

[6]With the increasingly integrated global economy, the importance, frequency and scope of such local shocks have become more relevant. For example, in the semiconductor industry, factory fires in Japan and a drought in Taiwan recently reduced the worldwide semiconductor supply—a key input for many industries. In maritime shipping, world container shipments were recently affected by the temporary blockage to the Suez Canal, the Houthis attacks on cargo ships in the Red Sea, and a historical draught in the Panama Canal.

[7]More broadly, our results on the international trade dynamics add to the literature on cross-country business cycle co-movement (DiGiovanni and Levchenko, 2010, among others).

[8]A related paper in this regard is Baqaee and Farhi (2022). They employ a quantitative macro model to disentangle demand and supply shocks at the outbreak of the pandemic. In contrast, our paper focuses on identifying a precise type of demand, supply and transportation shocks—local disruptions—exploiting rich granular data and a stylized trade model.

productivity and labor supply shortages. Second, we construct a novel measure for port productivity. We use the number of hours each container ship spends in the ports to capture port efficiency and document how local labor shocks can lead to *changes in* port productivity. Third, we have direct measures of freight costs, and we show how local shocks to foreign ports can push up freight costs to importers. By focusing on a labor supply shock at seaports, we also contribute to the growing literature on endogenizing the international transport sector (see, e.g., the role of round-trips in Wong, 2022, networks effects in Brancaccio et al., 2020, and price discrimination in Ignatenko, 2020.)

Finally, this paper contributes to recent research studying the impact of the pandemic on trade and economic activity in general. Our understanding of the nature of the pandemic is consistent with papers that document the impact of the pandemic on labor markets, income, consumption, and expectations using real-time data (Coibion et al., 2020a,b).[9] Several papers develop quantitative models to simulate the impact of country- or region-level pandemic shocks on supply-chain disruptions (Guan et al., 2020; Inoue and Todo, 2020; Bonadio et al., 2021). Other papers employ aggregate time-series and sectoral data in combination with general equilibrium quantitative models to study the aggregate impact of supply disruptions (Alessandria et al., 2023; DiGiovanni et al., 2023). A few papers use actual trade data to study the pandemic disruptions (Liu et al., 2021; Lafrogne-Joussier et al., 2022), focusing on exports from China during the early pandemic period. To the best of our knowledge, we are the first to use detailed measures of actual international trade outcomes, port performances, and human mobility at the sub-national level to causally estimate the disruptive impact of pandemics on international trade and disentangle their impact on different economic margins.[10]

The rest of the paper is organized as follows. Section 2 introduces the data and presents changes in trade, transportation, and human mobility during the pandemic. Section 3 presents a simple trade model and outlines our empirical strategy. Section 4 presents results on the relationship between exporter and importer local mobility shocks and Colombian imports at the product level. Section 5 focuses on the impact of mobility changes at seaports on port performance and freight unit values. Section 6 presents results on the contribution of the different margins affected by disruptions to the direct impact of the pandemic, along with its relationship with its indirect impact over time. Section 7 explores the relationship between international trade shocks and domestic inflation. Section 8 concludes.

[9]Relatedly, Antràs et al. (2023) develop a theoretical framework to study the impact of globalization where trade also spreads diseases through human interactions and generate labor shocks. Guerrieri et al. (2022) presents a framework where negative supply shocks translate into demand shortages. The underlying assumptions of these theories are consistent with the aforementioned empirical evidence.

[10]Complementary to our international trade analysis, Khanna et al. (2022) use variation in lockdown stringency across Indian districts to characterize domestic supply chain resilience at the firm-to-firm level.

2 Data and Descriptive Statistics

In this section, we present the datasets used in the analysis and document the variation of key measures over time and across locations.

2.1 Trade Data

We employ import Colombian customs records collected by the DIAN (the Colombian Office of Taxes and National Customs by the Spanish acronym) and made available by DANE (the National Administrative Statistical Office). This data set includes transaction-level information on the importer location, exporter location, 6-digit HS product codes, import values in US dollars, quantities, weights, and freight and insurance costs.[11] In our analysis, we include the 27 major exporting countries/regions to Colombia and the top 60 Colombian municipalities in terms of 2018 imports—which accounted for about 90% and 99% of total imports respectively in 2018.[12] We identify the importer location at the Colombian municipality level and the exporter location at the exporter countries' second-highest sub-national administrative level whenever possible, and we refer to them as *importer cities* and *exporter cities*, respectively.[13] We then aggregate the information to the month-exporter-city-importer-city-product level.

Figure 1 presents the total monthly imports from January 2018 to October 2021, relative to the pre-pandemic averages. These are 2018–2021 imports demeaned by the month-specific average total import value of 2018 and 2019. We see that before the pandemic, aggregate imports did not show large swings, with changes always smaller than 6% of the month-specific 2018–2019 average. However, when the COVID-19 pandemic hit, by April 2020, aggregate imports declined by almost 40% — 1.4 billion US dollars, and they increased by as much as 35% — 1.2 billion US dollars — during 2021.

We present further descriptions of trade outcomes in terms of quantities, prices, and transportation costs in Appendix Section A.1.3. When we flexibly control for importer-exporter-product level characteristics such as the 2018-2019 trends and seasonality, we find that the average changes in import values across products and locations over time were

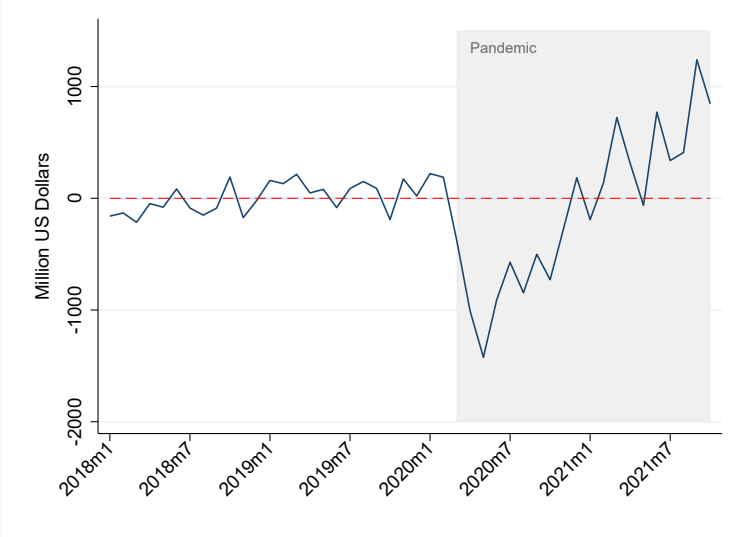
[11] See Appendix A.1.1 for the fields in the customs form from which we extract this information.

[12] These countries/regions include Argentina, Austria, Belgium, Bolivia, Brazil, Canada, Switzerland, Chile, China, Germany, Ecuador, Spain, France, the United Kingdom, Hong Kong, India, Italy, Japan, South Korea, Mexico, the Netherlands, Panama, Peru, Taiwan, Uruguay, the United States, and Vietnam. Venezuela is excluded.

[13] We do not use all exporting countries because within-country exporter locations require extensive cleaning. Among the 27 exporting countries/regions, Argentina, Bolivia, Japan, South Korea, the UK, Uruguay, and Vietnam's exporter locations are at the highest sub-national administrative level due to the reporting of the customs data, and Hong Kong is treated as one city. See Appendix A.1.2 for details about the data cleaning process.

similar to the aggregate: a sharp decrease at the beginning of the pandemic and a slow, non-monotonic recovery. This pattern is explained mostly by changes in the quantities imported. Export prices had a small increase during 2020 and the first quarter of 2021 but had a sharp increase in the second quarter. Transportation costs started rising early in the pandemic and kept increasing over the entire period of our study.

Figure 1: Aggregate Colombian Imports Relative to Pre-Pandemic Levels



Note: Data is from the Colombian customs office. Each month's value is calculated as the total Colombian imports minus the 2018–2019 month-specific average, covering the twenty-seven major exporters to Colombia.

How much of the change in each outcome is driven by shocks to demand, supply, and in the transportation sector? In our empirical section, we will use variation at the month-exporter-city-importer-city-product level to systematically study how the local disruptions at each end affected each of these trade outcomes.

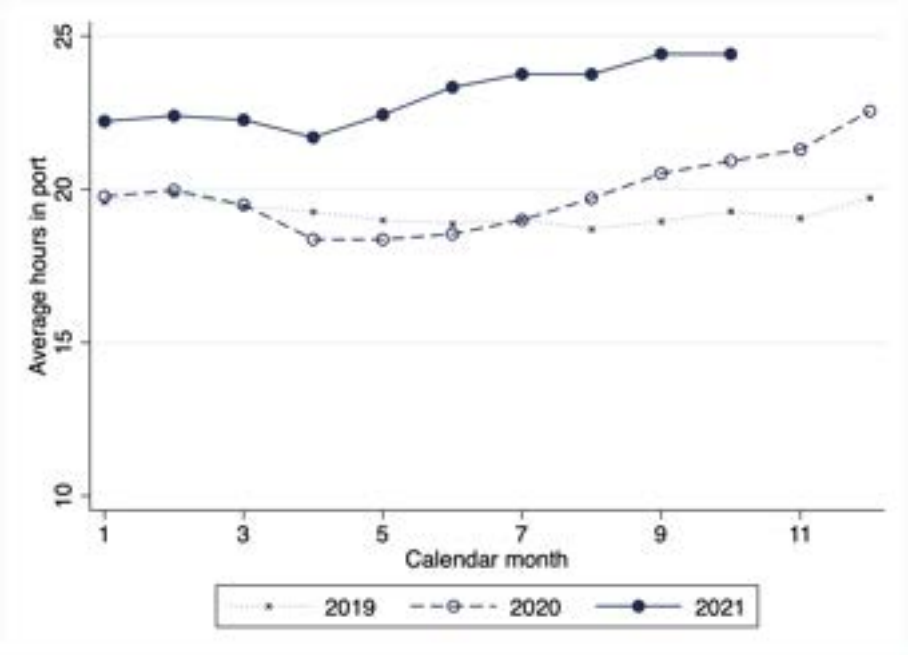
2.2 Container Ship Port Call Data

We use port call data on 150 ports in 27 countries and regions from January 2018 to October 2021 to measure seaport performance. The data on container ship movement is from IHS Markit's Maritime & Trade Platform.[14] The platform collects and processes AIS (automatic identification system) data on ship movements of over 220,000 ships of 100 gross tonnages and above around the world. The 27 countries include 25 countries and regions that are top trade partners with Colombia (excluding Switzerland and Bolivia, which are landlocked), Colombia, and Singapore (as an important intermediate port). We include the

[14]See `https://ihsmarkit.com/industry/maritime.html`.

most important ports in these countries, with each port having at least 10 ships arriving at the port from January 2018 to October 2021. We focus on container ships as in Ganapati et al. (2021) and Heiland et al. (2019) since containerized seaborne trade makes up the majority of world trade on merchandise. The list of ports and their 2019 capacity is shown in Appendix Table A2.

Figure 2: Average Number of Hours in Port, From January 2019 to October 2021, 150 Ports in 27 Countries



Note: Data is from the IHS Markit Maritime & Trade Platform. The figures use port calls made by container ships at 150 ports in 27 countries. The hours in port are measured as the difference between the sailed time and the arrival time at the port.

Figure 2 presents the trend in the average number of hours each container ship spent at the port from 2019 to 2021.[15] The number of hours in port is measured using the difference between the sailed time and the arrival time for the port call. Arrival time is the first AIS position that appears within the designated port zone, and sailed time is the first AIS position recorded that appears outside of the port zone. Thus, the number of hours in port can measure the efficiency of port services and proxy for port congestion. Intuitively, labor shortages in the port can increase the processing time, and ships will need to spend more hours in the port. We can see that while the number of hours in port was stable in 2019, it experienced a steady increase since July 2020, with an about 25% increase in October 2021 compared to October 2019.

[15]We will also use 2018 data in the empirical analysis. The 2018 time series is not in Figure 2 to avoid overcrowding of the lines.

We present additional trends in the maritime shipping industries in Appendix A.2.3. We found that even at the end of 2021, the total number of port calls made at these seaports did not recover to the 2019 level. However, there was a substantial reorganization of shipping activities. For example, due to an early recovery of Chinese production from the initial Covid shock, the share of port calls whose last port call was made in China increased substantially in our study period.[16,17]

In our empirical analysis, we will exploit within-city mobility changes in the port cities to understand the impact of port disruptions on port efficiency and freight cost. Additionally, the potential reshuffling of main exporters across the world will likely generate cumulated disruptions in the shipping industry.

2.3 Human Mobility Data

Countries around the world experienced declines in mobility during the pandemic, because of government restrictions, sickness, voluntary containment efforts, and business closures.[18] We measure the reductions in economic activities within cities using the change in log daily mobility, where the baseline is the same day-of-week in the pre-Covid mobility. For China, the data is from Baidu Mobility Map, and the pre-Covid period is defined as the first two weeks in January.[19] The Baidu mobility measure captures the extent of within-city movement, by using the indexation of the share of people who leave home for at least 500 meters for more than 30 minutes. It is available for 12 months, March to May 2020 and September 2020 to May 2021, for 333 prefectures in China. For Colombia and its other 26 major trade partners,

[16]Theoretically, it is possible that ships spending more time at the ports or having fewer port calls served are not the results of port congestion, but the optimal choice of shipping companies given other considerations. However, empirically, labor shortages at the ports and long waiting times at the ports are costly for the shipping companies, the exporters, and the importers, as documented in multiple news articles. See, for example, a report on the Los Angeles port congestion here: `www.wsj.com/articles/why-container-ships-cant-sail-around-the-california-ports-bottleneck-11632216603?mod=article_inline`. Note that our measure of the number of hours in port will only capture the time container ships spend in the port once it has entered the port zone, but not the time they spend waiting outside the port zone. Our assumption here is that our measure is proportional to the overall delay the container ships experienced. In the empirical analysis, we will present further evidence on why our congestion measure captures the results of labor constraints, and how the congestions are related to actual increases in freight cost.

[17]We don't observe the number of containers unloaded and loaded during a port call. Heiland et al. (2019) provide a method to infer the weight of a ship using its nautical draught, and we do observe the arrival and departure draught of ships in our port call records. However, a ship may have no change in its draught from arrival to departure if the weight of unloaded containers is the same as the weight of the newly loaded containers. Thus, the information on draughts will not be very useful in our analysis.

[18]Camehl and Rieth, 2023 show that containment shocks and incident shocks, such as superspreaded events, led to a decline in mobility lasting between one to two months and Alexander and Karger, 2023 show that stay-at-home mandates had an almost immediate impact on mobility in the US.

[19]Source: Baidu Mobility Map at `https://qianxi.baidu.com/`.

the data is from Facebook, and the pre-Covid period is defined as February 2020.[20] The Facebook data uses the location information of users who enable location services on their mobile Facebook app to measure the change in the log average number of 0.6 km squares visited during a day. The data is available at the second-highest sub-national region level, and only cities with more than 300 users are included. The Facebook data is available for 20 months, from March 2020 to October 2021. Then we average across the working days in a month (i.e., Monday to Friday) to measure the average change in mobility in a month.

There is substantial within-country variation in mobility. Figure 3 (a) presents the local mobility variations in Colombia in September 2020.[21] In Figure 3 (b) we take Europe as an example and show the distribution of mobility declines across the eight European countries included in the analysis in September 2020. Overall, Spain and the UK had larger mobility declines than Germany and France. However, within each country, regions experienced differential declines as well.[22]

In our empirical analysis, we will employ month-specific within-country variation in mobility changes to identify local trade disruptions.

2.4 Trade and Human Mobility Correlation

We match the geographic units in the trade data and the ones in the mobility data. While the mobility data is always available at the second-highest sub-national level, the exporter cities in the trade data are not always available at the same level. In Appendix A.4, we present (a) the level of aggregation of each data set in each country, (b) the number of units per country, (c) the final number of exporter cities we include in the analysis after merging the two data sets, and (d) the share of trade we cover for each country.

Before proceeding to our formal empirical estimates of the impact of shocks on the trade outcomes at the product and location level, we first present correlational evidence on the relationship between changes in mobility and import values at the city level. We regress the importer city-time level changes in log import values on the changes in the log mobility in the importer city, controlling for time fixed effects. Figure 4 Panel (a) shows that there is a positive correlation. This means that disruptive shocks captured by lower mobility at importer locations in Colombia were associated with a decline in the value of imports directed to that location. We don't observe this positive correlation when we regress the 2018-2019 import on the 2020-2021 mobility changes.

[20] See `https://dataforgood.facebook.com/dfg/tools/movement-range-maps`.

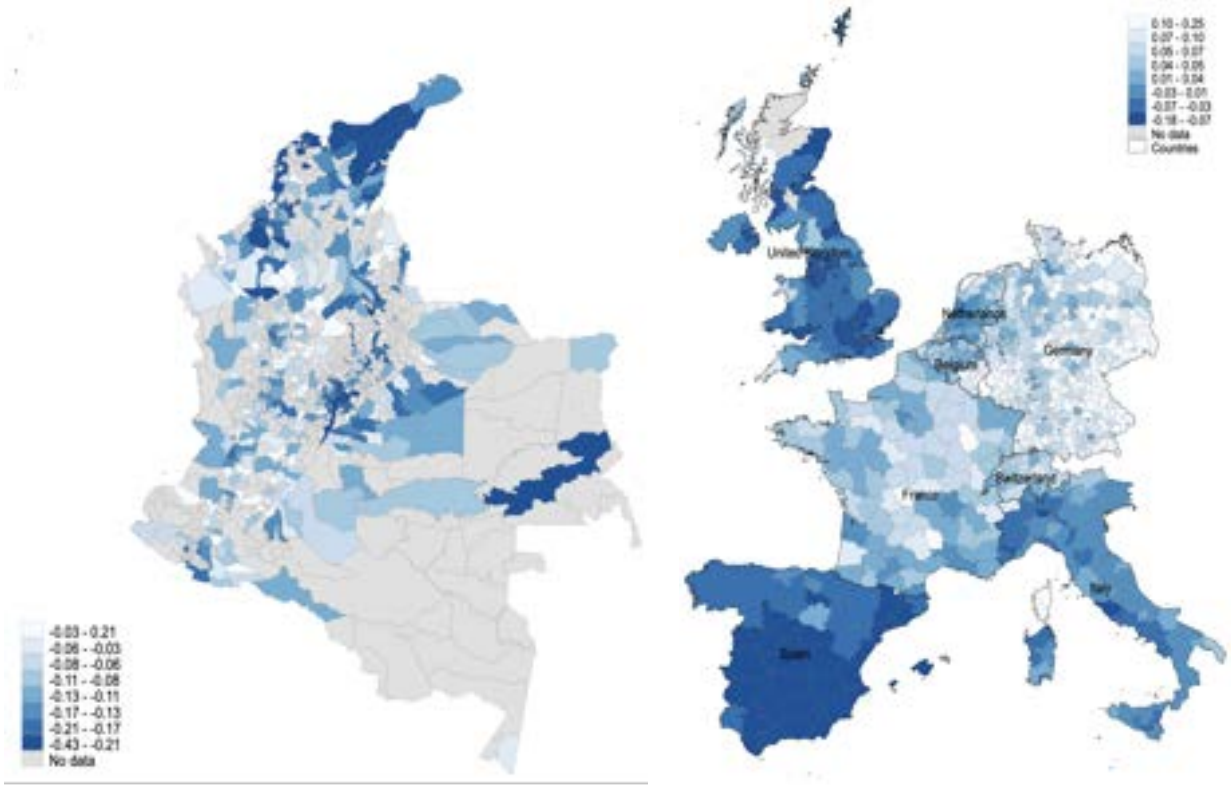
[21] Facebook covers 530 out of 1,065 municipalities in Colombia.

[22] We present aggregate trends in mobility in Appendix A.3.1 and within-country variations in the U.S., China, and Mexico in Appendix A.3.2.

Figure 3: The Decline in Mobility Across Municipalities in Colombia and Across NUTS3 Units in Eight European Countries, September 2020 Compared to February 2020

(a) Colombia

(b) Europe

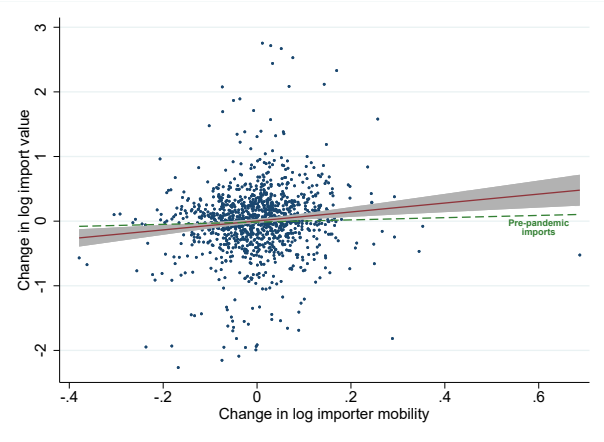


Note: Data is from Facebook. The Colombian data covers 530 municipalities. The European countries include the UK, France, Spain, Italy, Switzerland, Belgium, the Netherlands, and Germany. The NUTS (Nomenclature of Territorial Units for Statistics) classification is a hierarchical system for dividing up the economic territory of the EU and the UK, and NUTS3 is the second-highest sub-national level. See details of the classification here: `https://ec.europa.eu/eurostat/web/nuts/background`.

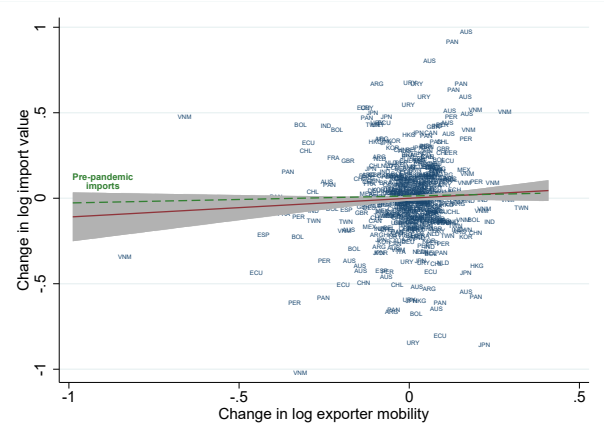
We then conduct a similar analysis at the exporter-city level by regressing the changes in log import values at the exporter-city-time level on the changes in log mobility in the exporter city, controlling for time and exporting country fixed effects. Figure 4 Panel (b) shows that there is a positive but insignificant correlation between the exporter shock and import values, potentially resulting from the exporter shock having opposite effects on the price and quantity. Again, we don't find pre-trends at this level by using 2018-2019 log import changes.

Figure 4: Relationship Between Changes in Log Import Value and Changes in Human Mobility at the Importer City and the Exporter City

(a) Imporer mobility



(b) Exporter mobility



Note: In both figures, each dot represents a city-time pair. Panel (a) is the residual plot of the log change in import value at the importer city regressed on the log change in importer mobility, controlling for time fixed effects. The red solid line is the corresponding fitted line with a slope of 0.692(0.197), with the robust standard errors in parenthesis used for the confidence intervals (i.e., the grey areas). The green dashed line shows the pattern when using the 2018-2019 trade outcomes, with a slope of 0.173(0.153). Panel (b) is the residual plot of the log change in import value at the exporter city regressed on the log change in exporter mobility, controlling for exporting country fixed effects and time fixed effects. The red solid line is the corresponding fitted line with a slope of 0.101(0.068), with the robust standard errors in parenthesis used for the confidence intervals (i.e., the grey areas). The green dashed line shows the pattern when using the 2018-2019 trade outcomes, with a slope of $-0.003(0.067)$.

3 Theoretical Framework and Empirical Strategy

In this section, we lay out our strategy for estimating the impact of exporter shock, importer shock, and transportation sector disruptions on Colombian imports. We first construct a simple trade model to guide our empirical estimation. We then present our empirical strategy and discuss identification assumptions.

3.1 Theoretical Framework

We assume each city i in the world has two types of firms. The first type of firm produces products indexed by k. The second one is a competitive bundler that sells goods domestically to either consumers or domestic firms.

Producing firms combine local labor and capital with a Cobb-Douglas technology to produce, where $\tilde{\alpha}_L$ is the labor share parameter. We assume that capital is fixed in the short run—the time frame we assume for the model. Given that we focus on their international trade activity, we call them "exporters." We use the index ik to identify an exporter located at city i (in country c) exporting product k.

Bundlers' technology is Cobb-Douglas in combining labor and the sourced product k to sell domestically. They can source product k from cities in a pre-determined set Ω_{jk}, where j indexes the city of this firm as a buyer importing product k. Importantly, we assume that bundlers cannot perfectly substitute across exporter cities, i.e., their production function is constant elasticity of substitution (CES) with an elasticity of substitution η over varieties of a product produced by different cities. Given our focus on international sourcing, we call these firms importers.

International trade is subject to a per-unit international transport cost T_{ijk}. Therefore, the import price p_{ijk}^M is equal to $p_{ik}^X + T_{ijk}$, where p_{ik}^X is the export price.

Import Demand Import city j's demand of product k from city i is given by a standard constant elasticity of substitution (CES) demand function:

$$q_{ijk} = (p_{ijk}^M)^{-\eta}(P_{jk}^M)^{\eta-1}Z_{jk}, \tag{1}$$

where $P_{jk}^M \equiv [\sum_{i\in\Omega_{jk}}(p_{ijk}^M)^{1-\eta}]^{\frac{1}{1-\eta}}$ is the CES price index over exporter cities, and Z_{jk} is a product k-specific local demand shifter. This term can include a variety of factors. First, it can capture a decline in current and expected future revenue due to changes in consumer expected income. For instance, we would expect a decline in quantities imported if a local shock increases layoffs and leads to a decrease in household income—the bundler would see the demand for its goods reduced. We call this an "income effect." Second, it can capture a "substitution effect" to or from other goods, including those produced domestically. In this case, the impact of the pandemic can be either positive or negative depending on substitution patterns. Finally, it can also capture shocks to preferences. For example, instead of going to local restaurants and office spaces, people prefer to do home cooking or set up home offices due to health concerns. These additional furniture and home supplies are likely to be imported.[23]

Export Supply We assume exporters combine labor and a fixed amount of capital to export over the period we consider using Cobb-Douglas technology. Their cost function is:

[23]We can characterize these different effects using a CES demand system with two upper-level nests. First, assume the composite imported product k can be imperfectly substituted at a rate $\sigma < \eta$ with varieties produced domestically. Second, assume that all products can be imperfectly substituted at a rate ε. Third, let's explicitly introduce a taste shifter ϕ_{jk} for each importer-product. Then, the import price index exponent would be $\eta - \sigma$, and $Z_{jk} = \phi_{jk} \times (P_{jk}^D)^{\sigma-\varepsilon} \times (P_j)^{\varepsilon-1} \times \text{Income}_j$, where P_{jk}^D is the composite price index combining the import and domestic price indices, P_{jk}^M and P_{jk}^{CO} respectively, and P_j is the aggregate price index of all goods at j. A reduction in income would reduce Z_{jk} and thus lower demand for the variety jk; an increase in P_{jk}^D would increase Z_{jk}; an increase in P_j would increase Z_{jk} if $\varepsilon > 1$ (substitute goods) or decrease it if $\varepsilon < 1$ (complement goods); and an increase in ϕ_{jk} relative to other products' shifters would increase Z_{jk}.

$$C_{ik} = A_{ik}^{IK} Q_{ik}^{\alpha}, \tag{2}$$

where A_{ik} is a cost-shifter specific to product k, $Q_{ik} \equiv \left[\int_{j \in \Omega_{ik}} q(j)_{ik} dj \right]$ is total production, Ω_{ik}^{IK} is the set of locations served by i, and $\alpha \equiv 1/\tilde{\alpha}_L > 1$ captures the degree of decreasing returns to scale in the short run due to fixed capital. The cost-shifter A_{ik} can capture different factors that make production more costly. First, it can capture local changes in wages, which may have increased if the pandemic reduced the local labor supply. This will lead to an increase in production costs. Second, it can capture changes in productivity, for instance, due to work-from-home patterns induced by the pandemic. For example, communication frictions induced by this change in work arrangements can lead to a decline in firm productivity. Finally, it can also capture idiosyncratic supply shocks.[24]

Exporters maximize profits by choosing export prices given the CES importer demand and their technology. Therefore, they charge the following optimal export price:

$$p_{ijk}^{X} = \frac{\eta}{\eta - 1} \alpha A_{ik} Q_{ik}^{\frac{\alpha - 1}{\alpha}} + \frac{1}{\eta - 1} T_{ijk}. \tag{3}$$

This expression captures several features of export prices.[25] First, cost shocks to location i increase prices through A_{ik} (e.g., labor shortages that increase local wages). Second, the price to all importers rises if there is an increase in demand from sizable importers given short-run decreasing returns to scale through $Q_{ik}^{\frac{\alpha - 1}{\alpha}}$. Finally, an increase in transportation costs can also raise export prices because it shifts the demand curve inwards, decreasing marginal revenue.

Transportation We assume the transportation sector is operated by a global firm. The short-run supply curve of the shipping service to ship products from city i to city j is given by:

$$T_{ijk} = B_{ij} v_{ij}^{\rho} g_k, \tag{4}$$

where B_{ij} is the cost shifter that captures the disruptions experienced in the shipping route from i to j, v_{ij} is the total volume of goods transported, $\rho > 1$ is the decreasing returns to scale parameter and g_k captures product-specific fundamental characteristics (e.g. volume). Transport costs per unit may rise if, for example, labor shortages in exporter country ports,

[24] Given the technology assumptions, $A_{ik} \equiv \left[\frac{w_j}{a_{ik} \bar{H}_i^{1 - \tilde{\alpha}_L} k} \right]^{\frac{1}{\tilde{\alpha}_L}}$, where a_{ik} is a Hicks-neutral productivity parameter and $\bar{H}_i k$ is the fixed amount of capital.

[25] Exporters maximize $\Pi_{ik} = \sum_{\Omega_{ik}^{IK}} p_{ijk}^{X} q_{ijk} - C_{ik}$ by choosing p_{ijk}^{X}. See details of the derivation of optimal exporter prices in the Appendix C.1.

importer country ports, or intermediate shipping ports increase B_{ij}.

Solution in Changes Our goal is to associate local disruptions with human mobility indicators to understand their effect on equilibrium import and transport prices and quantities. To do so, we first log-differentiate import prices to get the following expression in changes:

$$\hat{p}^M_{ijk} = \iota_{ijk}\hat{A}_{ik} + \iota_{ik}\frac{\alpha-1}{\alpha}\hat{Q}_{ik} + (1-\iota_{ijk})\hat{B}_{ij} + (1-\iota_{ijk})\rho\hat{v}_{ij}, \tag{5}$$

where $\hat{x}$ means the log-change of variable x with respect to the equilibrium value, and $\iota_{ijk} \equiv \frac{p^D_{ik}}{p^M_{ijk}}$, assuming that transport costs of shipping to the domestic market—where the exporter is located—are zero and thus the domestic price p^D_{ik} is determined only by the local marginal cost of production and producer markups. As expected, import prices increase when exogenous production costs rise ($\hat{A}$), but also when the total production increases ($\hat{Q}$), given that the marginal cost increases through congestion in the short run. Finally, an increase in transportation costs due to exogenous shocks ($\hat{B}$) or an increase in the volume shipped ($\hat{v}$) also leads to an increase in import prices.[26]

Given prices, the log changes in import quantity can be expressed as follows:

$$\hat{q}^M_{ijk} = -\eta\hat{p}^M_{ijk} + (\eta-1)\hat{P}^M_{jk} + \hat{Z}_{ijk}, \tag{6}$$

and it is evident that, on top of the price change effect, the price index P^M and the demand shifter Z also lead to changes in import quantities.

3.2 Empirical Strategy

Our goal is to estimate Equations (5) and (6), the structural price and quantity equations in changes, using trade and mobility data. We start by assuming that there is no congestion to focus on the direct channels, i.e., $\alpha = 1$. The three main direct sources of trade disruptions in the model are at the exporter location ($\hat{A}$), importer location ($\hat{Z}$), and during transportation ($\hat{B}$). In Section 4, we focus on the first two terms by controlling for the transportation disruptions using fixed effects. We study the role of $\hat{B}$ in Section 5.[27] We also provide evidence that production congestion, i.e. $\alpha > 1$, had a role in shaping trade flows during the pandemic, but did not affect the estimates of the direct impact.

[26] The impact of transport prices on import prices comes from both their accounting relationship and the optimal export price set by the exporter.

[27] We study it separately because not all international trade is conducted through seaborne shipping, and we only have direct measures of seaport performances to capture the disruptions in the transportation sector.

Measurement of Local Demand and Supply Shocks We measure local demand and supply shocks using changes in within-city human mobility from Facebook and Baidu. In Appendix Section A.3.3, we provide evidence on how the number of new Covid cases and government containment policies are correlated with our mobility measures.[28] In the model, local disruption shocks during the pandemic can be interpreted as shifts in costs (A) and demand (Z). For instance, a lockdown in a city may suddenly reduce labor supply, increasing wages and thus A. Moreover, a local pandemic shock may affect the demand for product k through the income effect, domestic substitution effect, and preference change effect, as captured by Z. Mapping these changes to the data, we assume the following empirical relationships.

$$\hat{A}_{ik} = \gamma_A \hat{x}_i^I + \epsilon_{A,ik}, \tag{7}$$

$$\hat{Z}_{jk} = \gamma_Z \hat{x}_j^J + \epsilon_{Z,ik}, \tag{8}$$

where γ_A and γ_Z are the empirical shifters' elasticities with respect to local mobility changes, and $\epsilon_{A,ik}$ and $\epsilon_{Z,ik}$ are error terms.

Empirical Equations and Identification To get the final estimating equations, we plug Equations (7) and (8) into Equations (5) and (6) and control for changes in transportation costs and the import price index.

Specifically, to control for transport costs, we include an exporting country (c), main port of entry (MPOE, u), and time fixed effect δ_{cut}^{Tr}. We use these fixed effects since in the data, we can only observe the entry port into Colombia, but not (a) the exit port from the exporting country, (b) the shipping route from the exporter city to the exit port, (c) the shipping route from the entry port in Colombia to the importer city. We identify one main entry port for each exporter city, importer city, product, and time observation, where a "port" is the entry point into Colombia, including land and airport customs. Most of the observations in our baseline sample use only a single entry port to Colombia, and in 70% of them the main entry port accounts for the 90% imports.[29]

[28] We do so only for European countries, for which we have high-frequency information at a granular geographic level.

[29] We observe transportation costs at the exporter city, importer city, product, and time level, but we do not include it as a control since it is likely endogenous and correlated to the mobility indicators, thus potentially biasing the coefficients of interest. In Appendix Section B.4.1 we show that the estimated fixed effects are highly correlated with the observed transport costs.

In the model, the price charged by exporters does not depend on j characteristics other than through transport costs. However, import quantities demanded also depend on the state of competition through the import price index. We include product-time fixed effects to control for it.[30]

The resulting empirical equations are as follows:

$$\hat{q}^M_{ijkt} = \beta^q_J \hat{x}^J_{jt} + \beta^q_I \hat{x}^I_{it} + \delta^{P,q}_{kt} + \delta^{Tr,q}_{cut} + \varepsilon^q_{ijkt}, \tag{9}$$

$$\hat{p}^M_{ijkt} = \beta^p_J \hat{x}^J_{jt} + \beta^p_I \hat{x}^I_{it} + \delta^{P,p}_{kt} + \delta^{Tr,p}_{cut} + \varepsilon^p_{ijkt}, \tag{10}$$

where the error terms ε^q_{ijkt} and ε^p_{ijkt} result from the approximation error and the idiosyncratic shocks to the demand and cost shifters.[31]

The parameters of interest are β^q_J, β^q_I, β^p_J, and β^p_I. In Equation (10), the theory predicts a negative β^p_I since a Covid outbreak at the producer's location is likely to generate an increase in production cost, resulting in an increase in prices. In principle, there should be no role for the importer mobility to affect prices, so we expect β^p_I to be zero. In Equation (9), a positive β^q_J indicates that the income effect dominates the domestic substitution effect and preference changes; we take the sign of this coefficient as an empirical question. We expect β^q_I to be positive since an increase in price would lead to a reduction in quantities demanded.

The first identification assumption is that conditional on the fixed effects, there are no other variables driving both the changes in mobility and the changes in quantity and prices. Given the fixed effects, our identifying variation will come from within product-time, within import-route-time variation, and between exporter-importer pairs. Although we cannot validate this identification assumption directly, we provide evidence on the absence of pre-trends in our analysis. Second, in terms of reverse causality, the assumption is that product-specific j demand and i supply are "small" relative to i and j overall mobility changes. For example, if an increase in demand for goods in a Colombian city leads to more infections of Covid-19 in an exporter city, and thus a reduction in mobility there, this assumption is violated. We think that this situation is unlikely, since Colombia is a relatively small country in terms of global trade. Third, we need the mobility change to measure the Covid-induced demand shifters and supply shifters accurately. People may be sick or self-isolating due to the Covid-19 situation, the government may issue stay-at-home orders or other measures to encourage social distancing, and people can choose to stay at home to avoid human contact.

[30] This formulation assumes a national market and uncorrelated changes in internal transport costs from the importer location to final consumption.

[31] Note that we include the import price index fixed effect, $\delta^{P,p}_{kt}$, to both equations for symmetry and comparability, but the model only predicts it to be relevant for the quantity equation.

The mobility change will capture all three scenarios. In other words, we assume that the human mobility measures work as a sufficient statistic of Covid disruptions. In addition, we assume that workers in the manufacturing and the transportation sector are subject to the same shocks as people who work in the same city but in other sectors.

Finally, the sets of fixed effects $\delta_{kt}^{P,q}$, $\delta_{cut}^{Tr,q}$, $\delta_{kt}^{P,p}$ and $\delta_{cut}^{Tr,p}$ will capture other structural determinants of imports quantities and prices during the pandemic. For example, general equilibrium effects from aggregate income and price indices responses to local disruptions, aggregate demand shocks due to general changes in preferences not associated with local disruptions, and common productivity declines due to changes in work modalities. In Section 6, we will employ estimates of these fixed effects to distinguish between the direct impact of the pandemic via local disruptions and these other indirect effects.

We will discuss the empirical specifications for port disruptions in Section 5.

4 The Impact of Disruptions at Exporter and Importer Locations

In this section, we estimate the impact of the Covid disruptions experienced at the exporter city and the importer city on the total import value, quantity, and prices. We start with the baseline specification and present additional robustness analysis and checks on pre-trends. We also show heterogeneous effects by product categories (i.e., consumer, intermediate, and capital, or medical vs non-medical), by the pre-pandemic number of suppliers, and other product-specific characteristics (i.e., upstreamness, price stickiness, inventory intensity, and production differentiation). We then investigate (1) the role of production congestion, (2) the interaction effects of exporter and importer mobility changes, and (3) the effects on the probability of observing a positive trade flow in a given month. Finally, we use the previous estimates and the model to recover the importer city-product-specific elasticity of substitution across exporter cities.

4.1 Baseline Results

Main Results We start by estimating the empirical quantity (9) and price (10) equations, plus the sum of the two which corresponds to the impact on total import values (Table 1). Standard errors are clustered at the level of the mobility measures—exporter-time and importer-time. A decline in exporter mobility and a decline in importer mobility reduced import values as shown in Column (1). These effects are explained mainly by a reduction in the imported quantities (Column 2), while only the export mobility changes had a (negative)

effect on prices (Column 3). A 10% decrease in exporter mobility induced a 3.5% decrease in import quantities from that location and a 1% increase in prices. A 10% decrease in importer mobility lowered import quantities by 4.1%.[32] Interpreting the coefficients at the average importer and exporter reduction in mobility (25% and 14% respectively), we get that the impact on import values was -11% and -3% respectively.[33]

Table 1: The Impact of Exporter and Importer Mobility on Trade Outcomes, Baseline and With Pre-Trend Controls

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline			With pre-trend controls		
Dependent variable:	Δ log value	Δ log quantity	Δ log price	Δ log value	Δ log quantity	Δ log price
Δ log importer mobility	0.433***	0.410***	0.023	0.497***	0.512***	-0.013
	(0.068)	(0.073)	(0.053)	(0.099)	(0.100)	(0.061)
Δ log exporter mobility	0.249***	0.352***	-0.103**	0.201	0.342**	-0.140**
	(0.094)	(0.124)	(0.044)	(0.129)	(0.172)	(0.067)
Fixed effects	Exporting country-MPOE-time & product-time			Exporting country-MPOE-time & product-time		
N	537,100	537,100	537,100	257,049	257,049	257,049
R^2	0.100	0.101	0.076	0.147	0.147	0.107

Note: Standard errors are clustered at the exporter-time level and importer-time level. *** p<0.01, ** p<0.05, * p<0.1. This table shows the regression results of the price equation (Equation 9), the quantity equation (Equation 10), and the sum of the two, i.e., values. The baseline regressions (Columns 1–3) follow the equation specifications exactly, while Columns (4)-(6) control for pre-trends of the outcome variable. MPOE represents the main port of entry. In the baseline regression, the mean (s.d.) of changes in log value, quantity, and prices is -0.076(1.822), -0.117(2.032), and 0.041(1.342), respectively, and the mean (s.d.) of the changes in importer mobility and exporter mobility is -0.250 (0.264) and -0.135 (0.182), respectively.

Mobility shocks may have affected trade flows differently depending on their flow-specific seasonal patterns and pre-trends. In Table 1, Columns (4)-(6), we control for the corresponding value during the 2018-2019 period. Specifically, we add the 24-month lags of the respective dependent variable to the right-hand side of the equation. Results remain similar to the baseline both in terms of magnitudes and significance, suggesting the absence of confounding pre-trends.[34]

While the coefficient estimates of the importer and exporter mobility effects are consistent with the model prediction, one concern about the importer mobility effect is that the importer city might not be where the relevant demand is located. In Appendix Section B.1.1 we

[32]The coefficient of the import mobility in the quantity equation is γ_Z, the empirical elasticity of the demand shifter with respect to local human mobility.

[33]In Appendix Table A6, we show the summary of statistics of the variables used in this section.

[34]Note that the number of observations is not the same in Columns (1)–(3) and Columns (4)–(6) since not all product-specific bilateral flows are observed in both the current period and the pre-pandemic period. We confirm that when we estimate Columns (1)–(3) without pre-trend controls and with the same sample of observations, we get very similar results to the baseline.

construct several measures of importer mobility by focusing not only on the importer city but also regions nearby and find that city-level mobility changes are highly correlated with regional mobility changes. This is consistent with the fact that the Covid outbreaks were likely to be spatially correlated. Moreover, as we make the definition of the importer location broader, the relationship becomes weaker.

Robustness We conduct different robustness checks. The first is regarding fixed effects. In the baseline results, we control for the exporter country-MPOE-time fixed effects and product-time fixed effects since we think these fixed effects capture the terms predicted by the model most effectively. In Appendix Table B1, we replicate the baseline regression by controlling for different types of fixed effects. Second, we take a more conservative approach by clustering standard errors at higher levels of aggregation and allowing for auto-correlation, as shown in Appendix Table B2. Third, we allow for dynamic effects by including lags of both importer and exporter mobility changes. We show the pooled effects in Appendix Section B4. Finally, we restrict the sample to exporter-importer-products trade flows observed in all the 20 months between March 2020 and October 2021 plus the base period, February 2020, to confirm we observe the effect when we use a strict trade participation definition. Results are in Appendix Table B3). Our results are robust to all these alternative specifications and sample restrictions.

Elasticity of Substitution Across Exporters We can compute the elasticity of substitution across exporter cities using the estimated coefficients by taking the ratio of the quantity to price estimates of the export mobility shock, i.e., $-\hat{\beta}_I^q/\hat{\beta}_I^p = \hat{\eta}$. This parameter can help characterize supply resilience in the presence of local disruptive shocks.

Using the baseline estimates in Table 1, we get an elasticity of substitution of $\hat{\eta} = 3.4$ ($-\frac{0.352}{-0.103}$), which is in line with the assumption on the imperfect substitutability across exporters. In Table 2, we collect this and the other elasticity estimate to be discussed in this section.

This estimated elasticity of substitution differs conceptually from other estimates in the literature in two ways. First, we use monthly variations (i.e., a short-run measure) compared to annual variations (i.e., a long-run measure). As discussed in Anderson and Yotov (2020), our elasticity should be lower than standard values that employ longer horizons given that short-term adjustments have to deal with fixed factors of production and capacities. Second, our exporter locations (and thus varieties) are identified at the sub-national level in contrast to the estimations at the country level. It is reasonable to assume that it is easier to substitute across sub-national locations than across countries. All in all, our estimate is within the range

obtained in papers estimating this parameter at the product level.[35]

4.2 Heterogeneity

Heterogeneity by Type of Good We then estimate Equations (9) and (10) allowing for goods heterogeneity depending on the type of use. We use the Broad Economic Categories (BEC) classification to classify products into consumer, intermediate, and capital goods, and estimate the baseline specification allowing for different effects depending on the type. Intuitively, in terms of the impact of importer mobility, the relative magnitude of the income effect, domestic substitution effect, and preference change effects might be different for these three types of goods. In terms of the impact of exporter mobility, given different elasticity of substitution across varieties, the effects can also be different.

Results are shown in Appendix B.1.6. We find that importer mobility shocks affected the three types of goods similarly. Importantly, the theoretical prediction of not having an impact on import prices holds for all of them. Again, this suggests that Colombian demand is small on average from the suppliers' perspective. However, the impact of exporter mobility differs across types of goods. The coefficient estimate on intermediate goods is very similar both in signs and in magnitude to the baseline specification.[36] This is not the case for consumer goods, where we only observe an impact on prices but not quantities. One possibility is that the potential heterogeneity in the elasticity of substitution for consumer goods may be attenuating this coefficient estimate. Finally, exporter mobility only affected capital goods imports through quantities and not prices, potentially reflecting a higher degree of price stickiness in this type of good.

We also explore whether mobility shocks affected the demand and supply of medical products differently given the nature of the shock. We identified Covid-related medical goods based on a list of products put together by the World Customs Organization and World Health Organization. Since the importer mobility changes directly reflect the severity of the Covid outbreak on the demand side, a reduction in mobility may be associated with increased demand for Covid-related medical products, Our estimation results are consistent with this hypothesis.

Similar to the main results, we use the estimated coefficients for the price and quantity equations to calculate the elasticity of substitution across exporters by type of goods. Table 2 summarizes the results. The elasticity of substitution for consumer goods is lower than for intermediate goods. In addition, medical products were more easily substituted, potentially

[35]For example, see Soderbery (2015), who finds that depending on the estimating method used, the median elasticity of substitution across eight-digit product codes is between 2 and 4.

[36]Intermediate goods account for about 60% of the sample.

capturing that (a) differentiation across suppliers was less relevant given the urgency of the pandemic and (b) that medical goods are more homogeneous in the baseline.

Table 2: Elasticity of Substitution Estimates

	$\hat{\eta}$
Baseline	3.4
Consumer Goods	0.8
Intermediate Goods	3.4
Medical Goods	5.2

Note: Elasticities computed as $-\hat{\beta}_I^q/\hat{\beta}_I^p = \hat{\eta}$ using results in Table 1 (baseline), Table B5 (consumer, intermediate and medical goods), and Table B7 (high and low number of suppliers).

In Appendix Section B.2, we estimate Equation (9) and (10) using a more granular definition of products to study the consistency and distribution of elasticity of substitution estimates. To do so, we interact the mobility shocks with two-digit HS code indicators and compute 96 elasticities of substitutions, 26 of which are significant. The average elasticity for the sample of significant estimates is 2, with a range between 0.7 and 4.2.

Heterogeneity by Number of Suppliers We additionally investigate whether the number of exporter cities serving a specific importer city and product before the pandemic played a role in the severity of the disruption. The rationale is that importer-products with more suppliers could have found it easier to substitute away from affected foreign exporters.

We estimate two different specifications. First, we estimate Equations (9) and (10), allowing the estimated coefficient to be heterogeneous depending on whether the number of exporters in 2018-2019 serving each importer-product was above the in-sample median.[37] Second, we interact changes in mobility at the exporter and importer locations with the log of the number of suppliers.

Results are shown in Appendix B.2.1. We find that importer-products with a high number of suppliers did not experience a differential decline in the total value of trade when exporters were disrupted. This is the result of two countervailing forces: those with more suppliers had a larger decline in quantity and saw a lower increase in prices.

We parametrize the elasticity of substitution using estimates from the specification with the continuous measure. Note that we can write η as a function of the number of suppliers as follows:

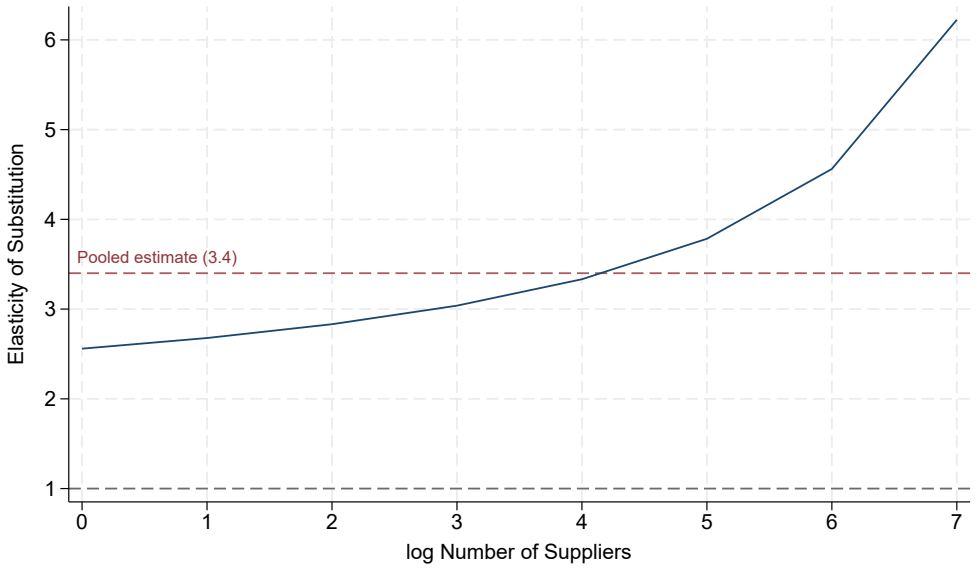
[37]The median was 63 suppliers per importer city-product.

$$\hat{\eta}(NS) = \frac{\hat{\beta}_I^q + \hat{\beta}_{I,NS}^q \times \log NS}{\hat{\beta}_I^p + \hat{\beta}_{I,NS}^p \times \log NS}, \tag{11}$$

where the subscript NS identifies the coefficients of the mobility shocks interacted with the log number of suppliers, and the variable NS identifies the number of suppliers.[38]

In Figure 5, we graph $\hat{\eta}(NS)$ as a function of the log number of suppliers using estimates from Appendix Table B7. The graph shows that the relationship between the elasticity of substitution and the pre-pandemic number of suppliers is positive and convex, i.e. a larger set of pre-shock suppliers seems to have made sourcing products easier during disruptions.[39]

Figure 5: Elasticity of Substitution across Exporter Cities and Number of Suppliers



Note: Each data point is an estimate of the elasticity of substitution computed as in Equation 11 using estimates from Table B7 Panel B. The dashed line uses the baseline estimates from Table 1.

Other Heterogeneous Effects We explore other potential heterogeneous effects using other product characteristics studied by the trade and macro literature. Specifically, we use measures of upstreamness from Antras et al. (2012), price stickiness from Nakamura and Steinsson (2008), inventory intensity from Fajgelbaum et al. (2020), and product differentiation from Rauch (1999).

Results are shown in Appendix B.2.2. We find that the impact of the change in importer

[38] The implicit assumption is that the set of available suppliers could not be updated in the short run.

[39] We can do a similar exercise using the discrete measure of high vs low number of suppliers. The elasticity of substitution for those below the median number of suppliers is 2.7 ($-\frac{0.430}{-0.161}$) and for those above is 5 ($-\frac{0.430-139}{-0.161+103}$).

mobility on quantity is smaller for goods that are more upstream. This is consistent with this type of goods being easier to substitute if they are more homogeneous.

We also find a smaller price adjustment for goods with higher price stickiness, and a larger impact of importer mobility on quantity for differentiated goods or goods with a higher inventory-to-sales ratio. In sum, we find that the heterogeneous effects by product characteristics are in line with predictions from general trade theories.

4.3 Additional Results: Congestion, Interaction, and Exporter-Importer Links

Congestion In our theoretical framework, we allow for production congestion in the short run due to decreasing returns to scale when there is a short-run fixed production factor such as capital. However, empirically, we do not have data on the total quantity produced by the exporters (Q). Thus, we construct two empirical measures to proxy for the potential congestion forces by using pre-existing cross-country trade flows and country-level mobility changes. We find that (1) adding these congestion controls does not affect our coefficient estimates of the export and importer mobility changes, and (2) demand-side congestion variable has a negative impact on the quantity and total value, indicating that when all other potential importers experience a negative Covid shock, the world demand declines, which eases the congestion in production (Appendix Table B9).

Interaction Between Importer and Exporter Mobility Exporter and importer mobility shocks may have had a stronger impact if both happened at the same time. We find that the interaction between the two mobility shocks is statistically significant for intermediate goods, negative for quantity, and positive for prices (Appendix Table B10). This suggests that shocks on the demand side and on the supply side intensified each other's effect on trade flows.

Exporter-Importer Links In Appendix Table B11, we explore the impact of exporter and importer mobility changes on the probability of observing trade at the exporter-importer-product level relative to the baseline period. Overall, we find a statistically significant but economically small effect. This is consistent with the fact that overall the adjustments in the number of exporter-importer-product flows during the pandemic were relatively small, with an average change in trade probability of -1.2% (Appendix Figure B4).

In sum, we presented a battery of results that point towards a robust effect of local exporter and importer trade disruptions on international trade flows, both for quantities

and prices. Specifically, export mobility shocks increased import prices and decreased import quantities, and import mobility shocks declined import quantities, consistent with our theoretical framework.

5 Trade Disruptions at the Sea Ports

In the last section, we studied the impact of importer-city mobility and exporter-city mobility on Colombian imports, including total value, quantity, and prices. In those estimations, we took into account the disruptions in the transportation process by controlling for the exporter-country-importer-port-time fixed effect. In this section, we focus on maritime shipping and investigate the impact of seaport disruptions on freight costs. Trade disruptions at the seaports include direct labor mobility changes at the port cities and cumulative effects of the pandemic-induced congestion in the transportation network. We focus on the exporter country and briefly discuss the role of intermediate countries.

5.1 Empirical Specification and Identification

First, we investigate the relationship between the mobility change at seaports and port performance in the exporter country using the following equation:

$$\hat{Y}_{cym} = \alpha_0 \hat{x}^{\text{Ports}}_{cym} + \delta_m + \delta_y + \delta_c + \epsilon_{cym}, \tag{12}$$

where $\hat{Y}_{cym}$ can be the change in the log number of hours each container ship spends in ports or the change in log the number of port calls made by container ships in exporter country c, year t, and calendar month m. We control for calendar month fixed effects (δ_m) to take into account seasonality, year fixed effects (δ_y) to allow for different levels in 2020 and 2021, and exporter country fixed effects (δ_c) to allow different countries to have different overall changes.

For exporter country c, we measure the average change in mobility in ports as the average mobility change in cities where the ports are located in:

$$\hat{x}^{\text{Ports}}_{cym} = \sum_{p(c)} \frac{\text{TEU}_{p(c)2020}}{\sum_{p'(c)} \text{TEU}_{p'(c)2020}} \hat{x}_{p(c)ym}, \tag{13}$$

where $\hat{x}_{p(c)ym}$ is the change in log mobility in the city where port p in country c is located in, year y, and month c, compared to February 2020, and $\text{TEU}_{p(c)2020}$ is the average monthly twenty-foot-equivalent units (hereafter, TEU) in port p in February 2020. This is calculated using all the container ships that arrived at port p in 2019, and the twenty-foot-equivalent

unit is a measure of the ship capacity. Intuitively, higher weights are assigned to ports that process ships with larger capacities. We aggregate across ports within an exporting country since in the Colombian trade data, we don't observe the exact city from where the exports are shipped.

Similarly, we compute the average change in the number of port calls made by container ships and the number of hours each ship spends in port (i.e., $\hat{Y}_{cym}$) using the same TEU weights and replacing $\hat{x}_{p(i)ym}$ with the $\Delta \log(\text{Call}_{p(i)ym})$ and $\Delta \log(\text{Hour}_{p(i)ym})$, respectively. Again, the differences are taken with respect to the corresponding values in February 2020.

The parameter of interest α_0 captures the impact of port mobility changes on port performances in the exporter country. More productive ports are able to process a larger number of port calls in a shorter period of time. Our hypothesis is that labor shortage in port cities will lead to a reduction in port productivity. We expect a negative α_0 when the outcome variable is the change in the log number of hours in port, and it indicates that smaller mobility in port cities leads to longer hours in port for each ship. The effect on the change in the log number of port calls should be the opposite since labor shortage in port cities will lead to fewer port calls being processed.

The set of identification assumptions is very similar to the ones in Section 3.2. The first identification assumption is that conditional on the fixed effects, there are no other variables that are driving both the changes in mobility and the changes in port performance. Second, we think that port performance is unlikely to cause changes in port-city mobility since the spread of the virus is more likely through passenger traffic rather than cargo traffic, and the bulk of the passenger traffic is via air and via land, instead of via sea. Third, we need the mobility change to measure the labor supply shock in ports accurately. In terms of port productivity, we assume that port workers are subject to the same shocks as production workers in other industries in the same city.

Our second set of analyses is to investigate the impact of the port mobility declines on freight costs using product-country level data. We keep the trade flows by sea as the method of transportation and also drop "fuel and lubricants" since they are not likely to be transported by containerized ships.[40]

We measure the cost of shipping using the Colombian customs data in two ways: freight costs per unit and freight costs per kilogram. We calculate the change in log freight cost using the February 2020 value as the baseline. The regression is as follows:

$$\hat{T}_{kcym} = \beta_0 \hat{x}_{cym}^{\text{Ports}} + \delta_m + \delta_y + \delta_c + \delta_k + \epsilon_{kcym}, \tag{14}$$

[40]We use the mapping between HS codes and Broad Economic Categories (BEC) codes from UN (2003) and drop goods that have a BEC code of 31, 32, and 322. The import value by sea in Colombia in 2019 was 68% of the total import value.

where $\hat{T}_{kcym}$ is the change in freight cost in product k, exported by country c, and in year y, and calendar month m. We control for month fixed effects to take into account seasonality, year fixed effects to allow for different levels in 2020 and 2021, product fixed effects, and origin country fixed effects.[41] The parameter β_0 being negative indicates that a decline in port mobility increases the cost of shipping through the port. The identification assumptions of β_0 are similar to the ones discussed earlier. In sum, we need the local labor supply shocks to be good measures of port labor supply shocks, and the freight costs should not determine in turn the disease transmission and corresponding mobility changes.

In our analysis, we will also use the pre-Covid period as a placebo test and to rule out confouding pretrends. Specifically, we use the outcome variables where the changes are calculated using the months starting from March 2018 until October 2019, compared to February 2020, instead of using March 2020 to October 2021.

5.2 Regression Results of Port Mobility Shocks

Table 3 presents the regression results for the country-level regression on port performance. Panel A presents the main results where the port performance measures are the changes in the post-Covid period (March 2020 to October 2021) compared to February 2020, and Panel B presents placebo results where the port performance measures are changed in the pre-Covid period (March 2018 to October 2019) compared to February 2018.

Panel A Column (1) regresses the change in the log number of hours each ship spends in port on the change in human mobility, following Equation 13. The coefficient estimate for the change in log mobility is -0.129, indicating that a one-percentage-point larger decline in mobility resulted in a 0.13-percentage-point increase in the number of hours in port. Evaluated at the average change in mobility (-0.16), this is a 2.1 percent increase in the number of hours in port. This result suggests that labor shortages lower port productivity and generate delays.

Importantly, the fixed effect for the year 2021 has a positive coefficient of 0.169, indicating that the average number of hours in port in 2021 is 17% higher in 2021 compared to 2020. Given that the overall mobility improved from 2020 to 2021, this positive coefficient may reflect the accumulated effects of supply chain disruptions. For example, suppose that the pandemic shifts the global trade pattern and that some regions become more important exporters. Then ports need to adjust to the changes in the ship movements under the new trade pattern. These changes can induce delays in processing time at the port. In addition,

[41] We present details of variation in port performance measures and freight costs in Appendix Section B.3.1. In both sets of measures, we find that there is a substantial shift of the distribution for 2020 and 2021. Thus, in the empirical specification, we allow for the 2021 and 2020 levels to be different.

Table 3: The Impact of Port Mobility in the Exporter Country on Port Performance Measures

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: 2020 and 2021	Δ log hours		Δ log number of calls		Δ log hours	
Δ log mobility, exporter country ports	-0.129**	-0.129**	0.108**	0.108**		
	(0.053)	(0.053)	(0.049)	(0.049)		
Δ log number of calls					-0.268***	-0.268***
					(0.090)	(0.090)
I (Year=2021)	0.169***		-0.021		0.149***	
	(0.021)		(0.020)		(0.018)	
Time trend		0.014***		-0.002		0.012***
		(0.002)		(0.002)		(0.002)
Constant	-0.042**	-0.106***	0.084***	0.092***	0.003	-0.052***
	(0.016)	(0.023)	(0.011)	(0.017)	(0.010)	(0.016)
N	492	492	492	492	492	492
R^2	0.654	0.654	0.727	0.727	0.661	0.661
Panel B (Placebo)	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: 2018 and 2019	Δ log hours		Δ log number of calls		Δ log hours	
Δ log mobility, exporter country ports	0.018	0.018	-0.022	-0.022		
	(0.020)	(0.020)	(0.023)	(0.023)		
Δ log number of calls					-0.072	-0.072
					(0.087)	(0.087)
I (Year=2019)	0.025**		0.005		0.028***	
	(0.009)		(0.009)		(0.009)	
Time trend		0.002**		0.000		0.002***
		(0.001)		(0.001)		(0.001)
Constant	0.014**	0.005	-0.157***	-0.159***	-0.001	-0.011
	(0.006)	(0.009)	(0.007)	(0.010)	(0.016)	(0.018)
N	492	492	492	492	492	492
R^2	0.749	0.749	0.883	0.883	0.749	0.749

Note: Standard errors are clustered at the exporter country level. *** p<0.01, ** p<0.05, * p<0.1. All columns control for exporter country fixed effects and calendar months fixed effects. In Panel A, the dependent variables are the changes starting from March 2020 until October 2021, compared to February 2020. The mobility changes are the changes in months starting from March 2020 until October 2021, compared to the pre-Covid period. The mean (s.d.) of mobility changes is -0.16 (0.20), the mean (s.d.) of the change in the log number of hours in port is 0.10 (0.13), and the mean (s.d.) of the change in log number of calls is -0.09 (0.11). In Panel B, the dependent variables are the changes in months starting from March 2018 until October 2019, compared to February 2020. The mobility changes are the same in Panel A. The mean (s.d.) of the change in the log number of hours in port is 0.02 (0.11), and the mean (s.d.) of the change in the log number of calls is -0.15 (0.14).

the pandemic has interrupted other transportation sectors, such as the trucking industry and railroads. If it is hard to load the goods from container ships to trucks and ship them domestically, ships have to stay longer at the port as well. Such disruptions have been extensively discussed in the case of the Los Angeles Port.[42]

Column (2) uses an alternative measure to capture the accumulated pandemic effect, by controlling for a time trend instead of the year fixed effect. The coefficient estimate for the change in log mobility stays the same, as expected, and we see an average of 1.4% increase in the number of hours in port for each additional month.

[42]See news reports: `www.wsj.com/articles/truckers-steer-clear-of-24-hour-operations-at-southern-california-ports-11637173872`.

Column (3) has the same specification as Column (1) and uses the change in the log number of port calls made by container ships as the measure for port performance. We find that increased mobility also allows more calls to be processed. Evaluated at the mean change in mobility (-0.16), it induces a 1.7 percentage decrease in the number of hours in port. Column (4) controls for the time trend and finds similar results.

Columns (5) and (6) confirm that in ports where more calls are processed, each call also takes a shorter time. In this sense, both shorter time in port and more calls are indications of a good performance in the port, similar to the quality and quantity aspects of a good produced by a firm.

In Panel B, we use the pre-Covid changes instead of the post-Covid changes in the outcome variable. The coefficient estimates for the change in log mobility are small and statistically insignificant, indicating that the mobility changes in the post-Covid period are not associated with the port performances in the pre-Covid period. In addition, there is no statistically significant association between the two measures of port performance. This suggests that in the pre-Covid period, the ports seem to be not constrained in their capacities.[43]

Table 4: The Impact of Port Mobility in the Exporter Country on Freight Costs per Unit

	(1)	(2)	(3)	(4)
Dependent variable:	Δ log freight cost per unit		Δ log freight cost per unit	
	2020 and 2021		2018 and 2019	
Δ log mobility, exporter country ports	-0.25**	-0.25**	0.04	0.02
	(0.11)	(0.11)	(0.03)	(0.04)
I (second year)	0.51***		0.02**	
	(0.08)		(0.01)	
Time trend		0.04***		0.00
		(0.01)		(0.00)
Constant	0.02	-0.17**	0.04***	0.03***
	(0.05)	(0.07)	(0.00)	(0.01)
N	245,995	245,995	261,967	261,967
R^2	0.11	0.11	0.09	0.09

Note: Standard errors are clustered at the product level and at the exporting country level. *** p<0.01, ** p<0.05, * p<0.1. All columns control for product fixed effects, exporter country fixed effects, and calendar month fixed effects. The outcome variable in Columns (1)–(2) are in 2020 and 2021, and one in Columns (3)–(4) are in 2018 and 2019. In the first four columns, the mean (s.d.) of the change in log freight cost by unit is 0.31 (1.38). In the last four columns, the mean (s.d.) of the change in log freight cost by unit is 0.05 (1.37). The mean (s.d.) of the change in log mobility is -0.14 (0.18) in the exporter country. The dummy for the second year is equal to one in 2021 in the first four columns and is equal to one in 2019 in the last four columns.

Then we proceed to investigate the impact of mobility changes on freight costs. Table 4

[43]Appendix Figure B7 shows the residual plots for results in Table 3 Panel A Columns (1) and (3) and Panel B Columns (1) and (3). Additionally, we find that the results are not driven by one particular country or period when dropping one country at a time and by dropping one period at a time (Appendix Figures B8).

shows the regression results. The outcome variable in Columns (1) and (2) is the change in log freight cost per unit in 2020 and 2021. Column (1) follows the specification in Equation (14), and the coefficient estimate for the change in log mobility in the exporter country is negative and statistically significant at the 5% level. This indicates that a one percent decrease in mobility results in a 0.25% increase in freight cost. Evaluated at the mean change in log exporter mobility (-0.14), there is a 3.8-percentage-point increase in the freight cost. Results are similar when Column (2) uses the time trend instead of year fixed effects. We don't find statistically significant effects when we run placebo regression using pre-Covid changes in Columns (3) and (4).[44]

Again, the fixed effect for the year 2021 has a large and significant coefficient, indicating that the 2021 level is 51% higher than the 2020 level (Column 1). Similarly, in the specification with a time trend (Column 2), the monthly increase in freight cost is 4%. This pricing effect can come from the increased demand in 2021 or the accumulated supply chain disruptions.[45]

Overall, we find that mobility reductions at the ports indeed have a negative impact on port performance and that the pandemic has an accumulated effect on port delays. In addition, these delays in seaports had significant impacts on the price of the transportation sector.

5.3 Intermediate Ports

The cost of shipping not only depends on the exporter country ports but also on the intermediate shipping ports. As shown in Ganapati et al. (2021) and Heiland et al. (2019), the majority of trade is indirect, making at least one stop along the way. We compute the average change in mobility, the number of port calls, and the number of hours in port for potential intermediate countries. We use the optimal country-to-country shipping routes computed in Ganapati et al. (2021) to measure the intermediate country shocks since we don't observe the actual shipping routes in the Colombian trade data. For each of the 25 major trading partners with Colombia, we consider two intermediate stops.

We present the details of measures of the shocks to intermediate ports, the estimation methods, and results in Appendix B.3.7. We find that the impacts of mobility declines

[44] Appendix Table B12 shows that the results are robust to controlling for alternative fixed effects and to using freight costs measured in weight instead of unit. Our main results drop the top and bottom 1% of freight cost, and we show that the results are robust to including all observations in Appendix Table B13.

[45] Unlike the port performance regressions, it is harder to visualize the coefficients for the product-level freight costs using a residual plot. Thus, we take the mean of price changes at the country-period level and run similar regressions as in Table 4. The residual plots are shown in Appendix Figure B9. Reassuringly, the country-level regression results are similar to the product-level results.

in the first and the second intermediate countries are even larger than the exporter ports. One interpretation is that the intermediate ports are likely to be entrepôts as discussed in Ganapati et al. (2021), and the reduction in mobility in those transportation hubs is more costly than in individual export countries.

6 The Contribution of Local Disruption Margins to Changes in Trade During the Pandemic

In previous sections, we documented the impact of local disruptions at the exporter and importer locations on the import quantity and prices, and disruptions at ports on port productivity and freight costs. In this section, we employ those results to characterize the (i) trade effect of the pandemic through different local disruption margins and (ii) the importance of these local disruptions relative to other factors during this period.

Method Based on the theoretical framework, we can decompose the total expected change in trade as follows:

$$\hat{m} = \textit{Local Disruptions} + \textit{Other Structural Determinants (OSD)}.$$

In Sections 4 and 5, we estimated the impact of disruptions at exporter, importer and port locations, plus freight cost trends associated with the international transportation sector. Therefore, we can write the average predicted change in trade through quantities and prices due to *Local Disruptions* at a given month as follows:

$$\hat{q}^D = \hat{\beta}_I^q \bar{x}_I + \hat{\beta}_J^q \bar{x}_J - \hat{\eta}(1-\bar{\iota})\hat{T}^D, \tag{15}$$

$$\hat{p}^D = \hat{\beta}_I^p \bar{x}_I + \hat{\beta}_J^p \bar{x}_J + (1-\bar{\iota})\hat{T}^D, \tag{16}$$

where $\bar{x}_I$ and $\bar{x}_J$ are the average change in mobility at exporter and importer locations, and $\hat{T}^D$ is the predicted change in transport costs due to disruptions at ports and freight cost trends. $(1-\bar{\iota})$ is the observed share of freight costs in the import price at the base period. This formulation allows us to decompose the direct impact of local disruptions on import quantities and prices in exporter ($\hat{\beta}_I^{q,p}\bar{x}_I$), importer ($\hat{\beta}_J^{q,p}\bar{x}_J$) and transportation ($-\hat{\eta}(1-\bar{\iota})\hat{T}^D$, $(1-\bar{\iota})\hat{T}^D$) margins.

We use the baseline estimates $\{\hat{\beta}_I^q, \hat{\beta}_J^q, \hat{\beta}_I^p, \hat{\beta}_J^p\}$ from Table 1 and the implied elasticity of substitution $\hat{\eta}$, along with month-specific averages for $\bar{x}_I$ and $\bar{x}_J$ to compute these margins. For $(1-\bar{\iota})$, we use 0.07, the average share of transportation cost in import price in 2018 and

2019.

To compute $\hat{T}^D$, the expected change in freight costs from port disruptions and transportation sector trends, we use estimates $\{\hat{\beta}_0, \hat{\beta}^{trend}\}$ from Table 3. Specifically:

$$\hat{T}^D = \hat{\beta}_0 \bar{x}_{Port} + \hat{\beta}^{trend} \times t,$$

where $\bar{x}^T_{Port}$ is the average change in mobility at ports associated with each exporting country.

We are also interested in computing *Other Structural Determinants* (OSD), i.e. other factors affecting trade not directly associated with the impact of local disruptions. Note that directly employing the fixed effects estimated in equations 9 and 10 would not be correct, as they contain disruptions in the transportation sector that systematically vary at the country-MPOE-time level. Therefore, we compute the residual fixed effects, $\hat{\delta}^{Tr,q}_R$ and $\hat{\delta}^{Tr,p}_R$, after subtracting the direct impact of disruptions in ports and freight cost trends from the estimated $\hat{\delta}^{Tr,q}$ and $\hat{\delta}^{Tr,p}$:

$$\hat{\delta}^{Tr,q}_R = \hat{\delta}^{Tr,q} - [-\hat{\eta}(1-\bar{\iota})\hat{T}^D],$$
$$\hat{\delta}^{Tr,p}_R = \hat{\delta}^{Tr,p} - [(1-\bar{\iota})\hat{T}^D].$$

Therefore, we compute the *Other Structural Determinants* as:

$$\hat{OSD}^q = \hat{\delta}^{P,q} + \hat{\delta}^{Tr,q}_R, \tag{17}$$

$$\hat{OSD}^p = \hat{\delta}^{P,p} + \hat{\delta}^{Tr,p}_R. \tag{18}$$

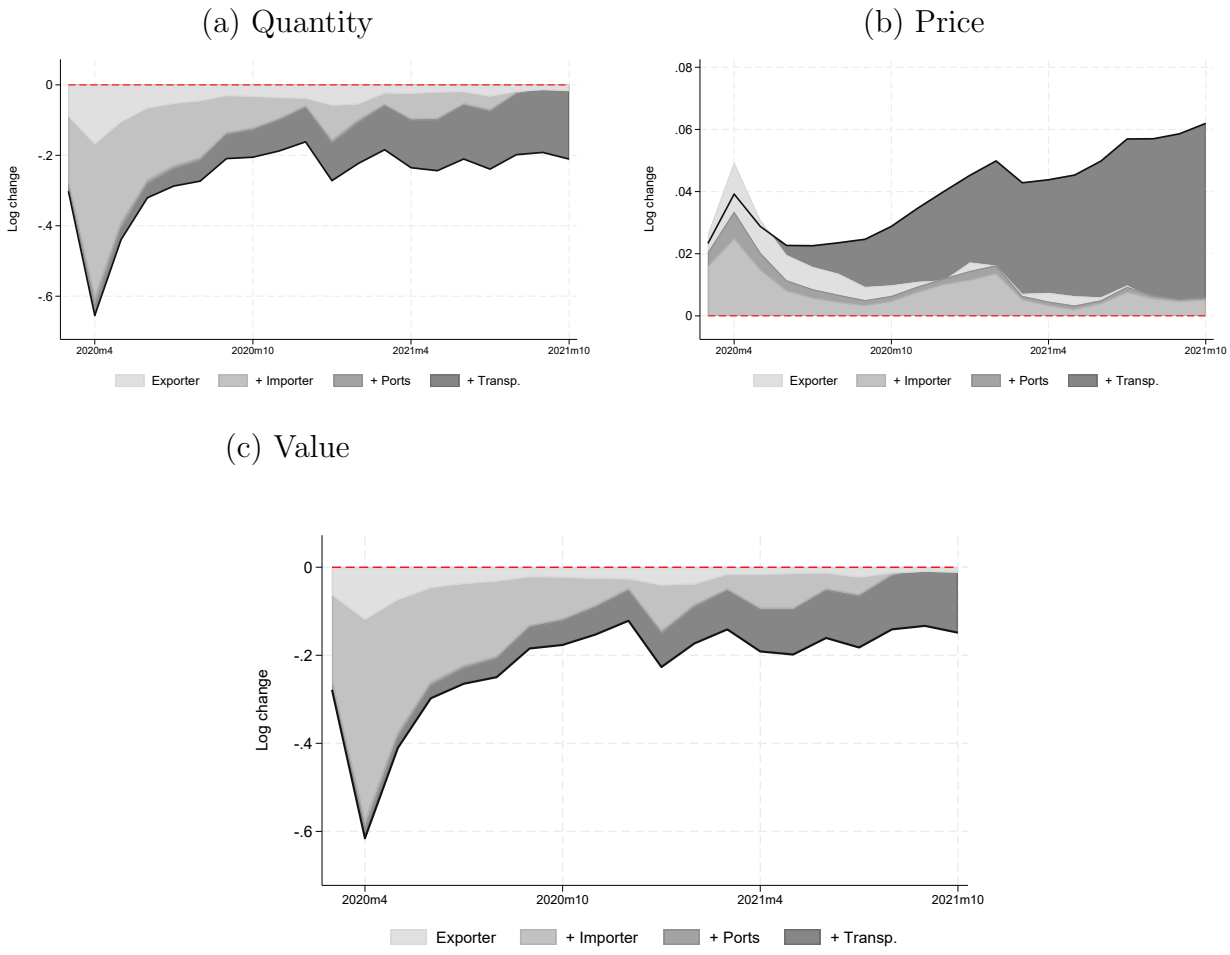
Using this strategy, we can characterize the relative importance of the different disruption margins in driving the direct impact of local disruptions on trade, and how such direct impact relates to other factors affecting trade not directly associated with those disruptions.[46]

Local Disruption Margins By using the average mobility changes in each month, we can decompose the direct impact of local disruptions over the 20 months we study. Results are shown in Figure 6. We find that for quantity, importer disruptions explained 67%, exporter shocks 26%, and port shocks 7% at the onset of the pandemic (April 2020). The transportation sector increased its importance over time as expected. For import prices, the

[46] In Appendix Section B.4.1, we show that the country-MPOE-time fixed effects are highly correlated with the log per-unit freight costs. To do so, we average the log per-unit freight costs in changes to the country-MPOE-time level, the same level as the fixed effects, and plot these averages against the estimated fixed costs. We confirm that the average freight costs are negatively correlated with the fixed effects estimated using the quantity equation ($\delta^{Tr,q}$) and positively correlated with the fixed effects estimated using the price equation ($\delta^{Tr,p}$), indicating that the fixed effects capture the disruptions in the transportation sector well. We are only able to provide direct evidence on maritime shipping due to data limitations.

direct price effect in April 2020 can be explained entirely by exporter disruptions. However, both port disruptions and the building-up in freight costs, likely due to congestion in the transportation network, also contributed significantly. Figure (c) puts together the quantity and price margins showing a similar decomposition over time as in the case of quantity, shifted up by the increase in prices.

Figure 6: Decomposition of Predicted Changes in Import Quantities, Prices and Values into Exporter, Importer, Port and Transportation Disruption Margins



Note: Each data point is computed using estimates in Table 1 (exporter and importer disruptions), Table 4 (port disruptions and transportation freight trends), and month-specific in-sample average changes in exporter, importer and port mobility.

Local Disruptions vs Other Structural Determinants In Figure 7, graphs (a) and (b) show the predicted changes in trade outcomes from local disruptions (solid black lines) and the total predicted changes (dashed blue lines) when we combine local shocks and other

structural determinants. We find that the difference between the two lines has different patterns in the early months of the pandemic vs. the later months. In the early months, for both the quantity and the price, the total predicted changes were more muted than the predicted changes from local disruptions. Thus, other structural factors had an offsetting effect for both quantity and price. In later months, however, the price effects were even larger in total predicted changes, suggesting that other structural factors had a differential impact on quantity and price.

Given these patterns, we can characterize the direct impact of local disruptions and OSDs as consisting of net supply and demand shocks. To do so, we graph the predicted changes in trade from local disruptions and OSDs separately in a quantity-price graph, in which the origin is the base period (February 2020). Therefore, each point can be read as the relative change in the equilibrium price and quantity in a specific month relative to the base period.

In Figure 7 (c), we include three months equally spaced from each other: May 2020, November 2020, and May 2021. Local disruptions increased import prices and decreased import quantities. Given this, the direct impact of local disruptions could be characterized as a net negative export supply shock from a small economy's perspective like Colombia.

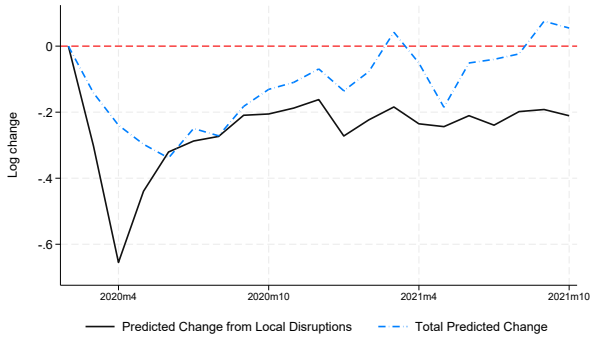
What about the other structural factors? In 2020, the residual structural factors were a net positive supply shock. This was anticipated in Figure 7 (a) and (b): given the seemingly offsetting price mechanism in place, the residual change in quantities was positive. In 2021, the residual structural factors changed to a sizable net positive demand shock. This is in line with the statistical evidence showing a trade boom as the pandemic progressed.[47]

Both local disruptions and other structural factors point to an average positive excess demand, potentially imposing upward pressure on domestic prices. In the next section, we provide suggestive evidence that local disruptions to foreign exporters had a role in the rise of domestic inflation in Colombia.

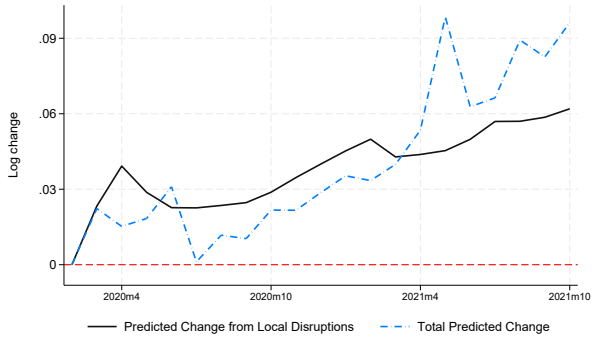
[47]The results in this section can be interpreted as the average change across exporter-importer-importer links, but they are not necessarily informative about the economy-wide impact of local disruptions and other factors. Even though we abstract from providing structure to compute aggregate effects, we provide graphs with exporter-importer-product weights constructed by employing 2019 Colombian imports in Appendix Figure B11. Conclusions remain.

Figure 7: Average Predicted Changes in Import Quantities and Prices in Total, from Local Disruptions and Due to Other Structural Determinants.

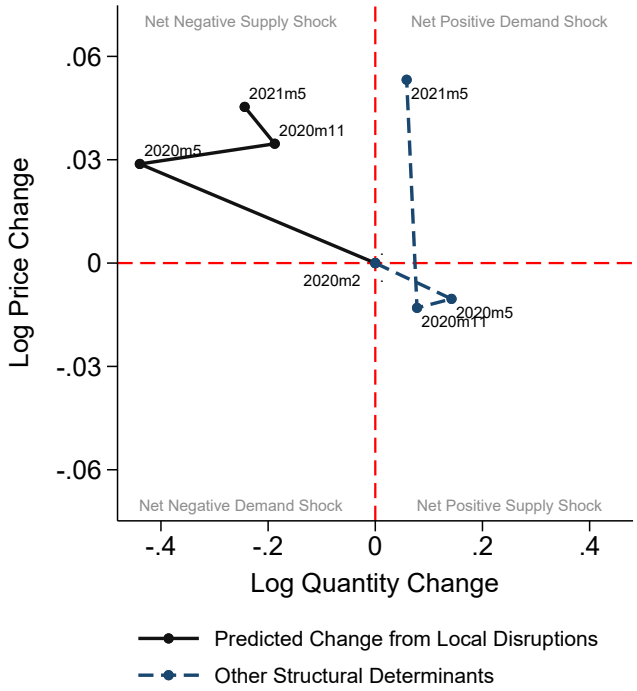
(a) Quantity



(b) Price



(c) Quantity x Price Changes



Note: Each data point is computed using estimates in Table 1 (exporter and importer disruptions), Table 4 (port disruptions and transportation freight trends), and month-specific in-sample average changes in exporter, importer and port mobility.

7 Trade Disruptions and Inflation

In this section, we explore the relationship between disruptions to foreign exporters and domestic consumer prices in Colombia. Specifically, we analyze if consumer goods for which its imported varieties were sourced from cities that experienced a local disruption had larger price hikes. To do so, we leverage monthly goods-specific national indices that form the building blocks of the Colombian Consumer Price Index (CPI).[48]

Consumer Price Index The aggregate Colombian CPI is constructed by aggregating indices defined at five-digit goods categories based on the Classification of Individual Consumption According to Purpose (COICOP).[49] This classification has 188 categories called "sub-classes" covering both goods and services. We are interested in the direct relationship between CPI's sub-classes and imports, and thus we generate a concordance between each consumer product at a six-digit HS level (k) and each five-digit COICOP sub-class (κ).[50,51] We find that, on average, 56 sub-classes observe direct positive imports each month.[52]

Figure 8 plots the month-specific distribution of these price indices rebased to February 2020 along with the aggregate CPI (blue circles). Aggregate indices are computed by weighting the sub-class indices by expenditure shares from the national household survey (the Encuesta Nacional de Presupuestos de los Hogares, i.e., ENPH) of 2016-2017. We find that consumer prices did not increase substantially in 2020 but started increasing in 2021. In October 2021, the median consumer price index was 7% higher than in February 2020, and the aggregate consumer price index was 5% higher.

[48] We do not have access to city-level goods-specific indices.

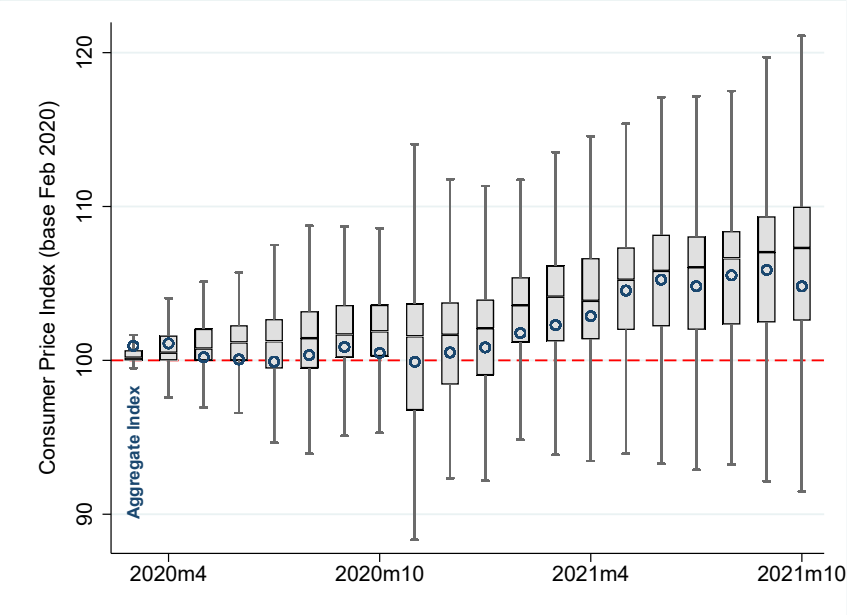
[49] The COICOP is a classification of goods and services designed by the UN to analyze the consumption pattern of households and non-profit institutions.

[50] We use the available UN concordances between the two and manually concord the few that did not have a direct correspondence. We only use the HS codes identified as consumer products by the BEC classification. The average (median) number of six-digit HS codes within a five-digit CPI code is 8 (4).

[51] We abstract from the indirect relation between intermediates imports and consumer goods.

[52] This number is fairly constant over time, varying from 52 to 59 sub-classes in the sample period (March 2020 to October 2021). These goods show a similar time series pattern to those without positive imports, including services, as shown in Appendix Figure A11.

Figure 8: Monthly Distribution of Consumer Price Indices over Goods with Positive Imports



Note: The grey boxes plot the month-specific distribution of goods-specific (sub-class) consumer price indices for which we observe positive imports each month. Hollow blue circles plot the aggregate indices, where each goods index is weighted using expenditure shares from the national household survey in 2016-2017.

Import Price Changes at the Consumer Goods Level To study changes in consumer prices associated with disruptions at foreign suppliers, we need to compute import price changes at a comparable level of aggregation. Thus, we aggregate $ijkt$ import price changes to the CPI goods sub-classes (κ) and month (t) level. We employ the above-mentioned concordance between k and κ and use 2019 ijk-specific weights within each κ to calculate the κ-month specific log import price changes:

$$\hat{p}^M_{\kappa t} \equiv \sum_{ijk \in \Omega_\kappa} \theta_{ijk} \hat{p}^M_{ijkt}, \tag{19}$$

where $\theta_{ijk} \equiv \frac{m^{2019}_{ijk}}{\sum_{ijk \in \Omega_\kappa} m^{2019}_{ijk}}$, and Ω_κ is the set of ijk combinations within κ goods that is observed in 2019.[53]

Relationship between CPI Changes and Predicted Import Prices To investigate the relationship between consumer price changes and import price changes, we estimate the following regression:

[53] In Appendix Figure A12, we plot the month-specific distribution of the resulting import price changes at the goods level, converted to import price indices with base in February 2020. The time series pattern is the same as in the case of the consumer price indices, but the magnitude of the changes is larger. In October 2020, the median import price index was 11% higher than in February 2020.

$$\hat{p}^C_{\kappa t} = \mu \hat{p}^M_{\kappa t} + \delta^T_t + \zeta_{\kappa t}, \tag{20}$$

where $\hat{p}^C_{\kappa t}$ are the CPIs rebased to 2020 converted to log changes, and μ captures the pass-through from import prices on Colombian consumer prices. In the baseline analysis, we control for time fixed effects δ^T_t to focus on the variation of goods price changes within a month, but we also present an alternative specification with κ fixed effects.

Table 5: Relationship Between Predicted Import Price Changes and Consumer Price Indices

Predicted from:	(1)	(2)	(3)	(4)
	Local Export Disruptions		Other Structural Factors	
Δ log import price	0.575***	0.568**	0.011*	0.007*
	(0.168)	(0.226)	(0.006)	(0.004)
Time FE	Yes	Yes	Yes	Yes
Goods FE		Yes		Yes
N	1,126	1,126	1,126	1,126
R^2	0.104	0.670	0.100	0.667

Note: Bootstrapped standard errors (200 reps) are shown in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the changes in the log consumer price index at the 5-digit CPI classification goods level from February 2020. The log import price changes are aggregated to that level using exporter-importer-product weights based on 2019 imports. In Columns (1) and (2), the log import price changes are calculated using import prices predicted by log exporter mobility in the full model in Column (3) of Table B5, only for consumer goods (BEC classification). In Columns (3) and (4), the log import price changes are calculated using import prices predicted by the full model in the same column minus the log export mobility margin.

In Table 5, Columns (1) and (2), we use the predicted import price changes only related to disruptions to exporters ($\hat{\beta}^p_I \bar{x}_{it}$). The estimated coefficient is $\hat{\mu} = 0.575$ in Column (1), with time-fixed effects, which indicates a pass-through of about 60%. Adding goods fixed effects in Column (2) does not change the magnitude of this estimate.[54,55]

In Columns (3) and (4), we use the expected import price changes from the full model, minus the impact of export disruptions ($\hat{p}^M_{ijkt} - \hat{\beta}^p_I \bar{x}_{it}$) to capture the role of other structural factors. We find a positive, but small passthrough of other structural factors to domestic

[54] In Appendix Figure B12, we plot the relationship between the residualized consumer price changes and the predicted import prices.

[55] This result is robust to using import price changes that include shocks to the transportation sector. We do so by projecting the country-port-time fixed effect on observed transport prices and using the predicted effects to construct transport price changes that are added to the export shocks.

prices.[56]

In conclusion, results in Table 5 suggest that trade disruptions at exporters' locations propagated through the international supply chain, playing an important role in driving up domestic inflation in Colombia.

8 Conclusion

In this paper, we develop a novel method to unpack a global shock. We dissect the impact of the Covid-19 pandemic on international trade by combining information from customs records, smartphone-based human mobility, and container ship port calls. We find that local demand shocks led to a reduction in import quantity, while local supply shocks and shocks at seaports led to both an increase in price and a reduction in quantity. We find that on net, local shocks were a negative supply shock, and the residual structural factors were a positive demand shock. This positive excess import demand contributed to the rise in domestic inflation.

Our paper contributes to the understanding of trade dynamics during substantial global economy-wide shocks. The Covid-19 pandemic affected people around the world by costing lives and income, disrupting work and life arrangements, shifting economic expectations, inducing substantial policy changes, and even generating geopolitical tensions. While the full ramification of the pandemic is yet to be seen, in this paper, we provide a short-to-medium-run analysis of its impact on international trade flows. Our analysis highlights the importance of trade in generating global co-movements, and our estimation of the short-run elasticity of substitution between locations and the decomposition of the effects from different parts of the supply chain are informative for policymaking in the future.

[56]This may seem surprising given that we observed a big impact of other structural shocks on prices in the previous section. Our interpretation is that other structural shocks could have affected prices of goods across the board, and this effect is partially absorbed by the time fixed effect in our regression.

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(Not for publication)

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A Additional Data Information and Descriptives

A.1 Trade Data

A.1.1 Colombian Customs Records

Figure A1: Import Declaration Form

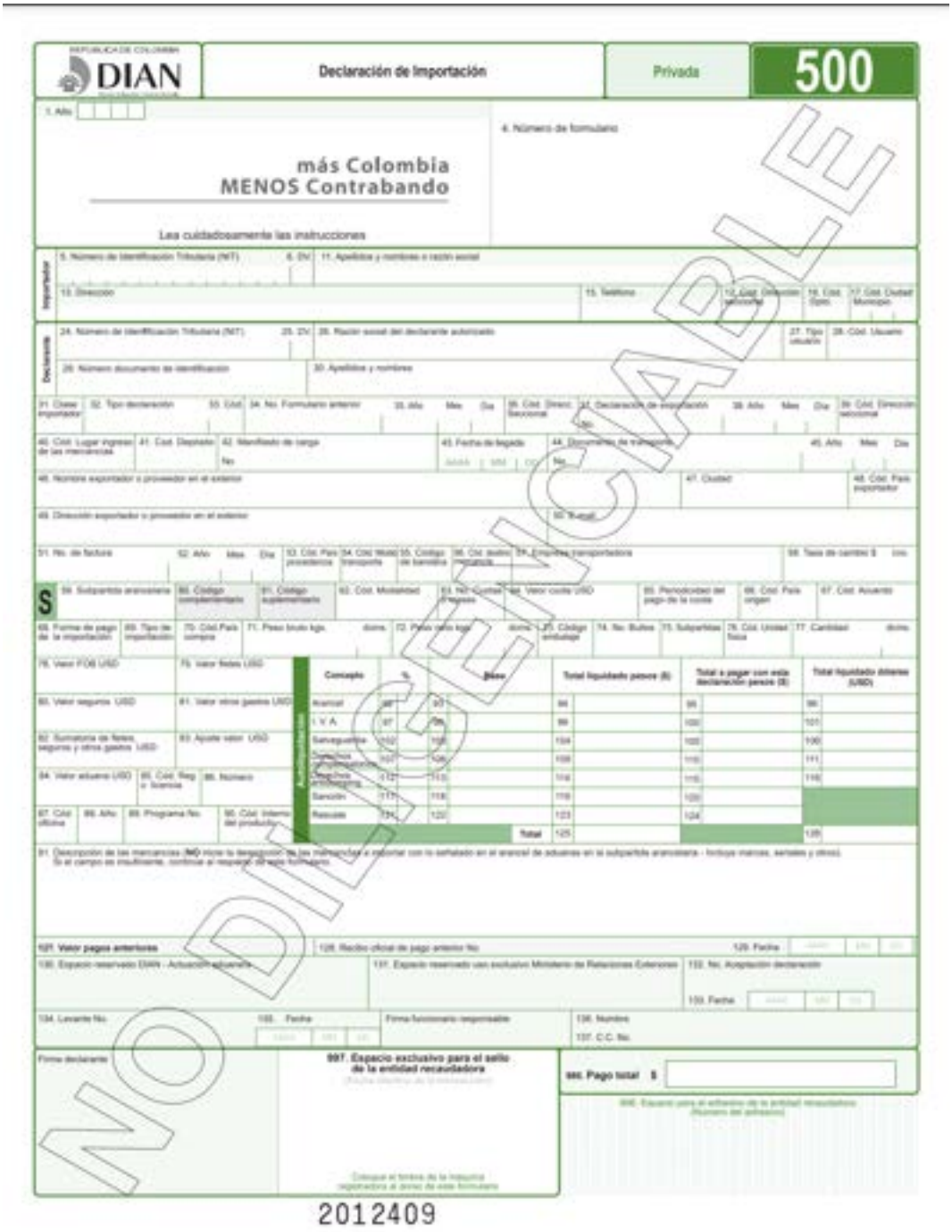


Figure A1 presents the customs declaration form required for importers by the DIAN (the Colombian Office of Taxes and National Customs by the Spanish acronym). The DIAN makes public the database generated by the fill-out of this form. This dataset contains each transaction that went through customs for each month and year.

We employ the following variables for the analysis:[57]

- Field 17 "Cod. Ciudad/Municipio" (city/municipality code) to identify the importer location within Colombia. The instruction to fill in field 17 is: "Indicate the department code and the city or municipality code of the importer's main address."
- Field 40 "Cod. Lugar ingreso de las mercancias" (place of entry of products) to identify the port through which goods entered Colombia.
- Field 47 "Ciudad" (city of the exporter) to identify the exporter location. The instruction to fill in field 17 is: "Indicate the name of the city of the exporter or supplier of the merchandise, who issues the invoice or certifies the operation that gives rise to the import transaction."
- Field 59 "Subpartida arancelaria" (tariff sub-code) to identify the products at 6 digits of the HS.
- Field 77 "Cantidad" (quantity in HS-specific units).
- Field 78 "Valor FOB USD" (FOB value in US dollars).
- Field 79 "Valor fletes USD" (Freight value in US dollars).
- Field 80 "Valor seguros USD" (Insurance value in US dollars).

CIF values are computed as the sum of fields 78, 79 and 80. We aggregate variables in fields 59, 77, 78, 80 and CIF values to the importer city (field 17), exporter city (field 47), product (field 59) and month, after cleaning field 47 as explained in Section A.1.2 below. We employ field 40 in the econometric analysis as a control.

A.1.2 Cleaning of City Names in the Customs Records

The export city name is crucial in our analysis, and we manually cleaned the name strings. The cleaning procedure is similar across countries, although the string may be messier in some countries than in others. Here, we use the cleaning procedure of the location names in the United States as an example.

[57] For more details about instructions to fill out the form see `https://www.dian.gov.co/atencionciudadano/formulariosinstructivos/Formularios/2019/Formulario_500_2018.pdf` (in Spanish, accessed in October 2023).

Step One We first clean the raw strings and extract the location information from the string. We obtain unique strings and sort them alphabetically. In total, we have 14564 strings of US locations. In Table A1, we show 14 records of the location strings. The number of records is the number of times a particular string shows up as the exporter location, and the total import value is the sum of the import value across records.

We can see that the information in the first four rows is very messy, and it is impossible to clean this type of record. Thus, this type of record is not included in our analysis.

Rows 5 through 7 are records containing "Abilene" or 'Abiline." Row 6 also contains the information of the state, which is Texas (abbreviated as TX). Since all records containing "Abilene" either have Texas as their state or have missing state information, we impute the state information in Row 5 with Texas as well. There is only one record containing 'Abiline," and there is no state information included. We search 'Abiline United States location" in Google, and Google suggests 'Abilne, City in Texas." Thus, we assume that 'Abiline" contains a typo, and we also classify it as "Abilene, Texas."

Rows 8 through 13 include all the records containing "Abingdon." In all rows except for Row 13, there is state information (Virginia, VA, or Maryland). In this case, we don't impute the state information in Row 13 since there is more than one state associated with "Abingdon" in other records.

Table A1: Location Information in Exports from the United States

ID	String	Country	Number of records	Total import value
1	612	USA	1	9011
2	7240 HAYVENHURST PLACE	USA	1	3469
3	7865267-4888	USA	1	101705
4	800 NW 31 STREET	USA	1	23133
5	ABILENE	USA	31	4463310
6	ABILENE, TX	USA	1	1165
7	ABILINE	USA	1	101896
8	ABINDGON.VA	USA	42	648594
9	ABINGDON, MARYLAND	USA	2	845
10	Abingdon, Maryland	USA	2	20212
11	ABINGDON,VA	USA	3	509480
12	ABINGDON, VA	USA	1	1670
13	ABINGDON	USA	27	223022

Step Two After the cleaning in Step One, we have a list of "places" with their corresponding State information (either one of the states in the US or a missing state). These "places" are cities, towns, Census Designated Places, and they are lower than counties. Note that within a state, there can be places with the same name in different counties.

We then merge this list with the list of "places" provided by the US Census Bureau. In the census list, each place is associated with a county and a state. For places with state information, we merge them with the census list directly and obtain their county and state information. For places with no state information, we check if this place name is unique among all counties and states in the US, and if it is unique and merges successfully, we are also able to obtain its county and state information. For all the records that don't merge successfully, we extract the list and do another round of manual cleaning using Google search.

Overall, as shown in Table A5, about 75% of imports from the US are captured by the list of locations where we are able to determine the county and the state information.

A.1.3 Trade Patterns in Detail: Prices, Quantity, and Freight Costs

The aggregate import values mask the underlying changes that took place in terms of quantities, export prices, transport costs, and import prices. In order to characterize the change in these variables, we aggregate the data to the exporter city, importer city, product, and month level to accurately define quantities and prices and document compositional changes. We decompose log import values m as follows:

$$m \equiv q + p^X + \tau, \tag{21}$$

where q is quantity, p^X is the export price in free on board (FOB) terms, and τ is the ad-valorem trade cost, including both freight and insurance cost. Log import prices are measured in cost, insurance and freight (CIF) terms, i.e., $p^M \equiv p^X + \tau$.

We calculate each variable in Equation (21) at the exporter city (i), importer city (j), product (k), and time level at the monthly frequency (t) for the 2018–2021 period. In order to characterize average changes over the pandemic, we estimate the following equation:

$$M_{ijkt} = \sum_{r=01/2020}^{10/2021} \delta^r \times \mathbb{1}\{t = r\} + \delta^{seas}_{ijkm} + \delta^{trend}_{ijk} \times t + \varepsilon_{ijkt}, \tag{22}$$

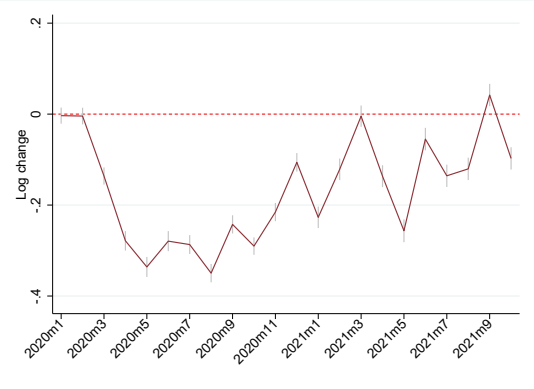
where M_{ijkt} can be imports or any of the other variables in Equation (21). We include an exporter-importer-product-calendar-month fixed effect δ^{seas}_{ijkm} to control for granular seasonality, and an exporter-importer-product-specific linear time trends δ^{trend}_{ijk}. The coefficients of interest are the δ^rs, with r ranging from January 2020 to October 2021. We interpret each of these coefficients as the average deviation from pre-pandemic trends in month r.

Figure A2 presents the results. Panel (a) shows that the profile of average changes in import values over time was similar to the aggregate: a sharp decrease at the beginning of the pandemic and a slow, non-monotonic recovery. This pattern is explained mostly by changes in the quantities imported, as seen in Panel (b). Export prices had a different dynamic (Panel c). They remained relatively unchanged during 2020 and the first quarter of 2021 but started rising in the second quarter. Ad-valorem transport costs increased steadily since the beginning of the pandemic (Panel d). In summary, quantities explain most of the changes in import values, and export prices showed relative upward rigidity up until the second quarter of 2021 but not afterwards. Transportation costs started rising early in the pandemic and kept increasing over the entire period of our study.

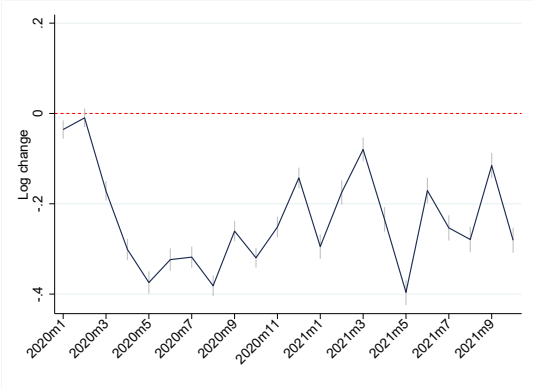
Measuring trade costs in ad-valorem terms is the standard approach in the trade literature, but we can directly measure freight and insurance unit values in our data, which helps us analyze their changes independently from import variables. Specifically, we construct freight unit costs as $p^F \equiv \frac{\text{Freight total costs}}{\text{Quantity shipped}}$, and insurance costs p^I similarly. In Figure A2 Panels (e) and (f) we show their dynamics using also Equation (22) specification. Panel (e) shows that freight unit values increased more than 10% during the June-July 2020 period—right after some developed countries started relaxing lockdown measures. However, they began a monotonic increase in October 2020 to reach an average increase of almost 75% in October 2021. Insurance unit values show a different pattern. As shown in Panel (f), they remained relatively unchanged up until the beginning of 2020, showing, if something, a downward trend. In March 2021, they started increasing, reaching an increase of about 12% in October

Figure A2: Average Changes in Trade Outcomes Relative to Pre-Pandemic Trends

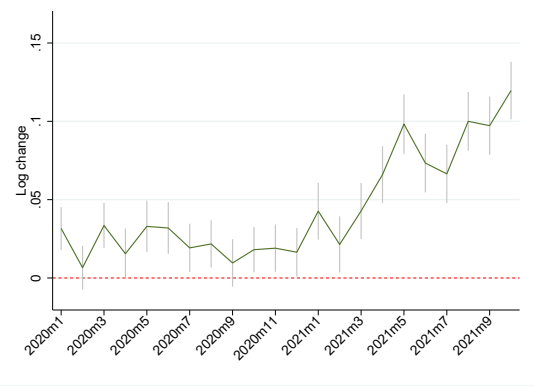
(a) Import values (M)



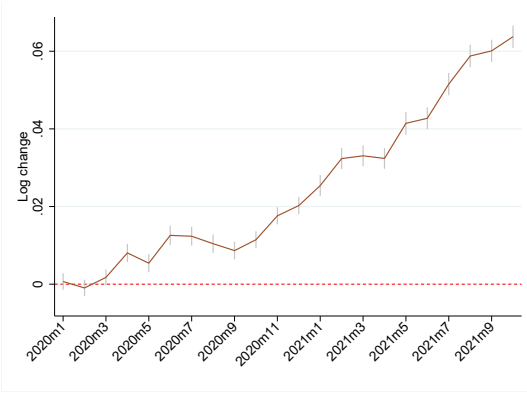
(b) Import quantities (q)



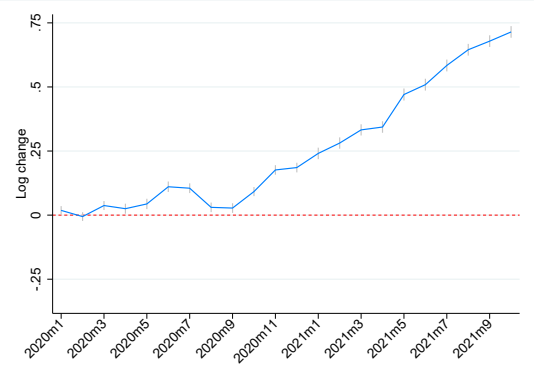
(c) Export prices (p^X)



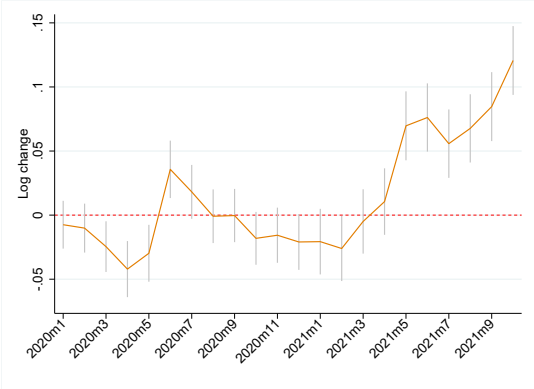
(d) Ad-valorem transportation costs (τ)



(e) Freight unit costs (p^F)



(f) Insurance unit costs (p^I)



Note: Data is from the Colombian customs office. Each point is the estimated coefficient of Equation (22), with 95% confidence intervals represented by the vertical lines. Standard errors clustered at the exporter-importer-product level. Log changes are relative to exporter-importer-product pre-pandemic trends and seasonality.

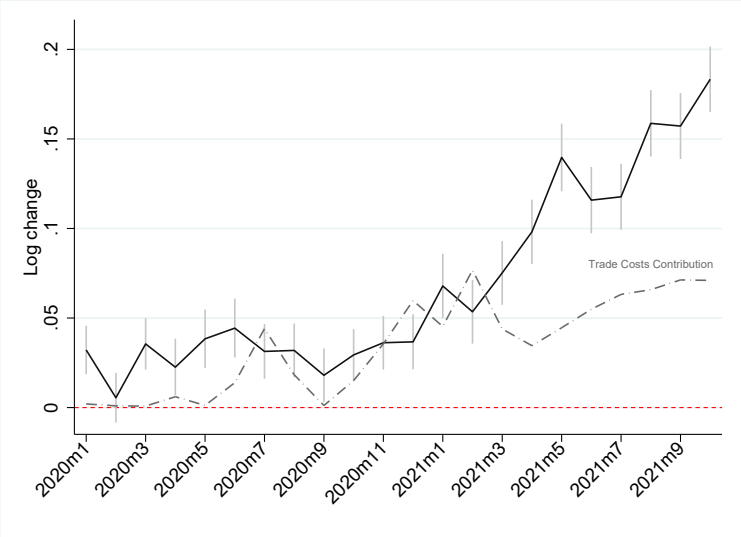
2021.[58]

Given the increase in exporter price, freight cost, and insurance cost, it is expected that import prices also increase, as shown in Figure A3. To understand the relative importance of each term's contribution to the increase in importer price, we conduct the following first-order decomposition:

$$\hat{p}^M = \theta^X \hat{p}^X + \theta^F \hat{p}^F + \theta^I \hat{p}^I, \tag{23}$$

where $\hat{\cdot}$ are differences with respect to pre-pandemic trends, and θ^X, θ^F, and θ^I are the average pre-pandemic share of export prices (92%), freight (7%), and insurance unit costs (1%) respectively. We then replace the $\hat{p}$ terms on the right-hand side with the corresponding deviation from pre-trends estimated in Equation (22). Figure A3 shows that the contribution of freight and insurance costs to the increase in import prices was close to 50% towards the end of 2021.

Figure A3: Decomposition of the Changes in Import Prices



Note: Each point in the solid line is the estimated coefficient of Equation (22) for the import price, with 95% confidence intervals represented by the vertical lines. Standard errors clustered at the exporter-importer-product level. Log changes are relative to exporter-importer-product pre-pandemic trends and seasonality. The dash-dotted line is the contribution of trade costs, calculated as the share of pre-pandemic trade costs (0.08) times the estimated change of freight and insurance unit value in Figure A2.

The graphs presented in Figure A2 capture changes in trade variables during the pandemic where all exporter-importer-product-time observations are equally weighted. It may be the case that when we consider the importance of the different products in aggregate trade, trade variable changes experienced a different time-series pattern.

To take into account the differential size of import by product, we re-estimate Equation (22) by weighting each observation by the importance of each product for Colombia in the 2018-2019 period. Specifically, we compute:

[58]Note that March 2021 saw the Suez Canal Blockage, which reportedly increased losses of global reinsurers. See `www.fitchratings.com/research/insurance/suez-canal-blockage-large-loss-event-for-global-reinsurers-29-03-2021`.

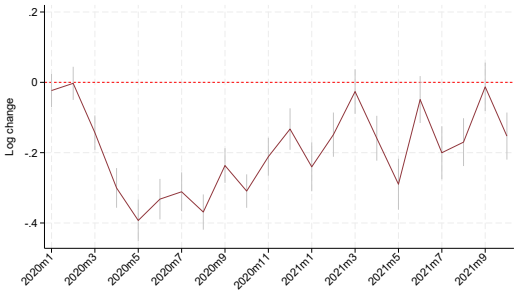
$$\text{weight}_k = \frac{\sum_{ijt \in \Omega_k^{2018-2019}} \text{Import Value}_{ijkt}}{\sum_{ijkt \in \Omega^{2018-2019}} \text{Import Value}_{ijkt}}, \tag{24}$$

and use these weights when estimating 22.

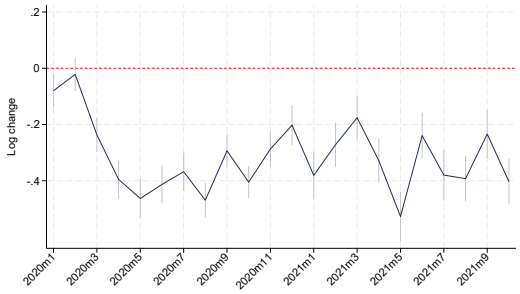
In Figure A4, we reproduce Figure A2 weighted using 24. Trends are both qualitatively and quantitatively similar to the unweighted results.

Figure A4: Product-Weighted Average Changes in Trade Outcomes Relative to Pre-Pandemic Trends

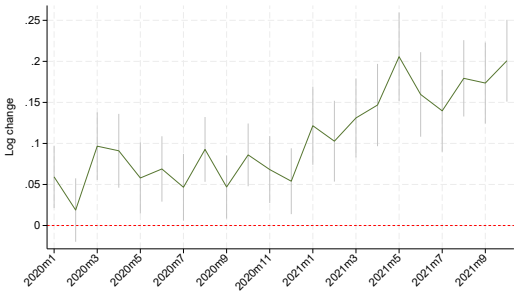
(a) Import values (M)



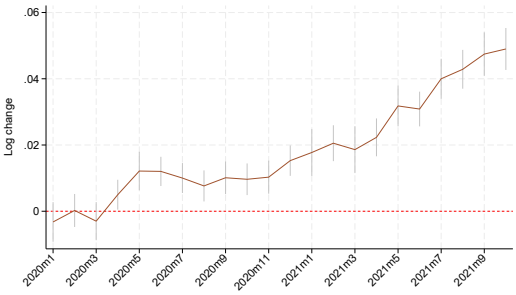
(b) Import quantities (q)



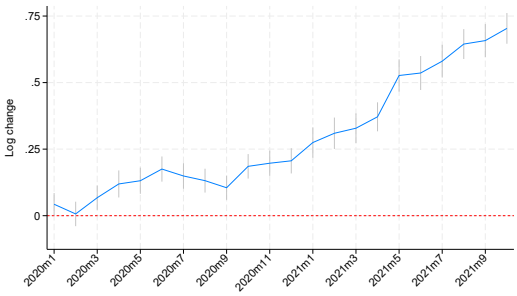
(c) Export prices (p^X)



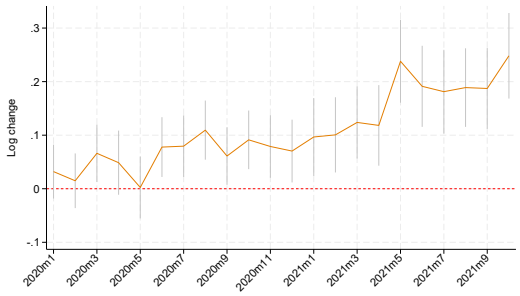
(d) Ad-valorem transportation costs (τ)



(e) Freight unit costs (p^F)



(f) Insurance unit costs (p^I)



Note: Data is from the Colombian customs office. Each point is the estimated coefficient of Equation (22), with 95% confidence intervals represented by the vertical lines. Standard errors clustered at the exporter-importer-product level. Log changes are relative to exporter-importer-product pre-pandemic trends and seasonality. Each observation is weighted by the product-specific import value between 2018 and 2019.

A.2 Port Call Data

A.2.1 Ports Included in the Analysis

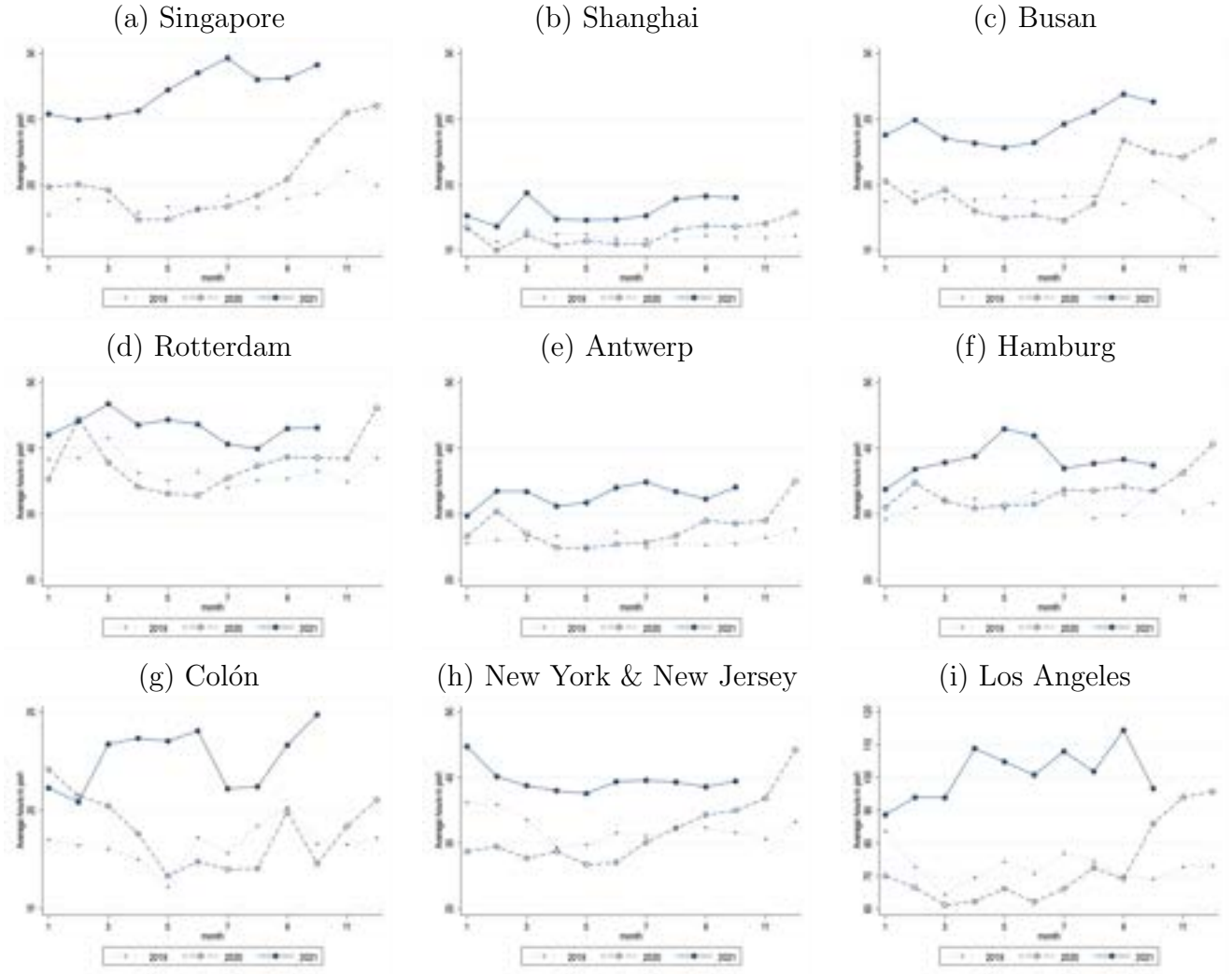
Table A2: The 150 Ports Used in the Analysis, with TEU in 2019 (Millions)

Country	Port	TEU (in millions)	Country	Port	TEU (in millions)	Country	Port	TEU (in millions)
ARG	Buenos Aires	3.93	DEU	Hamburg	17.83	JPN	Nagoya	8.38
AUS	Adelaide	2.27	ECU	Posorja	0.48	JPN	Kobe	8.98
AUS	Fremantle	2.47	ECU	Puerto Bolivar (Ecuador)	0.50	JPN	Tokyo	12.15
AUS	Brisbane	4.45	ECU	Guayaquil	3.50	JPN	Yokohama	12.54
AUS	Melbourne	4.74	ESP	Cartagena (Spain)	0.13	KOR	Gunsan	0.21
AUS	Port Botany	5.15	ESP	Sagunto	0.30	KOR	Pyeong Taek	0.74
BEL	Zeebrugge	1.94	ESP	Tarragona	0.31	KOR	Ulsan	2.47
BEL	Antwerp	22.10	ESP	Gijon	0.33	KOR	Incheon	4.26
BRA	Vila do Conde	0.36	ESP	Alicante	0.35	KOR	Yosu	10.27
BRA	Vitoria	0.40	ESP	Vigo	0.69	KOR	Busan	50.47
BRA	Manaus	0.66	ESP	Bilbao	0.70	MEX	Ensenada	2.00
BRA	Pecem	1.69	ESP	Castellon	1.07	MEX	Altamira	2.86
BRA	Sepetiba	1.70	ESP	Malaga	1.20	MEX	Veracruz	3.10
BRA	Suape	2.25	ESP	Barcelona	9.99	MEX	Lazaro Cardenas	4.28
BRA	Salvador	3.05	ESP	Algeciras	13.46	MEX	Manzanillo (Mexico)	8.70
BRA	Rio Grande (Brazil)	3.39	ESP	Valencia	14.70	NLD	Moerdijk	0.45
BRA	Rio de Janeiro	3.84	FRA	Nantes-St Nazaire	0.51	NLD	Vlissingen	0.61
BRA	Itapoa	3.99	FRA	Dunkirk	1.87	NLD	Rotterdam	32.24
BRA	Paranagua	5.58	FRA	Marseille	6.09	PAN	Balboa	5.12
BRA	Itajai	5.87	FRA	Le Havre	13.98	PAN	Colon	14.71
BRA	Santos	11.75	GBR	London Thamesport	0.11	PER	Paita	0.55
CAN	Halifax	1.45	GBR	Belfast	0.22	PER	Callao	7.70
CAN	Montreal	1.55	GBR	Greenock	0.23	SGP	Singapore	80.99
CAN	Prince Rupert	1.98	GBR	Bristol	0.24	TWN	Keelung	4.97
CAN	Vancouver (Canada)	5.02	GBR	Grangemouth	0.28	TWN	Taipei	6.04
CHL	Arica	0.62	GBR	Immingham	0.39	TWN	Kaohsiung	29.72
CHL	San Vicente	0.90	GBR	Hull	0.42	URY	Montevideo	3.66
CHL	Lirquen	1.00	GBR	Teesport	0.67	USA	Palm Beach	0.17
CHL	Iquique	1.06	GBR	Liverpool (United Kingdom)	1.53	USA	Wilmington (USA-Delaware)	0.32
CHL	Mejillones	1.21	GBR	Southampton	6.16	USA	Eddystone	0.36
CHL	Coronel	1.65	GBR	London	9.05	USA	Wilmington (USA-N Carolina)	1.29
CHL	Valparaiso	2.07	GBR	Felixstowe	9.29	USA	Philadelphia	2.36
CHL	San Antonio	4.17	HKG	Hong Kong	46.39	USA	Baltimore (USA)	2.55
CHN	Dalian	8.55	IND	Tuticorin	1.07	USA	Tacoma	2.72
CHN	Guangzhou	11.59	IND	Cochin	1.88	USA	New Orleans	2.72
CHN	Tianjin	19.61	IND	Jawaharlal Nehru Port	9.85	USA	Port Everglades	2.96
CHN	Xiamen	21.51	ITA	Bari	0.11	USA	Miami	3.57
CHN	Qingdao	31.69	ITA	Catania	0.15	USA	Seattle	3.57
CHN	Shenzhen	64.32	ITA	Ancona	0.61	USA	Houston	5.05
CHN	Ningbo	65.36	ITA	Ravenna	0.62	USA	Savannah	5.43
CHN	Shanghai	74.67	ITA	Salerno	1.18	USA	Los Angeles	7.35
COL	Barranquilla	0.50	ITA	Venice	1.19	USA	Long Beach	8.00
COL	Turbo	0.51	ITA	Naples	1.75	USA	Port of Virginia	8.37
COL	Santa Marta	0.51	ITA	Trieste	2.30	USA	Charleston	9.24
COL	Aguadulce (Colombia)	1.62	ITA	Livorno	3.16	USA	Oakland	9.99
COL	Buenaventura	3.30	ITA	La Spezia	5.20	USA	New York & New Jersey	13.40
COL	Cartagena (Colombia)	8.24	ITA	Gioia Tauro	6.43	VNM	Quy Nhon	0.57
DEU	Lubeck	0.10	ITA	Genoa	8.95	VNM	Danang	1.53
DEU	Wilhelmshaven	3.36	JPN	Shimizu	2.74	VNM	Saigon	2.93
DEU	Bremerhaven	12.66	JPN	Osaka	5.72	VNM	Haiphong	5.26

Note: Data is from the IHS Markit Maritime & Trade Platform.

A.2.2 Individual Port Performance

Figure A5: Average Hours in Port, Nine Important Ports



Note: Data is from the IHS Markit Maritime & Trade Platform. The number of hours in port is measured as the difference between the sailed time and the arrival time at the port.

A.2.3 Additional Port Performance Trends

Figure A6 presents the additional trends in port performance from 2019 to 2021. Panel (a) shows the total number of port calls. We can see that the container ship trade was at a lower level in 2020 and 2021 than in 2019. The first half of 2020 had an about 10% decline, and the second half of 2020 experienced some recovery. The recovery continued until May 2021, and since June 2021, the number of port calls was even below the 2020 level. Panel (b) presents a similar trend, by measuring trade volume using the total twenty-foot-equivalent units of the ships that made port calls.

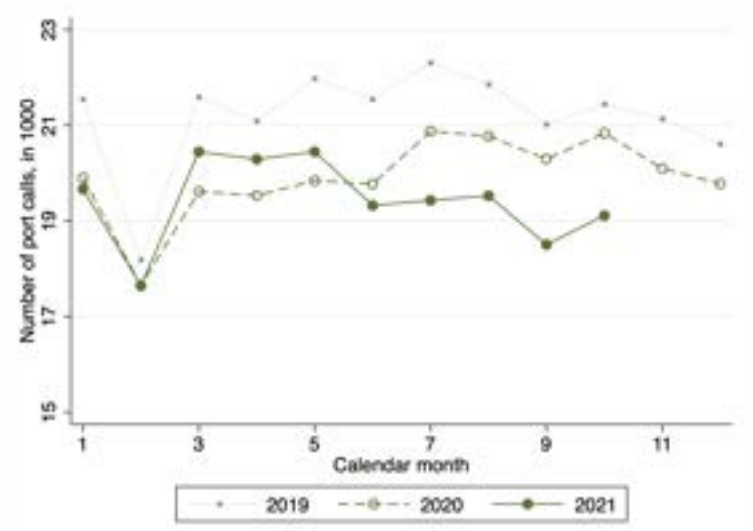
Panel (c) presents the trend in the share of port calls whose last port call was made in China. In 2019, the average share was around 22%. The first four months of 2020 experienced a decline since China experienced the initial Covid-19 outbreak and imposed strict mobility

restrictions. The share started to pick up in May 2020 and continued to rise until June 2021. The timing of the decline in 2021 coincided with the decline in the total number of port calls.

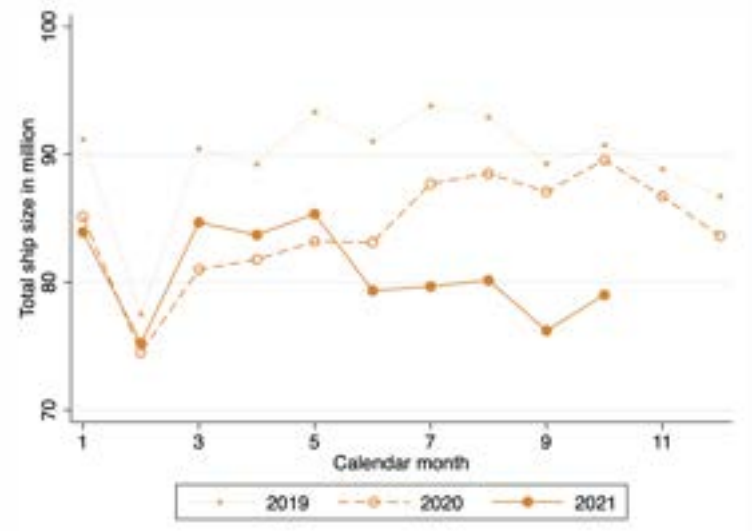
In sum, the world maritime trade was impacted by the pandemic and port congestion became more severe over time. In addition to the aggregate trends across the ports, Appendix Figure A5 confirms the increase in the number of hours in port in some of the largest ports around the world. One of the most famous incidents was in the Los Angeles Port (Panel i), where the number of hours increased from about 75 hours in 2019 to more than 100 hours in 2021 and peaked in September 2021.

Figure A6: Port Performance From January 2019 to October 2021, 150 Ports in 27 Countries, Additional Facts

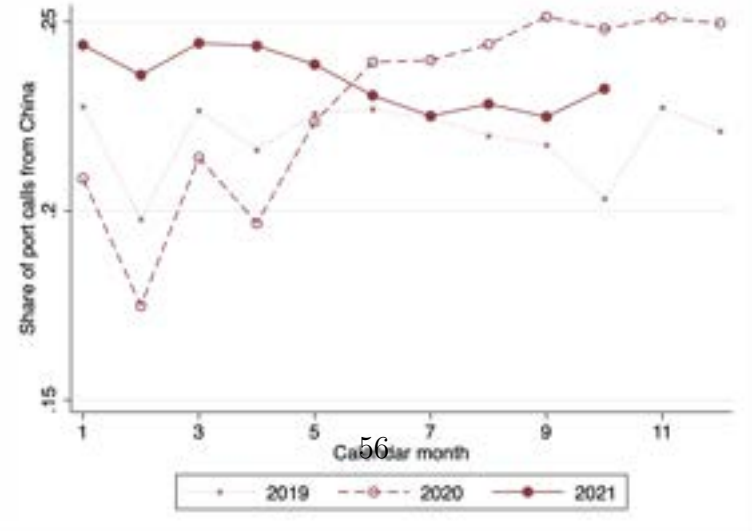
(a) Total number of port calls in 1000



(b) Total ship size in million



(c) Share of calls from China

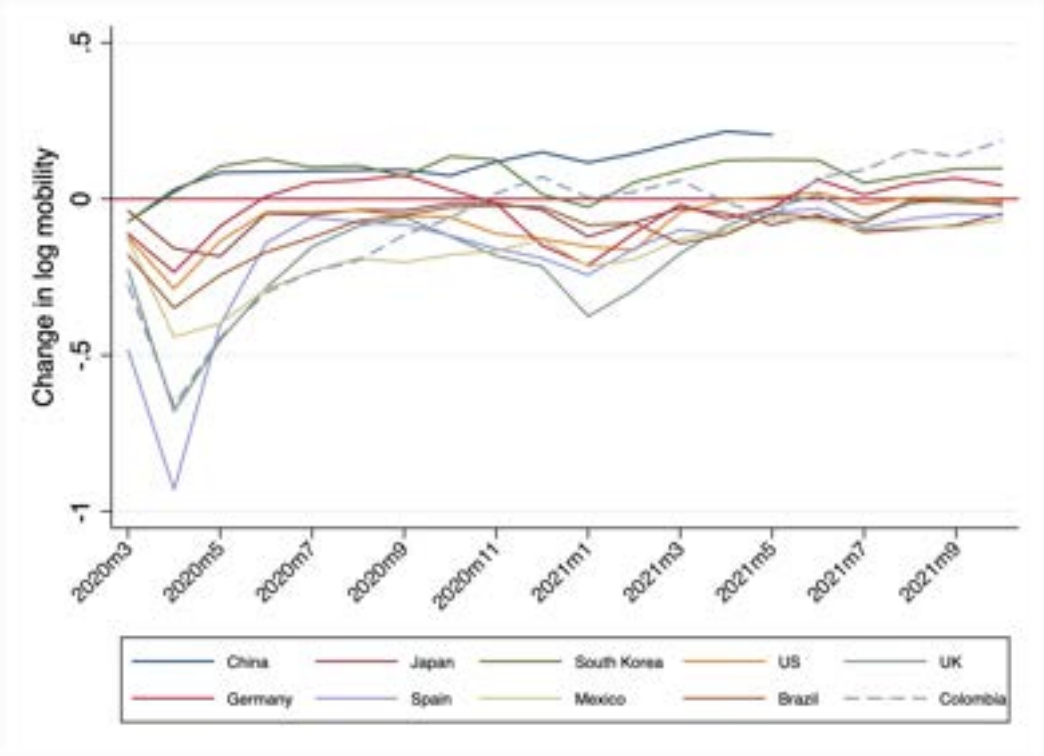


A.3 Mobility Data

A.3.1 Aggregate Trends in Mobility

Figure A7 presents the changes in mobility in Colombia and its trading partners. For the exporting countries, the trend is the average mobility change across all cities that export to Colombia and have mobility data. The biggest decline in mobility happened in April 2020 when many countries imposed lockdowns. Over time the mobility recovers, but not at the same rate across countries. For example, the mobility in Spain did not recover to the pre-Covid period even in October 2021. In contrast, South Korea experienced a fast recovery and had a level of mobility higher than the pre-Covid period in almost all months since April 2020. Colombia also experienced a large decline in mobility in April 2020, and had a rather steady increase over time.

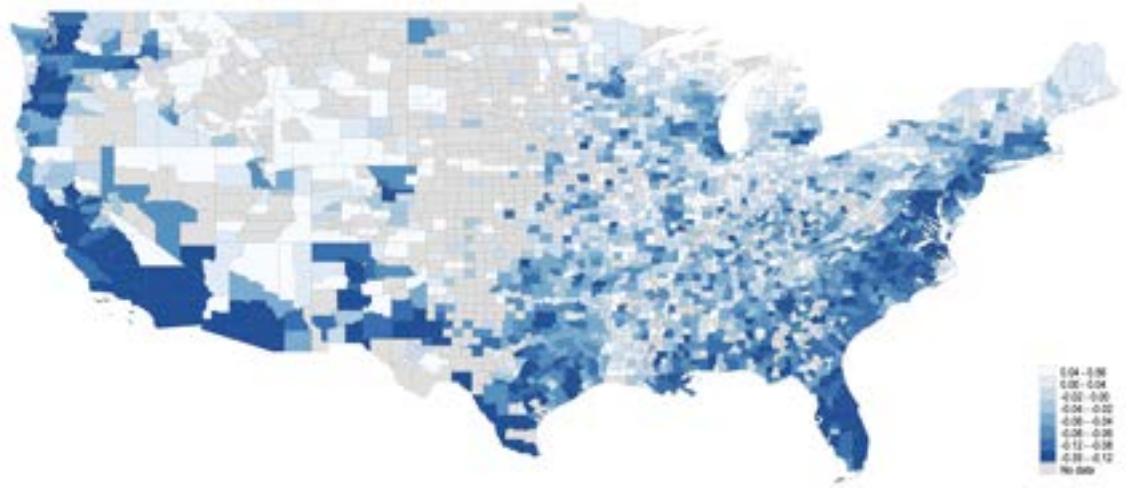
Figure A7: The Trend of Mobility in Exporting Cities Across Countries and in Colombia



Note: Data on Chinese mobility are from Baidu, and data for other countries come from Facebook. The exporting cities include only cities that export to Colombia and have mobility data. The Colombian average is taken over all municipalities that have mobility data. The data points for China in June, July, and August 2020 are imputed using the linear approximation with May and September 2020 values, given that these months have missing mobility data.

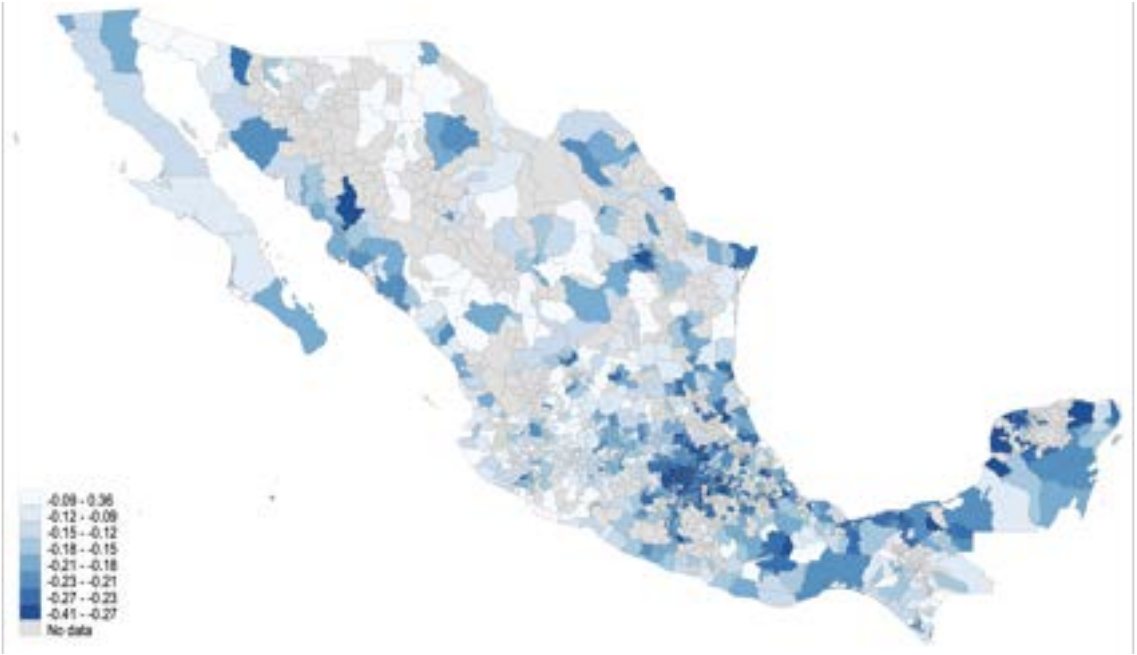
A.3.2 Mobility Change Maps (US, Mexico, and China)

Figure A8: The Decline in Mobility Across Counties in the US, September 2020 Compared to February 2020



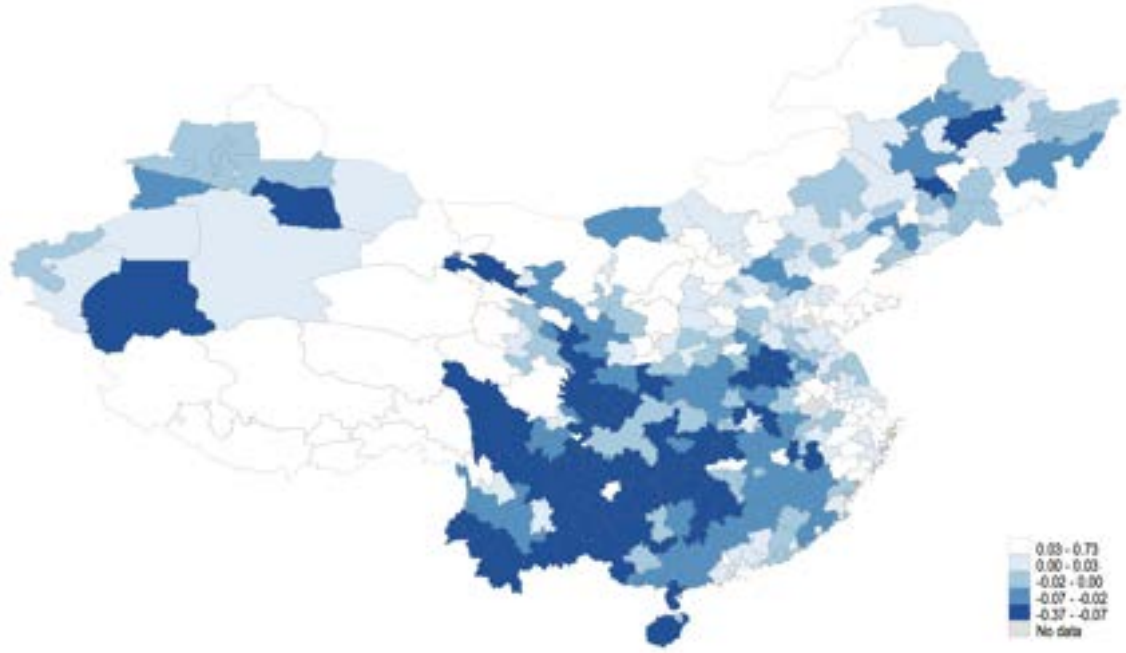
Note: Data is from Facebook.

Figure A9: The Decline in Mobility Across Municipalities in Mexico, September 2020 Compared to February 2020



Note: Data is from Facebook.

Figure A10: The Decline in Mobility Across Prefectures in China, September 2020 Compared to February 2020



Note: Data is from Baidu.

A.3.3 Validation of the Mobility Measure

In this section, we provide evidence of the relationship between mobility changes, local Covid outbreaks, and policies. In the paper, we use the observed mobility changes as an aggregate measure that captures the reduction in economic activity. The mobility reduction can be the result of increased risks of infection and associated policies that intend to contain the spread of the virus. On the other hand, a reduction in local mobility can in turn affect the rate of infection and policy, both through the reduction in human contact and the associated reduction in income. Thus, it is difficult to identify the causal relationship between observed mobility change, observed number of cases, and government containment policies. We don't intend to uncover this highly dynamic relationship and focus on documenting the association between them to show that regions with larger reductions in mobility also have a larger number of cases and more stringent policies.

We use the national level Covid-19 policies from Hale et al. (2021) and the daily number of new cases for European NUTS3 regions from March 2020 to August 2021 by Asjad (2021). We use the eight European countries (i.e., Belgium, Switzerland, Germany, Spain, France, UK, Italy, and the Netherlands) because of easy data access and sufficient variation at the sub-national level (in cases) and at the national level (in policy). In addition, except for the UK, the unit of analysis here will be the same as in the main regressions (i.e., time-city, where time is a month in a particular year). Both the data on cases and on government policies are on a daily basis, and we compute the average of each measure over time.

Table A3 presents the correlation between changes in log mobility at the region level and the average daily new cases. Column (1) shows that an increase in infection rate by one case

Table A3: The Relationship Between the Mobility Change and the Number of New Cases

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: Δ log mobility					
Average daily new cases	-0.111***	-0.150***	-0.018***	-0.009**	-0.046***	-0.036***
(per 1000 persons)	(0.007)	(0.007)	(0.005)	(0.004)	(0.006)	(0.003)
Constant	-0.091***	-0.086***	-0.103***	-0.104***	-0.099***	-0.101***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
N	16,443	16,443	16,443	16,443	16,443	16,443
R^2	0.012	0.593	0.742	0.787	0.933	0.978
Time FE		Yes	Yes	Yes		
Country FE			Yes			
Region FE				Yes		Yes
Country-time FE					Yes	Yes

Note: Robust standard errors clustered at the importer-time level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

per thousand population is associated with an 11 percent larger mobility decline. Columns (2) to (6) include various fixed effects, and the effect ranges from 1 percent to 15 percent depending on the specification. Our preferred specification is Column (6), where both region fixed effects and country-time fixed effects are included. This specification allows different regions to have different mobility declines with zero cases and control for policy changes at the country-time level. Thus, we are using the variation within countries.

Table A4 presents the results on policy effects. Since the policy data is only available at the country-time level, we only include region fixed effects and time fixed effects, as in Column (4) Table A3. Column (1) shows the relationship between the stringency index and the log change in mobility. The mean (s.d.) of the stringency index is 65 (12), thus a one-standard-deviation increase in the stringency index is associated with an 8.4 percent larger decline in mobility. The coefficient remains similar when controlling for the number of cases in Column (2). Columns (3) and (4) use alternative measures of the stringency index, which are the government response index and containment health index, and both indices have a similar relationship with the mobility change. Column (5) uses the economic support index, and there is a positive association. Unlike the government response index and the containment health index, the economic support index is not highly correlated with the overall stringency index.

Table A4: The Relationship Between the Mobility Change and Containment Policies

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Δ log mobility				
Stringency index	-0.007***	-0.007***			
	(0.000)	(0.000)			
Government response index			-0.008***		
			(0.000)		
Containment health index				-0.009***	
				(0.000)	
Economic support index					0.003***
					(0.000)
Average daily new cases		-0.034***	-0.022***	-0.028***	-0.013***
(per 1000 persons)		(0.004)	(0.004)	(0.004)	(0.004)
Constant	0.361***	0.369***	0.395***	0.452***	-0.262***
	(0.006)	(0.006)	(0.009)	(0.009)	(0.008)
N	16,445	16,443	16,443	16,443	16,443
R^2	0.855	0.856	0.822	0.839	0.803

Note: Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. All columns include region fixed effects and time fixed effects.

Overall, we find that a larger number of local cases and a more stringency government containment policy are associated with a larger decline in mobility. Thus, the mobility change we use does capture Covid-related reactions.

A.4 Levels of Aggregation

Table A5: Levels of Aggregation and the Matching Results Between the Facebook/Baidu Data and the Colombian Trade Data

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Country	Unit of geo divisions		Number of divisions						
	Colombian trade data		FB level 1	FB Level 2	Map level 1	Map Level 2	Merged	% merged	% trade
ARG	gadm 1	province	**24**	432	24	503	20	83%	100%
AUS	gadm 2	city	8	**310**	11	569	102	33%	87%
BEL	nuts 3	city		**44**		44	42	95%	99%
BOL	gadm 1	department	**9**	59	9	95	7	78%	100%
BRA	gadm 2	city/municipality	27	**3356**	27	5504	649	19%	90%
CAN	gadm 2	municipality	13	**269**	13	293	123	46%	70%
CHE	nuts 3	city		**25**		26	25	100%	99%
CHL	gadm 2	city	16	**51**	16	54	42	82%	98%
CHN	prefectures	prefecture	31	**333**	31	338	252	76%	76%
DEU	nuts 3	district		**401**		401	394	98%	99%
ECU	gadm 2	city	24	**176**	24	223	59	34%	99%
ESP	nuts 3	municipality		**59**		59	56	95%	98%
FRA	nuts 3	department		**101**		101	98	97%	96%
GBR	nuts 2	county	**41**	175	41	179	40	98%	70%
HKG	gadm 1		**1**	18	1	18	1	100%	99%
IND	gadm 2	district	36	**658**	36	666	193	29%	75%
ITA	nuts 3	city		**110**		107	105	95%	97%
JPN	gadm 1	prefecture	**47**	690	47	1811	35	74%	100%
KOR	gadm 1	province	**17**	224	17	229	17	100%	100%
MEX	gadm 2	municipality	32	**1111**	32	1854	220	20%	93%
NLD	nuts 3	COROP regions		**40**		40	39	98%	98%
PAN	gadm 2	district	9	**25**	13	79	13	52%	99%
PER	gadm 2	city	26	**151**	26	195	47	31%	98%
TWN	gadm 2	county/city	7	**22**	7	22	17	77%	96%
URY	gadm 1	department	**19**	71	17	204	15	79%	100%
USA	place		56	**2693**	56	3233	1232	46%	75%
VNM	gadm 1		**63**	707	63	710	38	60%	100%

Table A5 presents the summary of the level of aggregation and matching results between the Facebook/Baidu data and the Colombian import data. The Facebook/Baidu data is always available both at the highest subnational level and the second highest subnational level, and the number of divisions is shown in Columns (4) and (5). The coverage of the Facebook data can be seen by comparing Columns (4) and (5) with Columns (6) and (7), where Columns (6) and (7) show the total number of geographic units at corresponding levels. In the US, the second highest subnational level is county; NUTS3 in Europe, GADM2 in Latin American and Asian countries (GADM data from `https://gadm.org/`), and prefecture in China. For the Colombian trade data, the quality of the exporter location information varies by country. Column (2) shows the level of aggregation, and Column (3) shows the corresponding name of the geographic division in each specific country. For example, the US exporter's information is reported at the census place level, e.g., "Benton Harbor, MI," and we use the concordance by US Census Bureau to match places to counties. The bold number in Columns (4) and (5) indicates the level of aggregation when we match the trade data with the mobility data. For example, Argentina is at the province level (FB level 1), while Australia is at the city level (FB level 2). Column (8) shows the final number of merged geographic units, Column (9) shows the merge rate by dividing Column (8) with the bold

number in either Column (4) or Column (5), and Column (10) shows the share of trade values covered in the merged sample.

A.5 Covid-Related Medical Goods

A list by World Customs Organization and World Health Organization specifies the list of Covid-related medical goods at the HS6 level.[59] They include the following sections: (1) COVID-19 test kits/instruments and apparatus used in diagnostic testing; (2) protective garments and the like; (3) disinfectants and sterilization products; (4) oxygen therapy equipment and pulse oximeters; (5) other medical devices and equipment; (6) other medical consumables; (7) vehicles. Overall, these goods comprise about 7.7% of the total trade value in 2020 and 2021.

These goods can be consumption goods, intermediate goods, or capital goods. Examples of consumption goods include men's protective garments made of rubberized textile fabrics, tents for setting up field hospitals, including temporary canopies, alcohol solutions, undenatured, 75% ethyl alcohol. Examples of intermediate goods include laboratory, hygienic or pharmaceutical glassware, medical oxygen, and hydrogen peroxide in bulk. Examples of capital goods include intubation kits, and medical ventilators (artificial respiration apparatus).

[59] https://www.wcoomd.org/-/media/wco/public/global/pdf/topics/nomenclature/covid_19/hs-classification-reference_edition-3_en.pdf?la=en.

A.6 Summary of Statistics of Variables in Exporter and Importer Shocks Regressions

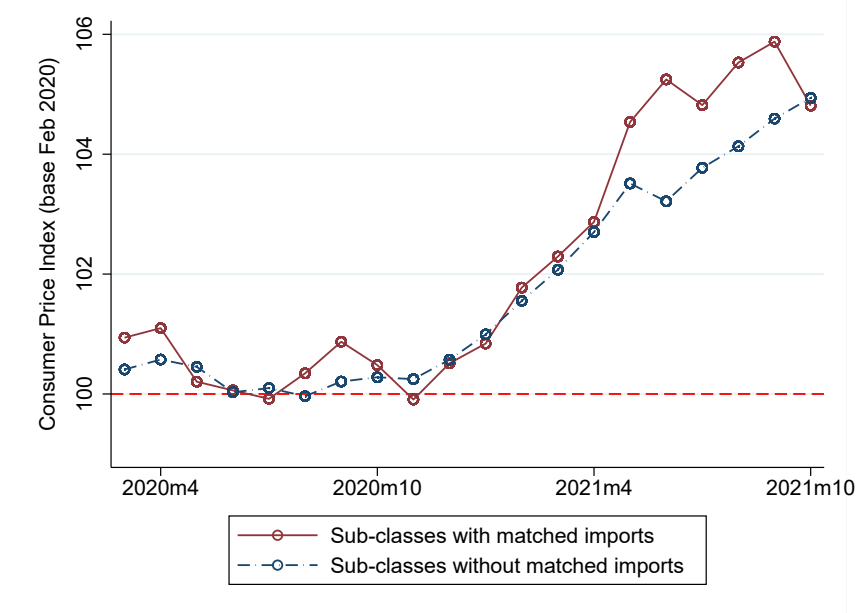
Table A6: Descriptive Statistics of Variables Used in Baseline Exporter and Importer Shocks Regressions

Variable	Mean	S.D.	Q1	Median	Q3	N
Baseline sample						
Δ log import values	-0.076	1.822	-1.008	-0.031	0.861	537,100
Δ log import quantities	-0.117	2.032	-1.099	-0.029	0.857	537,100
Δ log import prices	0.041	1.342	-0.347	0.021	0.429	537,100
Δ log importer mobility	-0.250	0.264	-0.340	-0.171	-0.082	537,100
Δ log exporter mobility	-0.135	0.182	-0.211	-0.118	-0.021	537,100
Δ log congestion $\hat{D}$	-0.264	0.205	-0.346	-0.235	-0.117	486,090
Δ log congestion $\hat{S}$	-0.226	0.203	-0.329	-0.183	-0.074	486,090
Consumption goods						
Δ log import values	-0.138	1.759	-1.054	-0.084	0.783	105,270
Δ log import quantities	-0.192	1.986	-1.174	-0.118	0.788	105,270
Δ log import prices	0.055	1.116	-0.246	0.021	0.330	105,270
Δ log importer mobility	-0.243	0.251	-0.325	-0.170	-0.082	105,270
Δ log exporter mobility	-0.141	0.189	-0.222	-0.121	-0.029	105,270
Intermediate goods						
Δ log import values	-0.060	1.831	-0.979	-0.016	0.864	329,990
Δ log import quantities	-0.095	2.065	-1.082	-0.011	0.875	329,990
Δ log import prices	0.034	1.355	-0.364	0.021	0.439	329,990
Δ log importer mobility	-0.251	0.267	-0.354	-0.170	-0.079	329,990
Δ log exporter mobility	-0.136	0.182	-0.210	-0.118	-0.019	329,990
Capital goods						
Δ log import values	-0.052	1.862	-1.053	-0.027	0.954	98,068
Δ log import quantities	-0.095	1.952	-1.099	0.000	0.894	98,068
Δ log import prices	0.043	1.505	-0.452	0.020	0.543	98,068
Δ log importer mobility	-0.254	0.265	-0.349	-0.183	-0.082	98,068
Δ log exporter mobility	-0.125	0.171	-0.206	-0.113	-0.013	98,068
Exporter-Importer Links sample						
$\Delta I(\text{imports} > 0)$	-0.012	0.373	0.000	0.000	0.000	10,888,687
Δ log importer mobility	-0.250	0.274	-0.374	-0.163	-0.066	10,888,687
Δ log exporter mobility	-0.130	0.192	-0.203	-0.103	-0.012	10,888,687
Δ log congestion $\hat{D}$	-0.268	0.210	-0.347	-0.234	-0.120	9,576,852
Δ log congestion $\hat{S}$	-0.226	0.206	-0.328	-0.181	-0.074	9,576,852

Note: This table presents the summary of statistics of variables used in Tables 1, B5, B9, and B11.

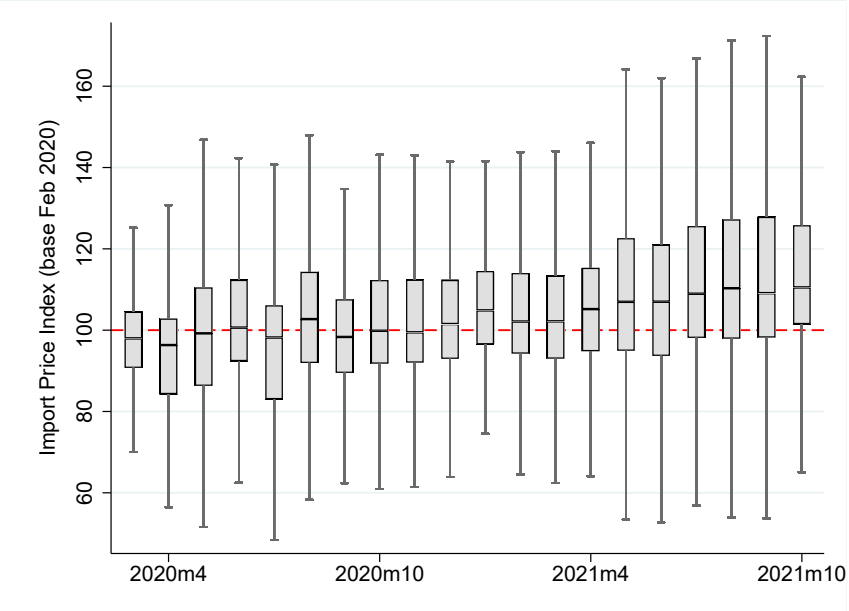
A.7 Additional Descriptive Statistics of Consumer Price Indices

Figure A11: Aggregate Consumer Price Index for Goods Sub-classes With and Without Matched Imports



Note: Each dot is a weighted average of goods-specific (sub-class) consumer price indices (base February 2020) for goods and services with observed or not observed imports as indicated by their color. Weights are expenditure shares from the national household survey in 2016-2017 within each of these two categories.

Figure A12: Monthly Distribution of Import Price Indices over Goods



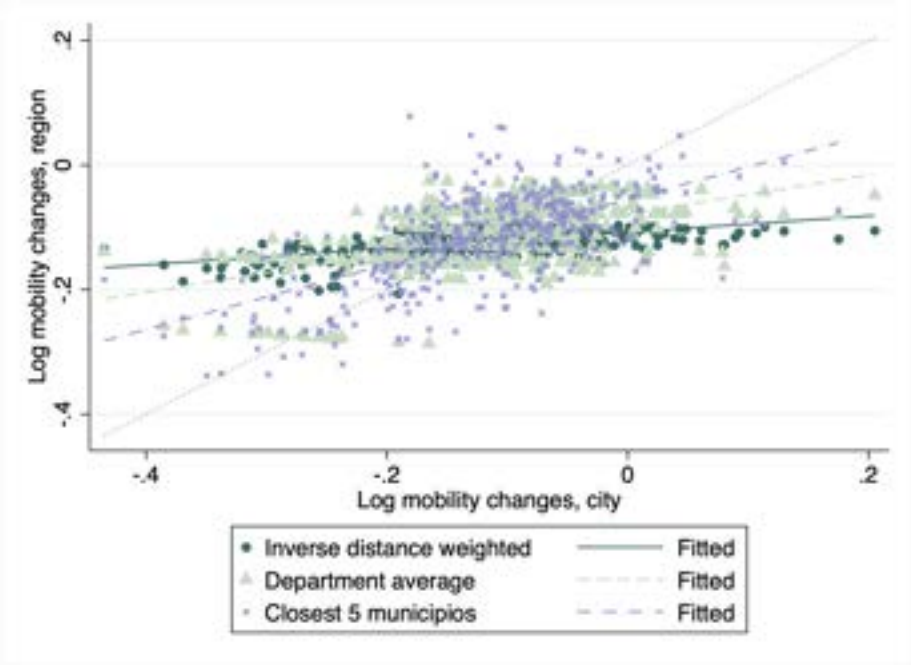
Note: The grey boxes plot the month-specific distribution of goods-specific (sub-class) import price indices, constructed by weighting exporter-importer-products observed within CPI sub-classes with Colombian imports from 2019.

B Additional Empirical Results

B.1 Robustness of the Effect of Exporter and Importer Shocks

B.1.1 Importer Region vs Importer City

Figure B1: The Relationship Between Regional Mobility Changes and City-Level Mobility Changes in Colombia, September 2020 Compared to Baseline



Note: The horizontal axis is the log mobility changes in Colombia cities, and the vertical axis is the log mobility changes in corresponding regions, where the definition of each region is specified in the legend.

B.1.2 Different Fixed Effects

Table B1: The Impact of Exporter and Importer Mobility on Trade Outcomes, Robustness with Alternative Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	No product-time fixed effects			No MPOE fixed effects		
Dependent variable:	Δ log value	Δ log quantity	Δ log price	Δ log value	Δ log quantity	Δ log price
Δ log importer mobility	0.484***	0.415***	0.069	0.503***	0.564***	-0.060
	(0.063)	(0.070)	(0.048)	(0.070)	(0.066)	(0.041)
Δ log exporter mobility	0.232**	0.333***	-0.101***	0.138	0.225*	-0.086**
	(0.090)	(0.114)	(0.037)	(0.100)	(0.125)	(0.040)
Fixed effects	Exporting country-MPOE-time			Exporting country-time & product-time		
N	551,155	551,155	551,155	537,559	537,559	537,559
R^2	0.029	0.029	0.015	0.085	0.083	0.064
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B	Exporter and MPOE fixed effect separability			Product-specific transport cost fixed effects		
Dependent variable:	Δ log value	Δ log quantity	Δ log price	Δ log value	Δ log quantity	Δ log price
Δ log importer mobility	0.426***	0.416***	0.010	0.450***	0.508***	-0.058
	(0.069)	(0.072)	(0.050)	(0.099)	(0.080)	(0.065)
Δ log exporter mobility	0.189*	0.282**	-0.093**	0.525***	0.760***	-0.235***
	(0.098)	(0.125)	(0.042)	(0.138)	(0.171)	(0.061)
Fixed effects	Exporting country-time, MPOE-time & product-time			Exporting country-MPOE-product-time		
N	537,549	537,549	537,549	308,249	308,249	308,249
R^2	0.088	0.089	0.068	0.301	0.302	0.275

Note: Standard errors are clustered at the exporter-time level and importer-time level. *** p<0.01, ** p<0.05, * p<0.1. This table replicates the regressions in Table 1 Columns (1)–(3) by including different types of fixed effects. For a summary of statistics in these specifications, see Table A6.

B.1.3 Alternative Standard Errors Clustering

Table B2: The Impact of Exporter and Importer Mobility on Trade Outcomes, Alternative Standard Errors Clustering

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Δ log value	Δ log quantity	Δ log price	Δ log value	Δ log quantity	Δ log price
Δ log importer mobility	0.433***	0.410***	0.023	0.433***	0.410**	0.023
	(0.092)	(0.080)	(0.045)	(0.099)	(0.180)	(0.175)
Δ log exporter mobility	0.249**	0.352**	-0.103**	0.249	0.352	-0.103**
	(0.108)	(0.145)	(0.051)	(0.197)	(0.232)	(0.040)
Clustering	Exporting country-time and importer department-time			Exporter and importer		
N	537,100	537,100	537,100	537,100	537,100	537,100
R^2	0.100	0.101	0.076	0.100	0.101	0.076

Note: Robust standard errors clustered as indicated on the clustering row. *** p<0.01, ** p<0.05, * p<0.1. Columns (1)–(3) and Columns (4)–(6) replicate Table 1 Panel A Columns (1)–(3) with alternative ways of clustering the standard errors.

B.1.4 Balanced Sample

Table B3: The Impact of Exporter and Importer Mobility on Trade Outcomes, Balanced Sample

	(1)	(2)	(3)
Dependent variable:	Δ log value	Δ log quantity	Δ log price
Δ log importer mobility	0.357**	0.400**	-0.043
	(0.168)	(0.183)	(0.063)
Δ log exporter mobility	1.372***	1.632***	-0.260**
	(0.228)	(0.323)	(0.120)
N	77,351	77,351	77,351
R^2	0.219	0.216	0.152

Note: Robust standard errors clustered at the exporting-time level and importer-time level. *** p<0.01, ** p<0.05, * p<0.1. Exporting country-main port of entry-time, and product-time fixed effects are included in all columns. This table replicates Table 1 Panel A Columns (1)–(3) with the sample of exporter-importer-product triplets observed in all months between March 2020 and October 2021, i.e., the balanced sample.

B.1.5 Pooled Dynamic Effects

In this section, we consider whether dynamic disruption effects at the exporter and importer locations modify our baseline results. To do so, we estimate the following equations,

$$\hat{q}^M_{ijkt} = \sum_{l=0,\dots,L} \beta(l)^q_J \hat{x}^J_{j,t-l} + \sum_{l=0,\dots,L} \beta(l)^q_I \hat{x}^I_{i,t-l} + \delta^{P,q}_{kt} + \delta^{Tr,q}_{cut} + \varepsilon^q_{ijkt}, \tag{25}$$

$$\hat{p}^M_{ijkt} = \sum_{l=0,\dots,L} \beta(l)^p_J \hat{x}^J_{j,t-l} + \sum_{l=0,\dots,L} \beta(l)^p_I \hat{x}^I_{i,t-l} + \delta^{P,p}_{kt} + \delta^{Tr,p}_{cut} + \varepsilon^p_{ijkt}, \tag{26}$$

which modify baseline Equations (9) and (10) by adding L lags of the mobility changes at the exporter and importer cities.

Including L lags reduces our sample period by L months, as our log differences are constructed relative to February 2020. We allow for a maximum of three lags to minimize sample differences with respect to our baseline sample. Therefore, we estimate four specifications where L takes the value of 0, 1, 2, and 3 alternatively. We use the same sample for all four specifications—the one limited by the three lags.

We report the pooled dynamic effects, $\hat{\beta}_{pooled} = \sum_{l=0,\dots,L} \hat{\beta}(l)$, for Equations (25), (26) and the sum of the two, import values, in Table B4 for each of the specifications.

Columns (1) to (3) reproduce the baseline specification for the restricted sample, showing the same as in our main results: both exporter and importer mobility declines reduced import quantities, whereas only exporter mobility declines increased prices. These results are qualitatively the same when we employ 1, 2, and 3 lags, as shown in Columns (4) to (6), (7) to (8), and (10) to (12) respectively. This confirms our baseline specification is robust to direct pooled dynamic effects.

Table B4: The Impact of Exporter and Importer Mobility on Trade Outcomes, Pooled Dynamic Effects

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Δ log value	Δ log quantity	Δ log price	Δ log value	Δ log quantity	Δ log price
Δ log importer mobility pooled	0.557***	0.464***	0.093	0.588***	0.491***	0.097
	(0.078)	(0.090)	(0.059)	(0.077)	(0.091)	(0.059)
Δ log exporter mobility pooled	0.257**	0.332**	-0.075*	0.293***	0.376***	-0.084**
	(0.110)	(0.129)	(0.041)	(0.104)	(0.120)	(0.040)
Number of lags pooled		No lags			1 lag	
N	443,431	443,431	443,431	443,431	443,431	443,431
R^2	0.100	0.101	0.078	0.100	0.101	0.078
	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable:	Δ log value	Δ log quantity	Δ log price	Δ log value	Δ log quantity	Δ log price
Δ log importer mobility pooled	0.594***	0.501***	0.094	0.608***	0.513***	0.094
	(0.077)	(0.090)	(0.060)	(0.077)	(0.090)	(0.060)
Δ log exporter mobility pooled	0.304***	0.388***	-0.084**	0.333***	0.416***	-0.084**
	(0.102)	(0.118)	(0.040)	(0.104)	(0.120)	(0.038)
Number of lags pooled		2 lags			3 lags	
N	443,431	443,431	443,431	443,431	443,431	443,431
R^2	0.100	0.101	0.078	0.100	0.101	0.078

Note: Robust standard errors clustered at the exporting-time level and importer-time level. *** p<0.01, ** p<0.05, * p<0.1. Exporting country-main port of entry-time, and product-time fixed effects are included in all columns. Each estimation includes the number of lags of the importer and exporter mobility variables. The results reported are the sum of the lags. Individual lag coefficients are omitted (available upon request).

B.1.6 Heterogeneity by the Type of Goods

Table B5: The Impact of Exporter and Importer Mobility on Trade Outcomes, by Goods Categories

Panel A	(1)	(2)	(3)
Dependent variable:	Δ log value	Δ log quantity	Δ log price
Δ log importer mobility × consumer	0.469***	0.387***	0.082
	(0.139)	(0.149)	(0.081)
Δ log importer mobility × intermediates	0.420***	0.393***	0.027
	(0.075)	(0.085)	(0.062)
Δ log importer mobility × capital	0.393***	0.417***	-0.024
	(0.107)	(0.110)	(0.061)
Δ log exporter mobility × consumer	-0.023	0.074	-0.096**
	(0.126)	(0.148)	(0.048)
Δ log exporter mobility × intermediates	0.280***	0.398***	-0.118***
	(0.094)	(0.121)	(0.045)
Δ log exporter mobility × capital	0.330***	0.322**	0.008
	(0.103)	(0.141)	(0.069)
N	533,312	533,312	533,312
R^2	0.100	0.101	0.077
Panel B	(1)	(2)	(3)
Dependent variable:	Δ log value	Δ log quantity	Δ log price
Δ log importer mobility	0.491***	0.457***	0.034
	(0.070)	(0.074)	(0.052)
Δ log importer mobility × medical	-0.383***	-0.254	-0.128
	(0.135)	(0.156)	(0.125)
Δ log exporter mobility	0.243***	0.349***	-0.106**
	(0.094)	(0.125)	(0.046)
Δ log exporter mobility × medical	0.302**	0.374***	-0.072
	(0.123)	(0.136)	(0.083)
N	537,100	537,100	537,100
R^2	0.100	0.101	0.076

Note: Standard errors are clustered at the exporter-time level and importer-time level. *** p<0.01, ** p<0.05, * p<0.1. This table replicates the results in Table 1 Panel A Columns (1)–(3), by dividing goods into different categories. Panel A categories include consumer, intermediate, and capital goods, based on the BEC classification. Panel B shows a heterogeneous effect of Covid-related medical goods (defined by the World Health Organisation and World Customs Organisation). For a summary of statistics of variables, see Appendix Table A6 for details.

B.2 Elasticity of Substitution Heterogeneity across Two-digit HS2 Product Codes

We estimate Equation (9) and (10) interacting the mobility coefficients with a more granular definition of product categories than in Section 4.2 to study the consistency of the elasticity of substitution. To do so, we interact the mobility shocks with two-digit HS code indicators. This yields 96 estimates.

In Table B6, we report the HS2-specific elasticities of substitution computed using the interacted regression (not reported), along with their significance level. Most of the estimates are positive and all the significant ones are so, confirming that this parameter is consistent with the theory in statistical terms. It is likely we lack the statistical power to estimate many of the others. This is also illustrated in Figure B2, where we estimate two kernel densities distinguishing between the significant and insignificant estimates at the 10% level.

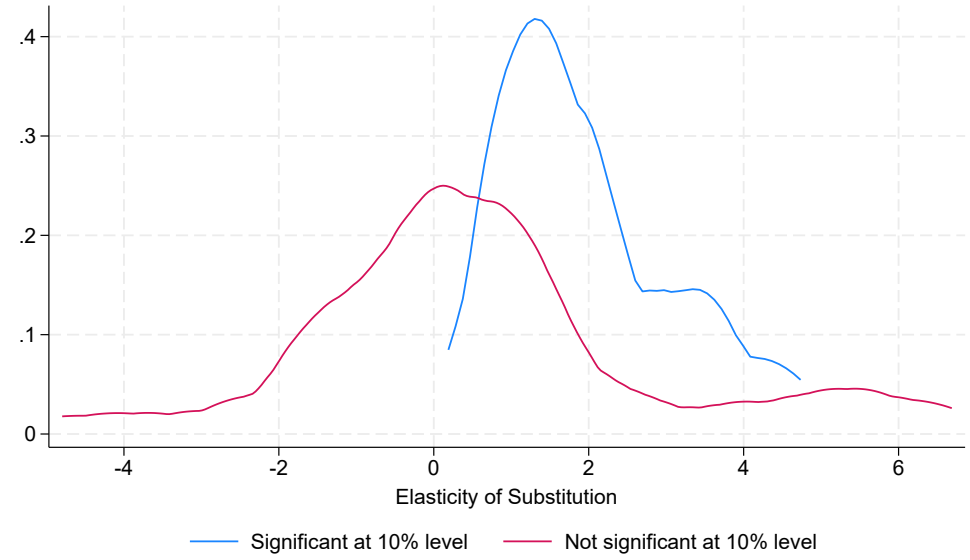
In Figure B3, we plot the positive ones distinguishing between the significant and the insignificant ones for exposition.

Table B6: Elasticities of Substitutions across Two-digit HS2 Product Codes

HS2 code	η	HS2 code	η	HS2 code	η	HS2 code	η	HS2 code	η
1	0.968	21	0.555	41	4.202***	61	-1.093	81	1.075**
2	14.826	22	-0.933	42	1.363	62	1.565	82	-0.27
3	2.77***	23	1.419**	43	0.758***	63	1.309*	83	3.486
4	0.437	24	0.688**	44	16.011	64	0.792	84	2.973***
5	1.485***	25	0.384	45	1.468*	65	0.374	85	-4.302
6	-0.708	26	0.8	46	13.322	66	-0.123	86	1.45*
7	-0.962	27	-7.771	47	0.535	67	-11.008	87	4.236**
8	23.391	28	0.128	48	0.693***	68	-3.138	88	0.115
9	0.593	29	6.686	49	1.519**	69	-0.981	89	2.818***
10	-7.85	30	-0.871	50	2.993*	70	-1.657	90	5.752
11	0.254	31	-1.641	51	2.334	71	4.515	91	1.564*
12	0.704	32	2.822	52	0.763	72	0.488	92	5.657
13	-2.526	33	8.619	53	4.815	73	-10.831		
14	-0.648	34	2.055	54	0.809	74	0.759	94	-0.73
15	1.177	35	1.228**	55	1.57**	75	1.802	95	0.741
16	3.977*	36	2.157***	56	2.969***	76	-0.992	96	13.631
17	372.424	37	-0.739	57	4.572			97	1.23*
18	0.224	38	1.019	58	-0.887	78	-2.036	98	22.641
19	-0.961	39	1.115*	59	-4.796	79	0.418		
20	6.051	40	1.536***	60	1.544**	80	1.179		

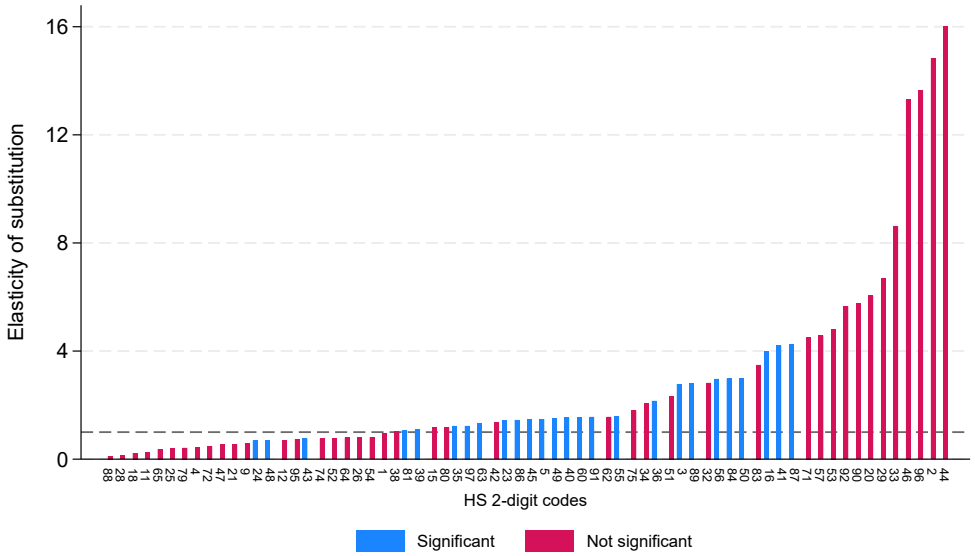
Note: Each estimate is computed as the ratio of the coefficient of the exporter mobility in the quantity regression to the one in the price regression interacted with the respective HS2 code (not reported). Standard errors (not reported) are clustered at the exporter-time level and importer-time level. *** p<0.01, ** p<0.05, * p<0.1.

Figure B2: Kernel Density of the Elasticity of Substitution across Exporter Cities by HS2 by Statistical Significance (10%)



Note: Each observation is computed as the ratio of the coefficient of the exporter mobility in the quantity regression to the one in the price regression interacted with the respective HS2 code (not reported).

Figure B3: Elasticity of Substitution across Exporter Cities by HS2 Products



Note: Each estimate is computed as the ratio of the coefficient of the exporter mobility in the quantity regression to the one in the price regression interacted with the respective HS2 code (not reported). We only report positive coefficients for exposition purposes. Dashed line indicates an elasticity of substitution of one. Standard errors (not reported) are clustered at the exporter-time level and importer-time level. *** p<0.01, ** p<0.05, * p<0.1.

B.2.1 Heterogeneity by the Number of Suppliers

Table B7: The Impact of Exporter and Importer Mobility on Trade Outcomes, by the Pre-Pandemic Number of Suppliers

Panel A	(1)	(2)	(3)
	Δ log value	Δ log quantity	Δ log price
Importer mobility	0.428***	0.390***	0.038
	(0.078)	(0.084)	(0.058)
Importer mobility × High N Suppliers	0.017	0.067	-0.051**
	(0.042)	(0.048)	(0.023)
Exporter mobility	0.269***	0.430***	-0.161***
	(0.096)	(0.124)	(0.047)
Exporter mobility × High N Suppliers	-0.036	-0.139**	0.103***
	(0.047)	(0.059)	(0.033)
Observations	537,100	537,100	537,100
R-squared	0.100	0.101	0.076
Panel B	(1)	(2)	(3)
Dependent variable:	Δ log value	Δ log quantity	Δ log price
Δ log importer mobility	0.452***	0.354***	0.098
	(0.115)	(0.125)	(0.070)
Δ log importer mobility × log N suppliers	0.001	0.018	-0.017**
	(0.016)	(0.018)	(0.008)
Δ log exporter mobility	0.317***	0.520***	-0.203***
	(0.103)	(0.127)	(0.055)
Δ log exporter mobility × log N suppliers	-0.015	-0.038*	0.023**
	(0.017)	(0.020)	(0.010)
N	535,677	535,677	535,677
R^2	0.101	0.101	0.076

Note: Standard errors are clustered at the exporter-time level and importer-time level. *** p<0.01, ** p<0.05, * p<0.1. This table replicates the results in Table 1 Panel A Columns (1)–(3) with interactions. In Panel A, the mobility variables are interacted with a dummy capturing a high number of exporter cities in 2018-2019 (above the in-sample median of 63). In Panel B, the interaction is with the log of the number of exporter cities in 2018-2019 for each importer-product. For a summary of statistics of variables, see Appendix Table A6 for details.

B.2.2 Additional Heterogeneity

Results are shown in Table B8. Panel A Columns (1) and (2) investigate the role of upstreamness. First, the impact of the change in importer mobility on quantity is smaller for goods that are more upstream. This is consistent with the possibility that the income effect is smaller for upstream goods. For example, a local factory in Colombia imports raw materials from the international market, and even with an increase in labor cost due to the pandemic, it is unlikely for them to cut back on material input. Second, upstream goods tend to be more homogeneous and, therefore, easier to substitute for importers. This may be reflected by the positive interaction between the upstreamness indicator and exporter mobility. Columns (3) and (4) explore price stickiness. As expected, the price adjustments when faced with a shock in exporter mobility is smaller for goods with higher price stickiness.

In Panel B Columns (1) and (2), we interact the shocks with the inventory intensity measured by inventory-to-sales ratios in the US. While in our model, we don't discuss the month-to-month dynamics of inventory adjustment, empirically, the importers may smooth their importing activities depending on their inventory conditions. We do find a larger impact of importer mobility on quantity, suggesting that for goods with a higher inventory-to-sales ratio, the importers reacted more strongly to a local Covid shock (potentially through the income effect), given their ability to deplete their inventory in the current period (and restock in the next period). Columns (3) and (4) explore the heterogeneous effects of differentiated vs homogeneous products. We find that negative importer mobility shocks reduced importer quantities by more when the product is differentiated. In the presence of an income effect, this may be expected, as consumers may more easily cut back on their spending on differentiated goods when the income declines if differentiated goods are also the ones with longer quality ladders.

Table B8: The Impact of Exporter and Importer Mobility on Trade Outcomes, by Product Characteristics

Panel A	(1)	(2)	(3)	(4)
Product characteristic (C):	Upstreamness		Price stickiness	
Dependent variable:	Δ log quantity	Δ log price	Δ log quantity	Δ log price
Δ log importer mobility	0.402***	0.016	0.271***	0.018
	(0.071)	(0.051)	(0.075)	(0.046)
Δ log importer mobility × C	-0.122*	-0.033	0.262***	0.042
	(0.065)	(0.037)	(0.069)	(0.042)
Δ log exporter mobility	0.366***	-0.101**	0.359***	-0.109***
	(0.125)	(0.044)	(0.116)	(0.042)
Δ log exporter mobility × C	0.070***	0.017	0.030	0.042*
	(0.025)	(0.016)	(0.036)	(0.022)
N	530,366	530,366	486,894	486,894
R^2	0.100	0.076	0.098	0.075
Panel B	(1)	(2)	(3)	(4)
Product characteristic (C):	Inventory intensity		Differentiated	
Dependent variable:	Δ log quantity	Δ log price	Δ log quantity	Δ log price
Δ log importer mobility	0.396***	0.030	0.238***	0.083
	(0.072)	(0.050)	(0.074)	(0.056)
Δ log importer mobility × C	0.137**	0.013	0.264***	-0.092*
	(0.056)	(0.034)	(0.097)	(0.051)
Δ log exporter mobility	0.353***	-0.123***	0.359***	-0.093*
	(0.125)	(0.042)	(0.121)	(0.048)
Δ log exporter mobility × C	-0.033	0.023	-0.011	-0.014
	(0.029)	(0.024)	(0.052)	(0.026)
N	524,115	524,115	537,100	537,100
R^2	0.100	0.075	0.101	0.076

Note: Standard errors are clustered at the exporter-time level and importer-time level. *** p<0.01, ** p<0.05, * p<0.1. This table replicates the results in Table 1 Panel A Columns (1)–(3), by interacting the importer and exporter mobility with different product characteristics. The upstreamness measure is from Antras et al. (2012), the price stickiness measure is from Nakamura and Steinsson (2008), the inventory intensity measure is from Fajgelbaum et al. (2020), and the dummy for differentiated goods is from Rauch (1999).

B.2.3 Congestion Controls

We construct two empirical measures to proxy for the potential congestion forces. First, we construct a "supply-side" congestion variable to capture an increase in marginal costs when an exporter faces a positive demand shock originating from its competitors' failure to produce due to their local Covid outbreak. Second, we construct a "demand-side" congestion variable to capture a decrease in world demand for a product when all potential importers experience more severe local Covid outbreaks. Given the fact that we don't observe the city-to-city trade flows across the world before the pandemic, we use country-level trade flows to construct these measures.

An exporter serving two locations may see an increase in demand from one of them, and given it cannot expand its capital, the result is higher marginal costs of production and prices for both importing locations. This is the first, supply-side source of congestion, which we proxy as follows:

$$\hat{S}_{ckt} = \sum_{\tilde{c} \in C|c} s^{2018}_{X,\tilde{c}k} \hat{x}_{\tilde{c}t}, \tag{27}$$

where $s^{2018}_{X,\tilde{c}k}$ are the exporter share of country $\tilde{c}$ in world trade of product k in 2018, and $\hat{x}_{\tilde{c}t}$ is the country-level mobility change at t.[60] We interpret a decrease in this measure as an indication of an increase in demand for exporter j, conditional on the pandemic shock at that location.[61]

Suppose only two locations import a given product and one of them experiences a mobility shock associated with the pandemic. The effect on the importing price and demand of the other location depends on the nature of the shock—e.g., whether the income or substitution effect dominates. We proxy for this mechanism as follows:

$$\hat{D}_{ckt} = \sum_{\tilde{c} \in C|c} s^{2018}_{M,\tilde{c}k} \hat{x}_{\tilde{c}t}, \tag{28}$$

where $s^{2018}_{M,\tilde{c}k}$ are the importer share of country $\tilde{c}$ in world trade of product k in 2018.

In Table B9, we estimate the baseline (Table 1 Panel A Columns 1–3) and include the demand and supply congestion proxy variables. We have two main findings. First, the coefficient estimates of the exporter and importer mobility are very close to the baseline without congestion. Second, while the supply-side congestion measure has no statistically significant effects, the demand-side congestion variable has a negative impact on the quantity and total value, indicating that when all other potential importers experience a negative Covid shock, the world demand declines, which eases the congestion in production. In this case, more trade takes place between the exporter i and the importer j.

[60] Mobility data is at the country level from Google since to generate country-level mobility measures from the Facebook/Baidu data, we need to use population in subnational regions as weights, but the population data is not readily available. Trade shares are constructed using UN Comtrade data.

[61] In terms of the model, the degree to which demand shifts due to congestion shocks depends on η^K.

Table B9: The Impact of Exporter and Importer Mobility on Trade Outcomes, With Congestion Controls

	(1)	(2)	(3)
Dependent variable:	Δ log Value	Δ log Quantity	Δ log Price
Δ log importer mobility	0.397***	0.350***	0.046
	(0.073)	(0.073)	(0.052)
Δ log exporter mobility	0.404***	0.528***	-0.124***
	(0.094)	(0.124)	(0.045)
Congestion, demand side	-2.049***	-1.743***	-0.306
	(0.351)	(0.339)	(0.230)
Congestion, supply side	0.095	0.063	0.032
	(0.222)	(0.234)	(0.118)
N	486,090	486,090	486,090
R^2	0.106	0.107	0.080

Note: Robust standard errors clustered at the exporting-time level and importer-time level. *** p<0.01, ** p<0.05, * p<0.1. Exporting country-main port of entry-time fixed effects and product-time fixed effects are included in all columns. This table replicates Table 1 Panel A Columns (1)–(3) by adding the demand side and supply side congestion variables.

B.2.4 Interaction of Exporter and Importer Mobility

In Table B10, we replicate Table B5 Panel A and include an interaction term between the exporter and importer mobility shock variables.

We find that the interaction between the two mobility shocks is statistically significant for intermediate goods, negative for quantity, and positive for prices. This means that the marginal effect on quantities and prices of both shocks increased in magnitude when there was a shock at the other end of the supply chain when evaluated at the mean exporter and importer mobility changes. The interaction effects for consumption goods and capital goods also have the same signs, although not always statistically significant.

Table B10: The Impact of Exporter and Importer Mobility on Trade Outcomes, Including the Interaction

Dependent Variable:	(1) Δ log value	(2) Δ log quantity	(3) Δ log price
Δ log importer mobility × consumer	0.315**	0.209	0.107
	(0.152)	(0.164)	(0.084)
Δ log importer mobility × intermediates	0.379***	0.313***	0.066
	(0.087)	(0.108)	(0.064)
Δ log importer mobility × capital	0.392***	0.342***	0.050
	(0.119)	(0.130)	(0.068)
Δ log exporter mobility × consumer	-0.439***	-0.388**	-0.051
	(0.131)	(0.154)	(0.080)
Δ log exporter mobility × intermediates	0.197*	0.228*	-0.031
	(0.117)	(0.131)	(0.053)
Δ log exporter mobility × capital	0.364**	0.148	0.216***
	(0.157)	(0.177)	(0.070)
Δ log importer mobility × Δ log exporter mobility × consumer	-0.957***	-1.087***	0.131
	(0.252)	(0.273)	(0.122)
Δ log importer mobility × Δ log exporter mobility × intermediate	-0.226	-0.448*	0.222**
	(0.214)	(0.260)	(0.109)
Δ log importer mobility × Δ log exporter mobility × capital	0.035	-0.452	0.487***
	(0.263)	(0.341)	(0.148)
N	533,312	533,312	533,312
R^2	0.100	0.101	0.077

Note: Robust standard errors clustered at the exporting-time level and importer-time level. *** p<0.01, ** p<0.05, * p<0.1. Exporting country-main port of entry-time fixed effects and product-time fixed effects are included in all columns. This table replicates Table B5 Panel A by interacting the importer mobility and the exporter mobility, by product categories (consumer goods, intermediate goods, and capital goods).

B.2.5 Exporter-Importer Links

In this section, we explore the impact of exporter and importer mobility changes on the probability of observing trade at the exporter-importer-product level in a given month. Specifically, we estimate the following linear probability model in differences:

$$\hat{I}_{ijkt} = \beta^J \hat{x}^J_{jt} + \beta^I \hat{x}^I_{it} + \delta^{P,E}_{kt} + \delta^{Tr,E}_{cut} + + \varepsilon^E_{ijkt}, \tag{29}$$

where $\hat{I}_{ijkt} = I_{ijk,t} - I_{ijk,Feb20}$ is the difference of an indicator that takes the value of one if we observe a flow at the exporter-importer-product-time level. As with the baseline, we take the difference against February 2020, and thus the dependent variable can take three values, -1, 0, and 1.

Table B11 Column 1 presents the results for the baseline estimations. Both a reduction in exporter mobility and a reduction in importer mobility change reduced the export participation in Colombian import markets at the product level. A 10% larger decline in importer mobility led to a 0.4% larger decline in the probability of trade, and a 10% larger decline in importer mobility led to a 0.2% larger decline in the probability of trade. Column 2 controls for congestion variables and finds no differences in the mobility coefficients. We find similar

effects of the demand-side congestion effect to the intensive margin and some evidence of the supply-side congestion effect. A negative supply-side congestion measure captures a decline in the world supply due to producer Covid outbreaks, and we find that this reduces the probability of trade between exporter i and importer j, since exporter i experiences congestion in production when faced with (redirected) world demand. Finally, we included the interaction between exporter and importer mobility shocks in Column 3, and we find a negative effect, indicating a reinforcement effect of disruptions on the importer and the exporter side, similar to the one in the intensive margin. However, the effect is statistically insignificant.

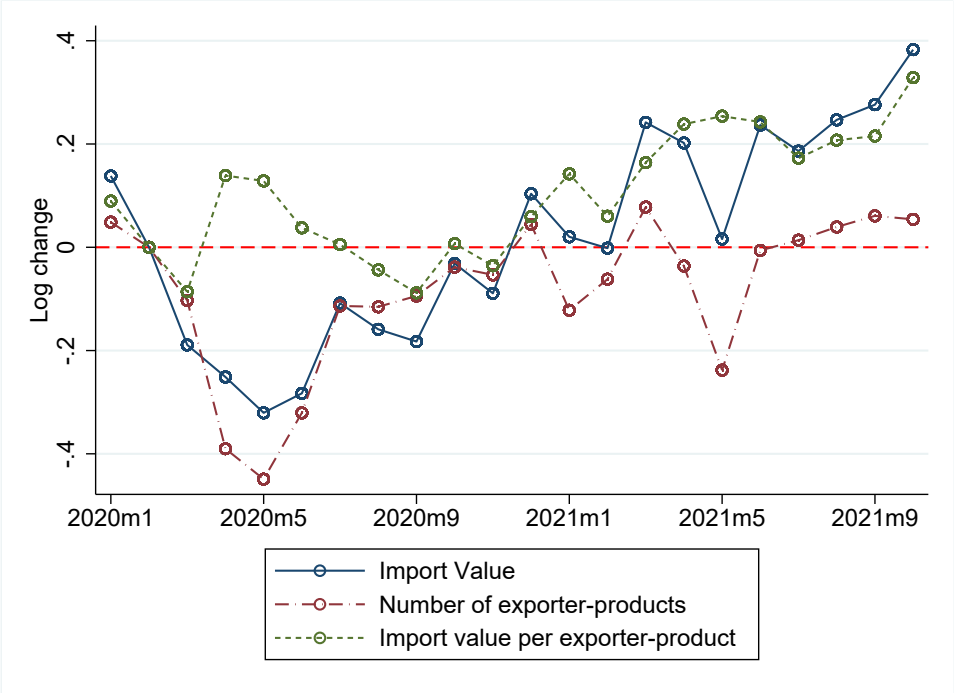
Table B11: The Impact of Importer Mobility and Exporter Mobility on Exporter-Importer Links

	(1) Baseline	(2) Congestion	(3) Interaction
Δ log importer mobility	0.039***	0.036***	0.038***
	(0.005)	(0.006)	(0.005)
Δ log exporter mobility	0.021***	0.034***	0.019**
	(0.007)	(0.007)	(0.008)
Congestion, demand side		-0.082***	
		(0.017)	
Congestion, supply side		0.017*	
		(0.010)	
Δ log Export mobility $\times$ Δ log importer mobility			-0.003
			(0.017)
N	10,888,687	9,576,408	10,888,687
R^2	0.012	0.013	0.012

Note: Robust standard errors clustered at the exporter-time and importer-time level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. OLS regressions at exporter, importer, product, and time level, where time is at the monthly frequency. The dependent variable is the dummy of whether a trade flow happened in this period minus the dummy for the baseline period, February 2020. Exporting country-main port of entry-time, and product-time fixed effects are included in all columns.

One thing to note is that overall adjustments during the pandemic in the form of observing positive trade at the exporter-importer-product level were relatively small, with an average change in trade probability of -1.2%. As shown in Figure B4, while at the beginning of the pandemic, the changes in Colombian imports were mainly driven by the decline in the number of exporter products at the importer level, since July 2020, the trade dynamics were mostly driven by the average export value. In other words, we don't observe substantial reconstructions in the supply chain linkage during the pandemic over the two-year period, suggesting that both the demand side and the supply side viewed the pandemic as a short or medium-run shock, rather than a long-run shock.

Figure B4: Changes in Log Imports, Log Number of Exporter-products and Log Imports per Exporter-Product Relative to February 2020



Note: Import values and the number of exporter-products are computed at the importer city-month level. Each dot is a log change at period t in the respective variable relative to February 2020.

B.3 Robustness of Results in the Transportation Sector

B.3.1 Variation in Port Performance and Freight Costs

Figure B5 Panel (a) shows the distribution of country-level changes in the log number of hours each ship spend in port in the post-Covid time (March 2020 to October 2021). The distribution is spread out, ranging from -0.4 to 0.6, and more N are having a positive change than negative changes. This is consistent with the aggregate trend in Figure 2 Panel (c). In addition, as shown in Figure B5 Panel (c), the positive changes are concentrated in 2021.

Panels (b) and (d) present the distribution of changes in the log number of port calls in the post-Covid time. Note that the baseline time is February 2020. As noted in Figure 2 Panel (a), the aggregate number of port calls is the lowest in February in all three years (2019, 2020, and 2021). This is likely to be driven by the fact that the Chinese New Year is usually in late January and late February, and the number of port calls made in Chinese ports is small in this time.[62] Panel (b) shows that the distribution is spread out, ranging from -0.4 to 0.65, and Panel (c) shows that the 2021 distribution is to the left of the 2020 distribution. This is consistent with the overall trend in Figure 2 Panel (a), where we observe a decline in the number of port calls since June 2021.

Figure B6 presents the variation in the changes in freight costs. Panels (a) and (c) show the distribution of the change in log freight cost per unit, and (b) and (d) for the change in

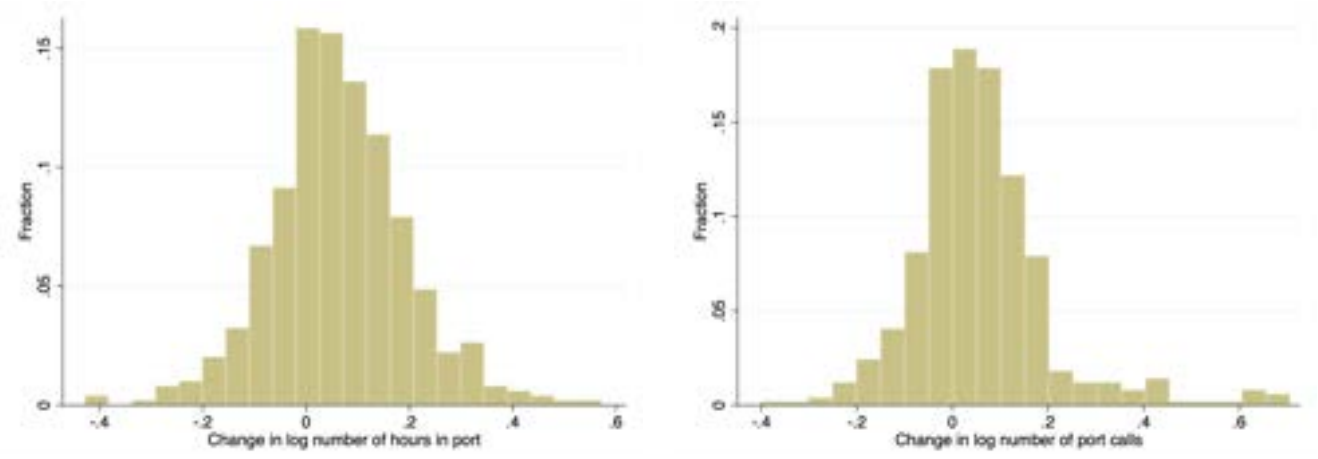
[62] An alternative way of measuring the changes is to use the monthly average in 2019 as the baseline. Our regression results are robust to using this alternative measure.

log freight cost per weight. The top and bottom one percent of the N are dropped for both variables.[63] In both cases, there are more N with positive changes, indicating an increase in the freight cost. In addition, the positive changes are more prominent in 2021 than in 2020.

Figure B5: Histograms of Country-Level Port Performance Variations

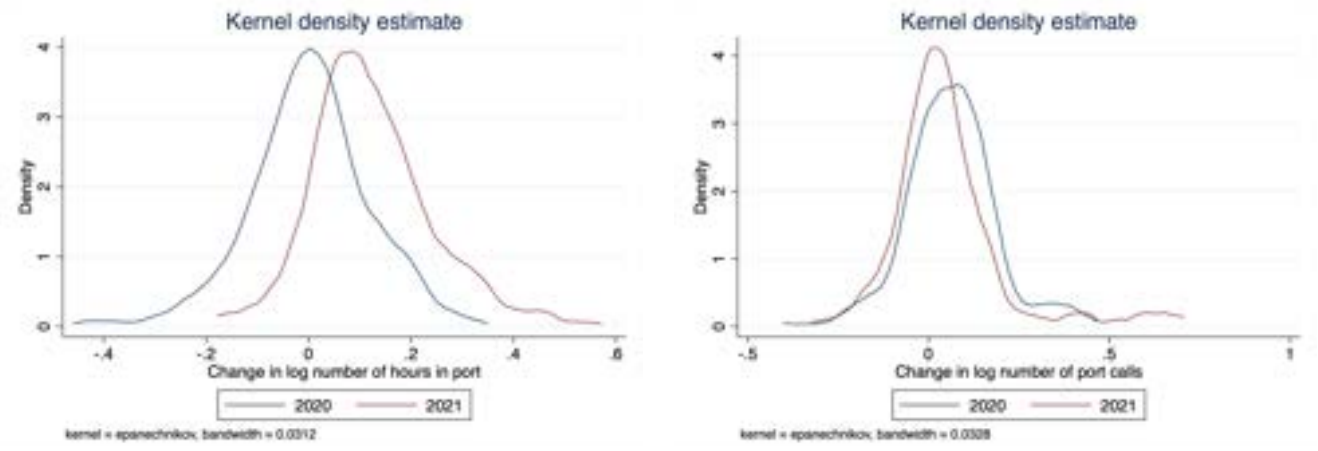
(a) Changes in log number of hours in port March 2020 to October 20201

(b) Changes in log number of port calls March 2020 to October 20201



(c) Changes in log number of hours in port 2020 versus 2021

(d) Changes in log number of port calls 2020 versus 2021

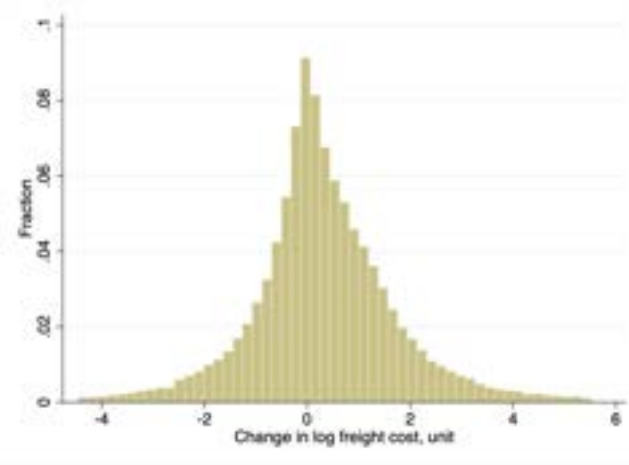


Note: Panels (a) and (b) are the histograms of the changes in port performance in the post-Covid time (March 2020 to October 2021), compared to February 2020. Panels (c) and (d) show the variation in 2020 and 2021 separately, using kernel densities.

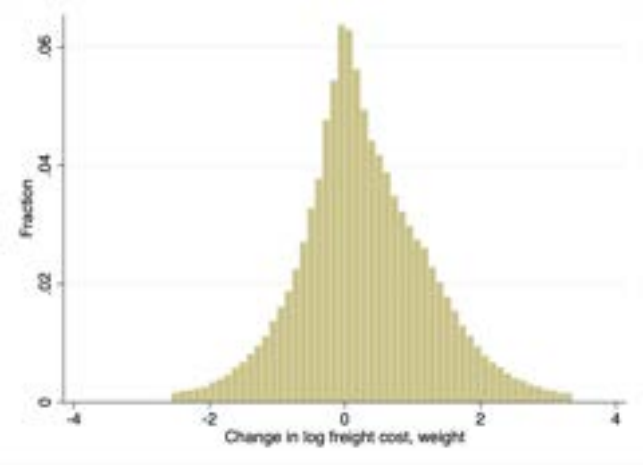
[63] Our regression results are robust to keeping all N.

Figure B6: Histograms of Product-Level Freight Cost Variations

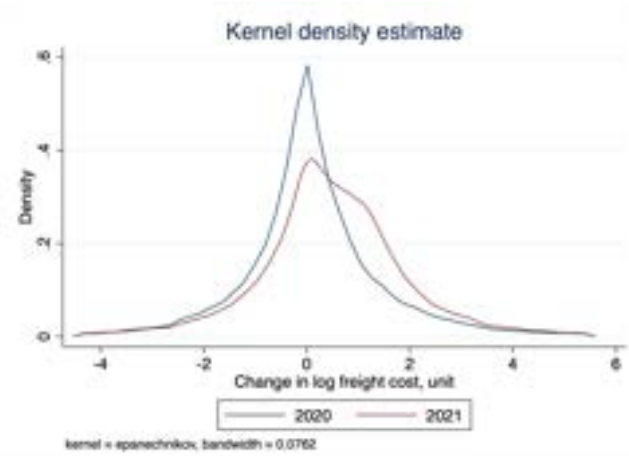
(a) Changes in log freight cost, unit March 2020 to October 20201



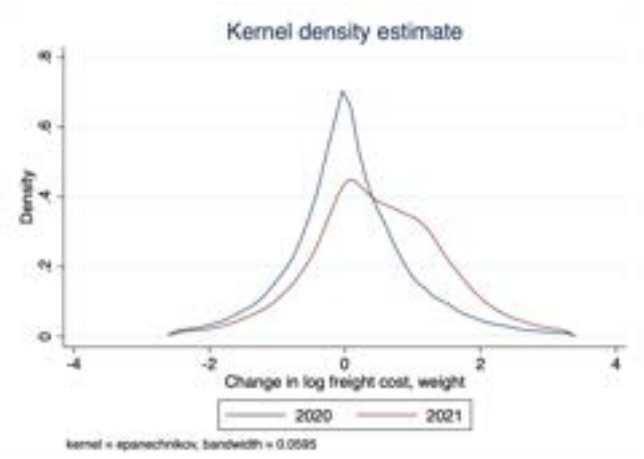
(b) Changes in log freight cost, weight March 2020 to October 20201



(c) Changes in log freight cost, unit 2020 versus 2021



(d) Changes in log freight cost, weight calls 2020 versus 2021

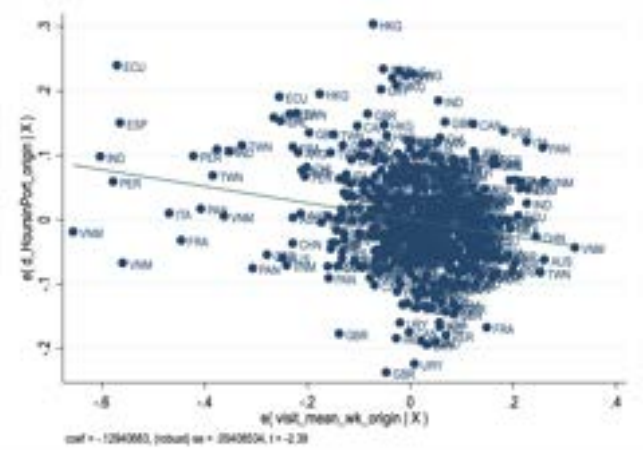


Note: Panels (a) and (b) are the histograms of the changes in log freight cost in the post-Covid time (March 2020 to October 2021), compared to February 2020. Panels (c) and (d) show the variation in 2020 and 2021 separately, using kernel densities. Panels (a) and (c) do not include the changes in log freight costs (unit) in the top 1% and the bottom 1% of the distribution. Panels (b) and (d) do not include the changes in log freight costs (weight) in the top 1% and the bottom 1% of the distribution.

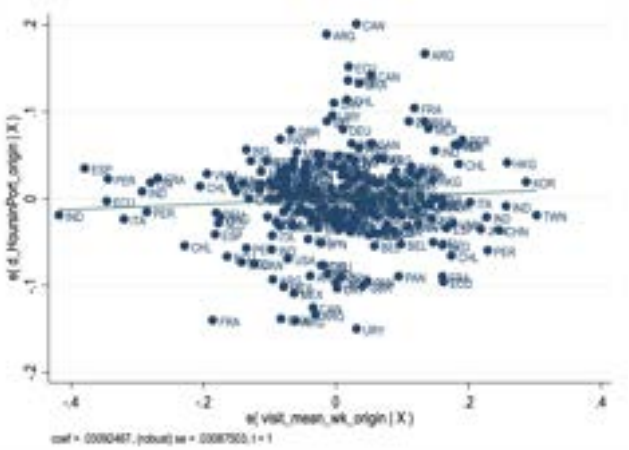
B.3.2 Residual Plots of Port Performance Results

Figure B7: The Impact of Exporter Country Port Mobility Changes on Port Performance, Residual Plots for the Post-Covid Time and the Pre-Covid Time

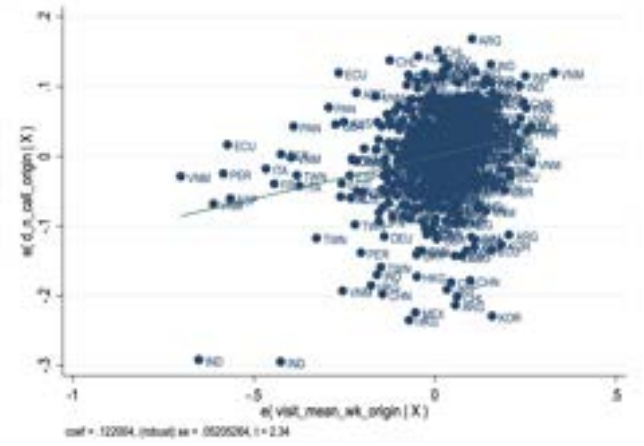
(a) Hours in port, 2020 and 2021



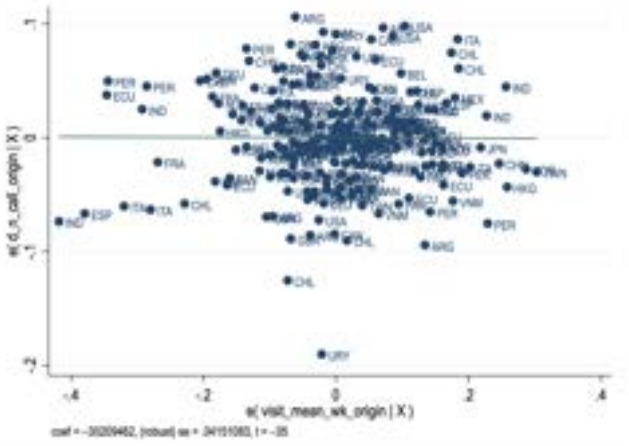
(b) Hours in port, 2018 and 2019



(c) Number of port calls, 2020 and 2021



(d) Number of port calls, 2018 and 2019

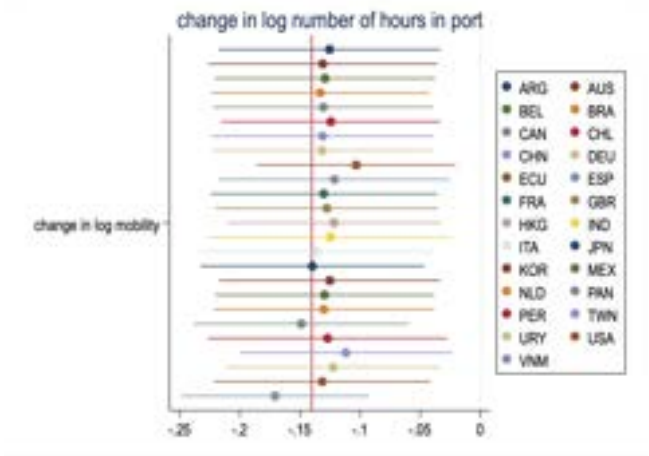


Note: Panel (a) is the residual plot for the results in Table 3 Panel A Column (1), and Panel (b) is the residual plot for Panel B Column (1). Panels (c) and (d) are the residual plots for the results in Table 3 Column (3) in Panels A and B, respectively.

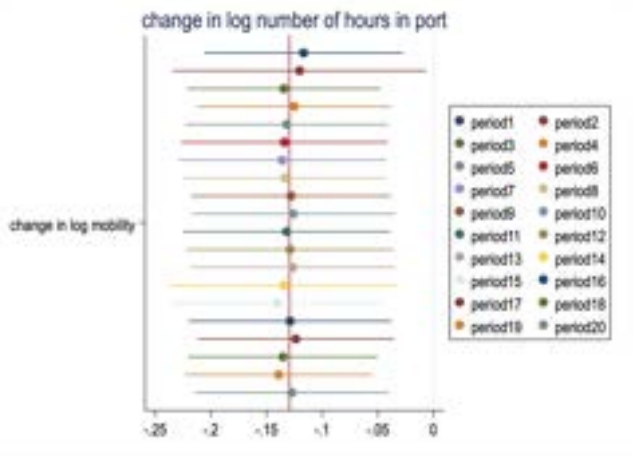
B.3.3 Robustness of Port Results When Dropping Countries and Periods

Figure B8: Robustness of Country-Level Results in Table 3, the Impact of Mobility Changes on Port Performance, Dropping One Country at a Time and Dropping One Period at a Time

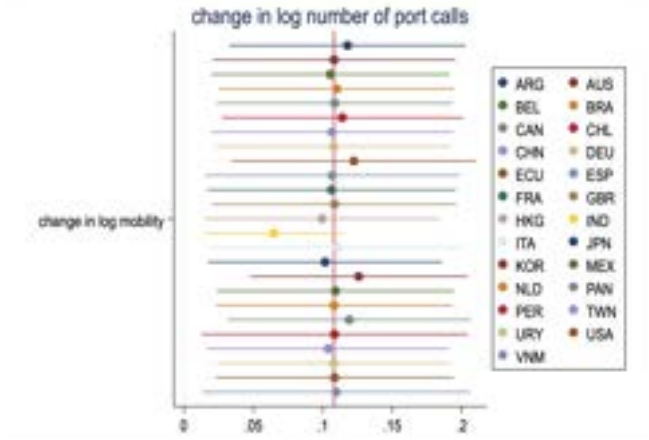
(a) Hours in port, drop country



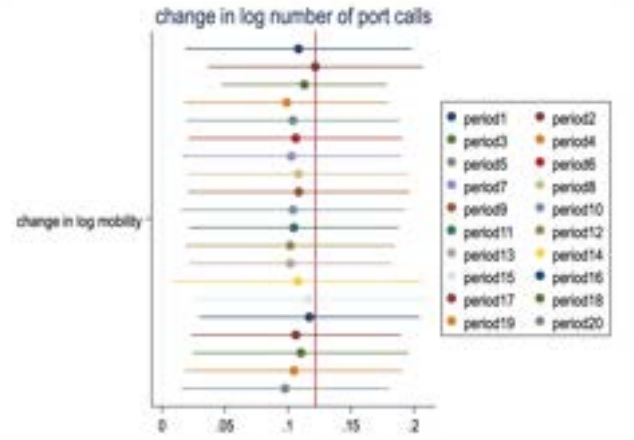
(b) Hours in port, drop period



(c) Number of calls, drop country



(d) Number of calls, drop period



Note: Panel (a) plots the coefficients when replicating results in Table 3 Panel A Column (1) and dropping one country at a time, and Panel (b) plots the coefficients when dropping one time at a time. Panel (c) plots the coefficients when replicating results in Table 3 Panel A Column (3) and dropping one country at a time, and Panel (d) plots the coefficients when dropping one period at a time.

B.3.4 Robustness of Freight Cost Results with Alternative Measures and Controls

Table B12: The Impact of Port Mobility in the Exporter Country on Freight Cost, Unit and Weight

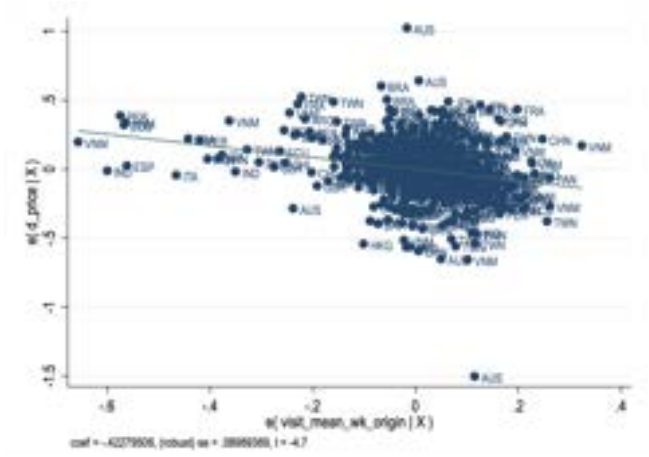
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable: 2020 and 2021	Δ log freight cost, unit				Δ log freight cost, weight			
Δ log mobility, exporter country ports	-0.25**	-0.25**	-0.29**	-0.53**	-0.30***	-0.30***	-0.34***	-0.57***
	(0.11)	(0.11)	(0.12)	(0.20)	(0.10)	(0.10)	(0.11)	(0.18)
I (year=2021)	0.51***		0.51***	0.54***	0.55***		0.55***	0.58***
	(0.08)		(0.08)	(0.08)	(0.07)		(0.07)	(0.07)
Time trend		0.04***				0.05***		
		(0.01)				(0.01)		
Constant	0.02	-0.17**	0.01	-0.04	-0.04	-0.25***	-0.05	-0.09*
	(0.05)	(0.07)	(0.05)	(0.06)	(0.04)	(0.07)	(0.04)	(0.05)
N	245,995	245,995	239,425	245,991	245,995	245,995	239,425	245,991
R^2	0.11	0.11	0.16	0.11	0.15	0.15	0.20	0.16
Panel B (Placebo)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable: 2018 and 2019	Δ log freight cost, unit				Δ log freight cost, weight			
Δ log mobility, exporter country ports	0.04	0.02	0.03	0.03	-0.01	0.00	-0.02	-0.04
	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)
I (year=2019)	0.02**		0.03**	0.03**	0.03**		0.03**	0.04**
	(0.01)		(0.01)	(0.01)	(0.01)		(0.01)	(0.01)
Time trend		0.00				0.00*		
		(0.00)				(0.00)		
Constant	0.04***	0.03***	0.04***	0.03***	-0.03***	-0.03**	-0.03***	-0.03***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	261,967	261,967	255,881	261,966	261,967	261,967	255,881	261,966
R^2	0.09	0.09	0.14	0.09	0.11	0.10	0.15	0.11
Month FE	Yes	Yes			Yes	Yes		
Product FE	Yes	Yes		Yes	Yes	Yes		Yes
Exporter country FE	Yes	Yes	Yes		Yes	Yes	Yes	
Product-month FE			Yes				Yes	
Country-month FE				Yes				Yes

Note: Standard errors are clustered at the product level and at the exporting country level. *** p<0.01, ** p<0.05, * p<0.1. This table shows the robustness of Results in Table 4 by using different freight cost measures and different fixed effects. Panel A Columns (1) and (2) replicate Table 4 Columns (1) and (2), and Panel B Columns (1) and (2) replicate Table 4 Columns (3) and (4). In Panel A, The mean (s.d.) of the change in log freight cost by unit is 0.31 (1.38), and 0.28 (0.96) by weight. The mean (s.d.) of the change in log mobility is -0.14 (0.18) in the exporter country. In Panel B, The mean (s.d.) of the change in log freight cost by unit is 0.05 (1.37), and -0.01 (0.90) by weight. The mean (s.d.) of the change in log mobility is -0.14 (0.18) in the exporter country.

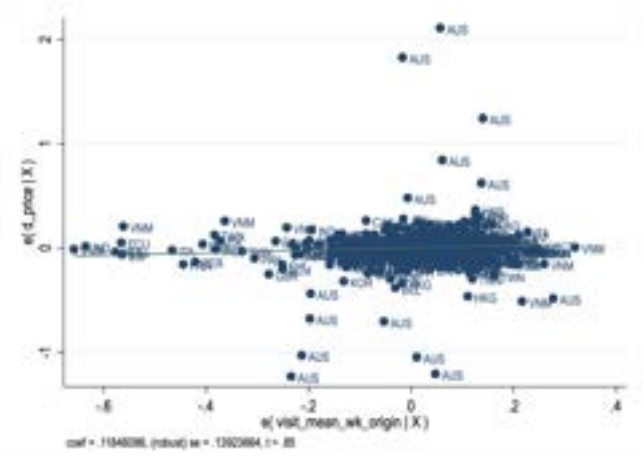
B.3.5 Residual Plots of Freight Costs

Figure B9: The Impact of Exporter Country Mobility Changes on Freight Costs, Residual Plots for the Post-Covid Time and the Pre-Covid Time

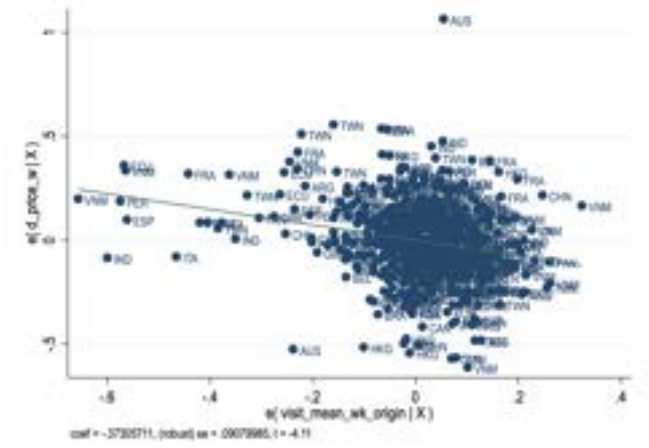
(a) Freight cost, unit, 2020 and 2021



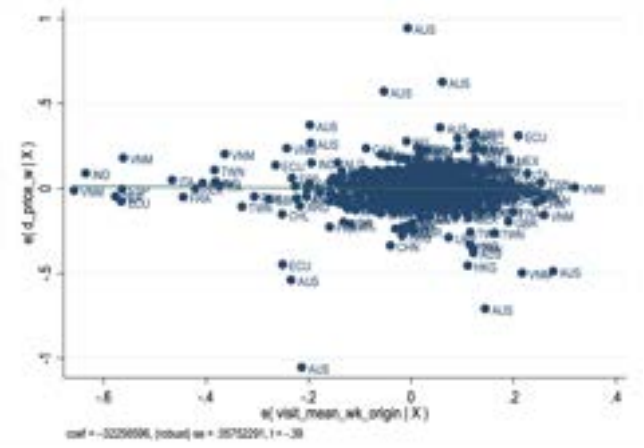
(b) Freight cost, unit, 2018 and 2019



(c) Freight cost, weight, 2020 and 2021



(d) Freight cost, weight, 2018 and 2019



Note: Panel (a) is the residual plot for the results in Table 3 Panel A Column (1), and Panel (b) is the residual plot for Panel B Column (1). Panels (c) and (d) are the residual plots for the results in Table 3 Column (3) in Panels A and B, respectively.

B.3.6 Robustness of Freight Costs Results Without Dropping Outliers

Table B13: The Impact of Port Mobility on Freight Costs, Without Dropping the Top 1% and the Bottom 1%

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome: 2020 and 2021	Δ log freight cost, unit				Δ log freight cost, weight			
Δ log mobility change	-0.31**	-0.31**	-0.35***	-0.62***	-0.34***	-0.34***	-0.37***	-0.63***
	(0.11)	(0.11)	(0.12)	(0.21)	(0.10)	(0.10)	(0.11)	(0.17)
I (year=2021)	0.57***		0.57***	0.60***	0.60***		0.60***	0.63***
	(0.08)		(0.08)	(0.08)	(0.07)		(0.07)	(0.07)
Time trend		0.05***				0.05***		
		(0.01)				(0.01)		
Constant	-0.02	-0.23***	-0.02	-0.08	-0.07	-0.29***	-0.07	-0.12**
	(0.05)	(0.08)	(0.05)	(0.06)	(0.04)	(0.07)	(0.04)	(0.05)
N	255,346	255,346	248,813	255,342	255,346	255,346	248,813	255,342
R^2	0.12	0.12	0.16	0.12	0.15	0.15	0.19	0.16
Panel B (Placebo)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome: 2018 and 2019	Δ log freight cost, unit				Δ log freight cost, weight			
Δ log mobility change	0.05	0.02	0.04	0.03	-0.02	-0.00	-0.03	-0.04
	(0.04)	(0.05)	(0.04)	(0.05)	(0.03)	(0.04)	(0.03)	(0.05)
I (year=2019)	0.02*		0.03*	0.03**	0.03**		0.03**	0.03**
	(0.01)		(0.01)	(0.01)	(0.01)		(0.01)	(0.02)
Time trend		0.00				0.00		
		(0.00)				(0.00)		
Constant	0.05***	0.04**	0.05***	0.04***	-0.02***	-0.03*	-0.02***	-0.03**
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	271,942	271,942	265,877	271,942	271,942	271,942	265,877	271,942
R^2	0.11	0.10	0.15	0.11	0.11	0.11	0.16	0.12
Month FE	Yes	Yes			Yes	Yes		
Product FE	Yes	Yes		Yes	Yes	Yes		Yes
Exporter country FE	Yes	Yes	Yes		Yes	Yes	Yes	
Product-month FE			Yes				Yes	
Country-month FE				Yes				Yes

Note: Robust standard errors are clustered at the product level and at the exporting country level. *** p<0.01, ** p<0.05, * p<0.1. This table replicates Table B12 by not dropping the top 1% and the bottom 1% of the outcome variable. The mean (s.d.) of the change in log freight cost by unit is 0.43 (1.62), and 0.36 (1.1) by weight. The mean (s.d.) of the change in log mobility is -0.14 (0.18) in the exporter country.

B.3.7 Intermediate Ports

We measure the average mobility change in the first intermediate country $O1$ as

$$\Delta \log(\text{mobility}^{O1}_{cym}) = \sum_{o1} \frac{\text{prob}(o1(c))}{\sum_{o1'} \text{prob}(o1'(c))} \Delta \log(\text{mobility}^{\text{Ports}}_{o1(c)ym}), \tag{30}$$

where $\Delta \log(\text{mobility}^{Ports}_{o1(c)ym})$ is the change in mobility in country $o1$'s ports where the exporter country c makes the first stop in international shipping, year y, and month m, compared to the

pre-Covid period, and prob($o1(c)$) is the probability that the optimal route from country c to Colombia uses country $o1$ as the first intermediate stop. We compute the second intermediate country's mobility change similarly ($\Delta \log(\text{mobility}^{O2}_{cym})$), by using the probability of being the second stop. We also use similar weights to calculate the number of port calls and the number of hours in port in the first intermediate country and the second intermediate country.

Note that we use the country-level port averages since the Colombian trade data does not report the exporting or intermediate ports, but only the exporting countries. By taking the averages, we assume that in a country, a large port for all container trade is also a large port for trade with Colombia. If this assumption is violated, then we will have an attenuation bias.

Table B14: The Impact of Port Mobility in the Exporter Country and in the Intermediate Country on Freight Costs

	(1)	(2)	(3)
Dependent variable:	Δ log freight cost, unit		
Δ log mobility, exporter country	-0.25**		
	(0.11)		
Δ log mobility, first intermediate		-0.53***	
		(0.16)	
Δ log mobility, second intermediate			-0.72***
			(0.20)
I (year=2021)	0.51***	0.57***	0.69***
	(0.08)	(0.08)	(0.11)
Constant	0.02	-0.06	-0.16*
	(0.05)	(0.06)	(0.09)
N	245,995	245,995	245,995
R^2	0.11	0.11	0.11

Note: Standard errors are clustered at the product level and at the exporting country level. *** p<0.01, ** p<0.05, * p<0.1. All columns control for calendar month fixed effects, product fixed effects, and exporter country fixed effects. The mean (s.d.) of the change in log freight cost by unit is 0.31 (1.38). The mean (s.d.) of the change in log mobility is -0.14 (0.18) in the exporter country, -0.15 (0.16) for the first intermediate country, and -0.17 (0.20) for the second intermediate country.

We run the regressions for port performance measures and freight costs using measures for the first intermediate country mobility and the second intermediate country mobility. Table B14 shows the results for the impact of mobility changes in the exporter country and in intermediate countries on the freight costs. Column (1) replicates Table 4 Panel A Column (1), and Columns (2) and (3) use changes in mobility in the first and the second intermediate country, respectively. Interestingly, the effects are even larger for mobility declines in the intermediate ports. The results are robust to using freight cost by weight, as shown in Appendix Table B15.

Table B15: The Impact of Port Mobility in the Exporter Country and in the Intermediate Country on Freight Costs, Weight

	(1)	(2)	(3)
Dependent variable:	Δ log freight cost, weight		
Δ log mobility, exporter country	-0.30***		
	(0.10)		
Δ log mobility, first intermediate		-0.59***	
		(0.15)	
Δ log mobility, second intermediate			-0.76***
			(0.20)
I (year=2021)	0.55***	0.62***	0.74***
	(0.07)	(0.08)	(0.11)
Constant	-0.04	-0.12**	-0.23**
	(0.04)	(0.06)	(0.09)
N	245,995	245,995	245,995
R^2	0.15	0.15	0.15

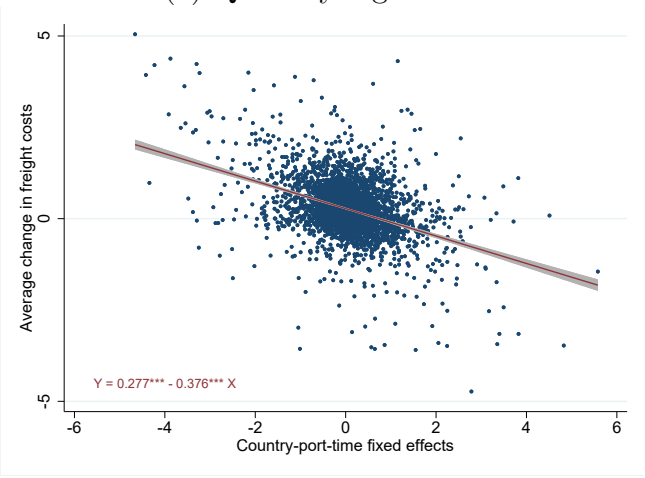
Note: Standard errors are clustered at the product level and at the exporting country level. *** p<0.01, ** p<0.05, * p<0.1. This table replicates Table B14 by replacing the outcome variable with the freight cost by weight. The mean (s.d.) of the change in log freight cost by unit is 0.28 (0.96) by weight. The mean (s.d.) of the change in log mobility is -0.14 (0.18) in the exporter country, -0.15 (0.16) for the first intermediate country, and -0.17 (0.20) for the second intermediate country.

B.4 Additional Contribution Results

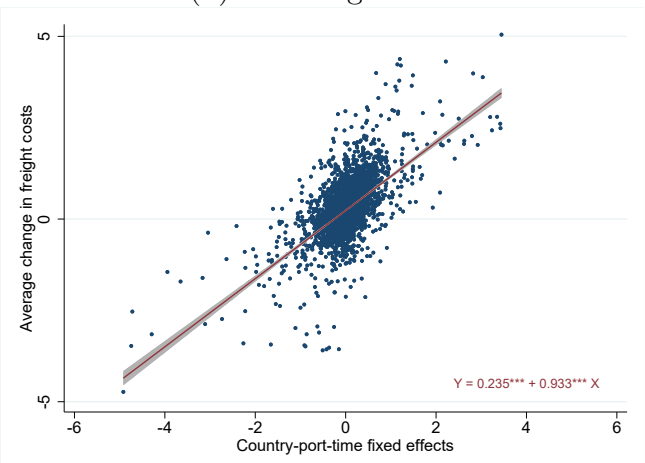
B.4.1 Correlation of Freight Costs and Country-Port-Time Fixed Effects

Figure B10: Correlation Between Average Changes in Freight Unit Values and Country-Port-Time Fixed Effects

(a) Quantity regression



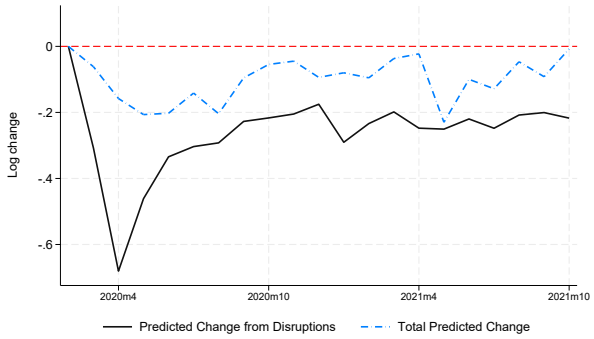
(b) Price regression



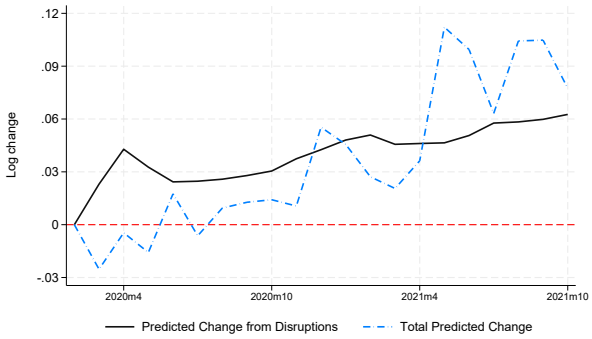
Note: Average changes in freight unit values are computed as averages over log changes in this variable relative to February 2020 in exporter and importer cities observed for each exporting country, product, and time. Country-port-time fixed effect estimates are from Table 1 Panel A Columns (2) (quantity regression) and (3) (price regression).

Figure B11: Average Predicted Changes in Import Quantities and Prices in Total, from Local Disruptions and Due to Other Structural Determinants. Weighted Average Using 2019 Imports.

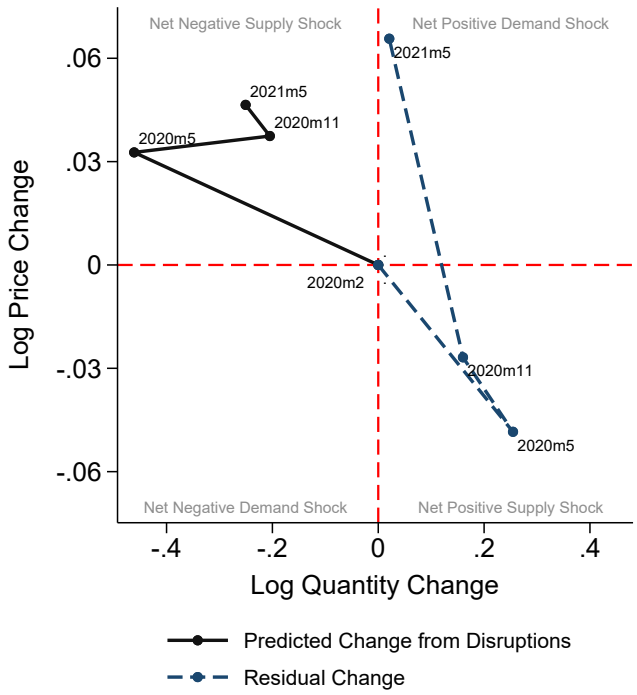
(a) Quantity



(b) Price



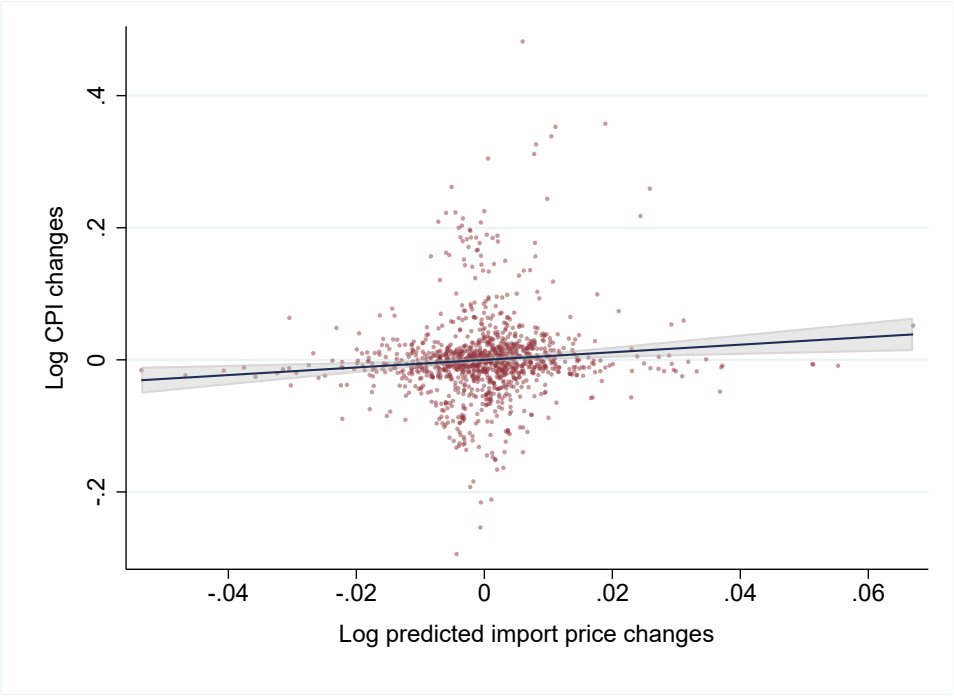
(c) Quantity x Price Changes



Note: Each data point is computed using estimates in Table 1 (exporter and importer disruptions), Table 4 (port disruptions and transportation freight trends), and month-specific in-sample weighted average changes in exporter, importer and port mobility. Month-specific weights are computed using exporter-importer-products-month Colombian imports in 2019.

B.5 Residual Plots of Inflation Regression

Figure B12: The Relationship Between Consumer Prices and Predicted Import Prices Changes due to Export Mobility Shocks, Residual Plot



Note: This figure is the residual plot for the result in Table 5 Column (3).

C Theory

C.1 Producer Problem

The representative firm selling k at i solves the following maximization problem:

$$\max_{\{p^X(j)\}\in\Omega^J} \int_{\Omega^J} p^X(j)q(j)dj - A\Big[\int_{\Omega^J} q(j)dj\Big]^{\alpha},$$

subject to $q(j) = (p^X(j)+t)^{-\sigma}(P^M)^{\sigma-1}Z(j)$, where I omitted subscripts i and k. The first order condition for $p^X(j)$ is as follows:

$$\begin{aligned}
q(j) + p^X(j)[-\sigma\frac{q}{p^M(j)}] - \alpha AC^{\frac{\alpha}{\alpha-1}}[-\sigma\frac{q}{p^M(j)}] &= 0 \\
-\frac{p^M(j)}{\sigma} + p^X(j) - \alpha AC^{\frac{\alpha}{\alpha-1}} &= 0 \\
-\frac{p^X(j)}{\sigma} - \frac{t}{\sigma} + p^X(j) - \alpha AC^{\frac{\alpha}{\alpha-1}} &= 0 \\
p^X(j)\frac{\sigma-1}{\sigma} &= \alpha AC^{\frac{\alpha}{\alpha-1}} + \frac{t}{\sigma} \\
p^X(j) &= \frac{\sigma}{\sigma-1}\alpha AC^{\frac{\alpha}{\alpha-1}} + \frac{1}{\sigma-1}t.
\end{aligned}$$