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Trade Disruptions Along the Global Supply Chain

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Abstract

In 2020, a pandemic generated by a novel virus caused a large and abrupt decline in world trade, only comparable within the last half-century to the great trade collapse during the 2008-09 financial crisis. This collapse followed naturally from the difficulty of locally producing, transporting, and consuming goods in the affected regions worldwide. In this paper, the authors study the impact of these disruptive local shocks on international trade flows during the COVID-19 pandemic. Using rich product-level import data from Colombia, we first show that import collapse at the onset of the pandemic was due to a decrease in import quantities, and the import recovery in later periods was partially explained by a rise in both foreign export prices and shipping costs. Using smartphone data tracking of local human mobility changes to identify local shocks, the authors decompose the trade effects into shocks originating from exporter cities, seaports, and importer cities. They find that while the decline in quantity was driven by both changes in exporter and importer shocks, the increase in price was entirely driven by exporter shocks. Using data on port calls made by container ships, they document a decline in port productivity during the pandemic. The authors show that mobility changes at port locations induced a decline in port efficiency and a rise in freight costs. They also document a positive correlation between product-level domestic inflation and mobility shocks to foreign exporters.

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Non-Technical Summary

In 2020, the pandemic generated by the SARS-CoV-2 virus caused one of the largest and most abrupt disruptions to world trade in the last century, comparable only to the trade collapse that followed the financial crisis in 2008. This collapse followed naturally from the difficulty of locally producing, transporting, and consuming goods in the affected regions worldwide. In this paper, we study the impact of these disruptive local shocks on international trade flows during the COVID-19 pandemic and its direct implications.

We characterise changes in trade and transportation by using import customs data from Colombia and shipping information from IHS Markit Maritime. We show that imports declined 35% on average in 2020 and recovered towards 2021, mainly due to increased export prices and transportation costs. In addition, we find that in late 2020 and 2021, the main 150 ports in the world processed fewer ships, with higher delays in terms of the number of hours per ship.

We then analyse the local impact of the pandemic, complementing the data mentioned above with human mobility data from Facebook for the 27 main trading partners of Colombia (excluding Venezuela) and Baidu in the case of China. These data record changes in human mobility at disaggregated geographic levels using geolocation from cell phones. We derive two structural equations for import quantities and prices using a simple trade model with exporters selling differentiated products by city of origin, importers with love for variety, and a transportation sector. We then map demand and supply shifters to the mobility indicators mediated by an empirical elasticity. The variation in the data we use for identification comes from shocks at different locations within each exporting country and the importing country, Colombia, for each month.

We find that a 10% reduction in observed mobility at the exporter's location during the pandemic reduced import quantities by an average of 3.5% and increased import prices by 1%. On the other hand, we find that importer mobility only affected import quantities and not import prices, reducing the former by 4.1% when importer mobility declines by 10%.

In order to estimate the impact on ports, we employ changes in mobility at ports' locations and construct country-level measures weighting each port by their importance in terms of tonnage processed. We find that a 10% reduction in the mobility indicator increased the average number of hours ships spent in ports by 1.3%, and decreased the number of ships processed by 1.1%. In addition, we found that a 10% reduction in the port mobility indicator was associated with a 2.5% increase in freight unit costs to Colombia.

Finally, we employ these results to perform two exercises. First, we use the model to decompose the direct impact of the pandemic on imports into a demand, supply, and transportation component. We find that the decline in import values was mainly explained by a demand contraction at the onset of the pandemic. Later, in 2021, the shock was mainly explained by increased transportation costs. In the second exercise, we estimate the pass-through from import prices to consumer prices. We found that 57% of an average change in import prices due to mobility shocks to exporters passed directly through to consumer prices in Colombia.

In conclusion, we showed that the pandemic had a significant negative impact on international trade. To do so, we employed rich trade, transport, and mobility data at a highly disaggregated geographical level to be able to study the disruptions close to where production, consumption, and transportation shocks occur.

Trade Disruptions Along the Global Supply Chain*

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Abstract

In 2020, a pandemic generated by a novel virus caused a large and abrupt decline in world trade, only comparable within the last half-century to the Great Trade Collapse during the 2008-09 Financial Crisis. This collapse followed naturally from the difficulty of locally producing, transporting, and consuming goods in the affected regions worldwide. In this paper, we study the impact of these disruptive local shocks on international trade flows during the COVID-19 pandemic. Using rich product-level import data from Colombia, we first show that import collapse at the onset of the pandemic was due to a decrease in import quantities, and the import recovery in later periods was partially explained by a rise in both foreign export prices and shipping costs. Using smartphone data tracking local human mobility changes to identify local shocks, we decompose the trade effects into shocks originating from exporter cities, seaports, and importer cities. We find that while the decline in quantity was driven by both changes in exporter and importer shocks, the increase in price was entirely driven by exporter shocks. Using data on port calls made by container ships, we document a decline in port productivity during the pandemic. We show that mobility changes at port locations induced a decline in port efficiency and a rise in freight costs. We also document a positive correlation between product-level domestic inflation and mobility shocks to foreign exporters.

Keywords: International trade, local shocks, COVID-19 pandemic, shipping costs, mobility, supply chain, inflation.

JEL codes: F10, F14, F16, I12, O18.

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1 Introduction

The flow of international trade depends on the ability to produce, transport, and consume goods at different locations globally. The Covid-19 pandemic generated disruptions in all three aspects (Baldwin and Tomiura, 2020). First, production capability was compromised by containment efforts, illness, and shifts in workers' preferences. Second, the transportation sector was hit by similar issues and also suffered from potential congestion when ports experienced reduced capacity due to lockdowns and subsequent disruptions in the transportation network. Finally, the demand for goods was likely affected by changes in present and future expected income, work modalities, and shifts in consumers' preferences. The result was a decline in the value of global trade of 2.17 trillion dollars in 2020— an 8.9% decline relative to 2019—only comparable within the last half-century to the 2009 trade collapse during the Financial Crisis when global trade declined 1.74 trillion dollars—a 9.9% decline relative to 2008.[1]

In this paper, we study the impact of local disruptions at different points of the supply chain on international trade in the context of Colombian imports to understand the role of demand, supply, and transport networks in driving the Pandemic trade dynamics. We combine three novel datasets: monthly trade data on Colombian imports, container ship port call data, and within-city human mobility data tracked by smartphones. First, we document the overall changes in trade and transportation outcomes over the pandemic. During 2020, import values declined due to a collapse of import quantities, while the recovery observed in 2021 was explained mostly by rising export and transportation prices. Second, we exploit information on the location of the exporter and importer along with local changes in human mobility to estimate the direct impact of disruptive shocks on Colombian imports. We find that disruptions to importers led to declines in quantities, whereas disruptions to exporters caused both a decrease in quantities and an increase in prices. Third, we estimate the impact of disruptions to the transportation sector by using the port performance and port-specific mobility declines, both in terms of direct labor cost increase and congestion. We find a decline in port productivity and an increase in freight costs in shipments going through them due to disruptions. With the help of a simple theoretical framework, we decompose the direct impact of the pandemic into exporter, importer, and transportation shocks. Initially, the import decline was explained mostly by shocks to importers, with the transportation sector explaining most of the decline towards 2021. Finally, we uncover a relationship between local disruption shocks at exporters' locations and the rise in inflation observed during the

[1]The subsequent recovery from 2009 to 2010 is 1.84 trillion dollars and 2.06 trillion dollars from 2020 to 2021. All in constant 2015 dollars, including both goods and services trade. Data source: `https://data.worldbank.org/`.

pandemic.

Colombia offers a unique opportunity to study 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 countries are not likely to be impacted by the demand and supply of goods in Colombia. Thus, it is reasonable to assume that the foreign mobility shocks are 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. Therefore, Colombia provides an ideal laboratory to study the consequences of the pandemic on international trade.

Our paper uses highly granular data on mobility, trade flows, and maritime transportation. Our trade outcomes are monthly trade information collected by Colombian customs, which allows us to identify exporters and importers at the sub-national level (city or city-equivalent level). The monthly imports are by 6-digit HS product, exporter city, and importer city, with detailed information on quantities, import prices, export prices, and freight and insurance costs. On the transportation side, we obtain 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. Importantly, the number of hours in port can be used to measure port efficiency.

We use changes in within-city human mobility relative to the pre-pandemic baseline to measure shocks to local producers, consumers, and ports. The monthly changes in mobility in Colombia and its 27 major trading partners' cities are obtained from Facebook and Baidu. The mobility declines can be due to government restrictions, sickness, voluntary containment efforts, and business closures. At the exporter location and the seaports, we interpret the mobility changes as capturing a negative labor supply shock. At the importer location, the mobility change can capture shocks from these channels: (a) a negative income effect due to loss in income for households, (b) a substitution effect due to an increase in prices of domestic goods, and (c) a potential change in preferences.[3]

We start by documenting trends in trade during the pandemic. Colombian imports experienced a 40% initial decline, explained mainly by a collapse in import quantities, and subsequent recovery. Export prices remained relatively constant until the first quarter of 2021, when they started rising to reach an increase of about 12% above pre-pandemic trends in October 2021, the last month we include in the analysis. Shipping costs steadily rose since

[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/`.

[3]For intermediate goods, there are similar income and domestic substitution effects on firms.

September 2020 and reached an increase of 70% in October 2021. Overall, import prices were 18% above pre-trends in October 2021, with shipping costs directly contributing 40% to that increase.

We exploit variations in local Covid outbreaks and 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 the average importer mobility reduction lowered imports to that location by about 11%, whereas the average reduction at the exporter location decreased imports by 3%. When decomposing into quantity and prices, a 10% decline in mobility at the importer location led to a 4.1% decline in quantity and no impact on prices. A 10% decline in mobility at the exporter location led to a 3.5% decline in import quantity and a 1% increase in import prices.[4,5]

We also observe salient trends in seaport performance across the world. In 2020 and 2021, the maritime shipping volume was about 5-10% below the 2019 level and did not fully recover even by the end of our study period, in October 2021. This pattern holds when we use either the total number of port calls or the total ship size in 150 ports across 27 countries used in our study. In addition, the average hours in port experienced a steady increase since July 2020, with an about 25% increase in October 2021 compared to October 2019. This suggests that port productivity declined substantially during the period, with fewer ships being processed and longer delays in processing time at ports.

We then use the mobility changes in port cities, optimal shipping routes, and changes in freight costs to investigate the impact of the pandemic on sea shipping. We find that an average change in mobility induces a 2.2% increase in the hours in port at the exporting country. Furthermore, this change in mobility in the exporting country's ports also translated to a 4% increase in the freight cost. In addition, we find that 2021 had a larger number of hours in port and a higher freight cost than 2020, even after controlling for mobility changes. This is likely to reflect the accumulated effect of the pandemic through disruptions in trade patterns across the world and disruptions in domestic transportation services, such as shipment by trucks and railroads.

Combining a simple theoretical framework and the reduced-form estimates, we conduct three exercises. First, using the impact of exporter location mobility changes on quantity and prices, we back out the elasticity of substitution between varieties (i.e., exporter-product pairs). There are two key features of this elasticity of substitution that are different from the

[4]We focus on the intensive margin in our analysis. On the extensive margin, we find a small effect and a relatively fast recovery.

[5]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 entirely through quantities. In our setting, both quantities and prices reacted due to the nature of the shock — instead of changes in trade cost, our shock captures changes in economic fundamentals such as consumer income and producer costs.

literature: (1) the exporter location is 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 that the short-run elasticity of substitution between sub-national level exporters is 3.4.[6]

Second, we conduct a time series decomposition of the pandemic impact into exporter, importer, and transportation shocks. At the onset of the pandemic, 67% of the total impact on quantity was explained by disruptions at the importer location, 26% by disruptions at the exporter location, and the remaining 7% by disruptions at ports. All the initial increase in import prices was explained by disruptions at the exporter location. Towards the end of our sample, most of the decrease in import quantities and increase in import prices were explained by the linear increase in transport prices not directly related to local mobility changes.

Finally, we explore the relationship between product-level predicted changes in import prices due to exporter shocks and observed changes in domestic prices. Results suggest an immediate and direct pass-through from local foreign shocks to consumers of about 50%.

Our paper contributes to several strands of literature. First, the literature on the impact of local shocks on firms and 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). Our main difference with the literature is that while we do measure shocks at the local level, these local shocks are part of a *big global* shock, potentially affecting all entities of the economy across the world.[7] Second, we add to the literature on the impact of economy-wide shocks, including pandemics, wars, and financial crises. Using historical data, Jordà et al. (2022) find that compared to capital-destructing wars, pandemics induce labor shortages and affect the rate of returns on assets. Benguria and Taylor (2020) disentangles the supply-side and the demand-side aspects of financial crises, by combining a model with aggregate trends in international trade flows. Novy and Taylor (2020) points out that uncertainty induced by the financial crisis makes international trade more volatile than GDP. 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 impact of these shocks.

[6]Anderson and Yotov (2020) shows that the short-run trade elasticity is one-quarter of the long-term due to fixed bilateral capacities. In our case, since the elasticity of substitution between sub-national locations is likely to be higher than the one between countries, this will result in a larger estimate. Overall, these two forces seem to offset each other.

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

Our paper is closely related 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: the labor shortage at port cities. Second, although we also use container ship port call data, our objective is not on shipping routes. Instead, 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 reduce port productivity. In addition, we have the measure of the number of port calls and the number of hours each container ship spends at the ports around the world over multiple years, allowing us to document the changes in port performance. In contrast, the aforementioned two papers use a cross-section. Third, we have direct measures of freight costs, and we show how shocks to ports push up freight costs.

The international trade literature has traditionally modeled transport costs as an exogenous iceberg cost. However, early work by Hummels and Skiba (2004) showed that shipping prices are positively correlated with export prices. In light of it, recent papers endogenized the international transport sector by stressing the role of round-trips (Wong, 2022), networks effects (Brancaccio et al., 2020), and price discrimination (Ignatenko, 2020) for shipping prices and their impact on trade. We contribute to this literature by showing that shipping prices also react to local shocks at ports, providing further evidence of its endogeneity.

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 (Chetty et al., 2020; Coibion et al., 2020a,b).[8] 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). Alessandria et al. (2023) combines aggregate time-series data on the US economy and a general equilibrium model to study the impact of supply disruptions. A few papers use actual trade data to study the pandemic disruptions (Liu et al., 2021; Lafrogne-Joussier et al., 2022). However, they mainly focus on export 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

[8]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.

mobility at the sub-national level to causally estimate the impact of local pandemic shocks on international trade.[9]

The rest of the paper is organized as follows. Section 2 introduces the data and presents trade, transportation, and mobility changes 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 in seaports on port performance and freight unit values. Section 6 presents results on the decomposition of the pandemic effects over time. Section 7 shows the inflation results. Section 8 concludes.

2 Data and Descriptive Statistics

In this section, we present different data sets used in the analysis, document the variation of key measures over time and across locations, and present the most salient aggregate trends of trade disruptions in Colombia during the pandemic.

2.1 Trade Data

In this section, we characterize the monthly changes in Colombian import patterns from 2018 to 2021. To do so, we use data 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 information on the importer location, exporter location, 6-digit HS product codes, import values in US dollars, quantities, weights, and freight and insurance costs at the monthly frequency. 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.[10] 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.[11]

[9]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.

[10]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.

[11]We do not use all exporting countries because within-country exporter locations required extensive manual cleaning. Among the 27 exporting countries/regions, Argentina, Bolivia, Japan, 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.

We start by documenting total monthly imports from January 2018 to October 2021, relative to the pre-pandemic averages. To do so, we take the month-specific average total import value of 2018 and 2019 and use them to demean 2018–2021 imports. As shown in Figure 1, 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 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.

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:

$$M \equiv q + p^X + \tau, \tag{1}$$

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 (1) 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:

$$M_{ijkt} = \sum_{r=01/2020}^{10/2021} \delta^r \times \mathbb{1}\{t = r\} + \delta^{seas}_{ijkm} + \delta^{trend}_{ijk} \times t + \varepsilon_{ijkt}, \tag{2}$$

where M_{ijkt} can be imports or any of the other variables in Equation (1). 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 2 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 2 Panels (e) and (f) we show their dynamics using also Equation (2) 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 2021.[12]

Given the increase in exporter price, freight cost, and insurance cost, it is expected that import prices also increased, as shown in Figure 3. To understand the relative importance of each term's contribution to the increase in importer price, we conduct the following first-order decomposition:

$$\hat{p}^M = \theta^X \hat{p}^X + \theta^F \hat{p}^F + \theta^I \hat{p}^I, \tag{3}$$

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 (2). Figure 3 shows that the contribution of freight and insurance cost to the increase in import prices was close to 50% towards the end of 2021.

In conclusion, Colombian imports experienced substantial changes relative to the pre-pandemic period. Import quantities declined and stayed below pre-pandemic trends, whereas import prices and their components increased steadily although with different timing. In the empirical section, we will systematically study how the local disruptions generated by the pandemic affected each of these import variables.

[12]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`.

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.[13] 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 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 4 presents the important trends in port performance from 2019 to 2021.[14] 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 average number of hours each container ship spent at the port. 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 very stable in 2019, it experienced a steady increase since July 2020, with an about 25% increase in October 2021 compared to October 2019.

Panel (d) 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

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

[14] The data in 2018 will be used in the empirical analysis. The 2018 time series is not in Figure 4 to avoid overcrowding of the lines.

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 A1 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.[15]

2.3 Mobility Data

Countries around the world experienced declines in mobility during the pandemic, because of government restrictions, sickness, voluntary containment efforts, and business closures. 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.[16] 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, the data is from Facebook, and the pre-Covid period is defined as February 2020.[17] 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.

[15]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 time 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.

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

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

Figure 5 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.

In addition, there is substantial within-country variation in mobility. Figure 6 (a) presents the local mobility variations in Colombia in September 2020.[18] In Figure 6 (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. Similar variations can be observed in other countries, such as the U.S., China, and Mexico as shown in figures in Appendix A.3.

2.4 Trade and 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.1, we present the level of aggregation of each data set in each country and the number of units per country, show the final number of exporter cities we include in the analysis after merging the two data sets, and the coverage for each country.

Before proceeding to our formal empirical estimates of the impact of shocks on the trade outcomes at the product 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 7 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. As a placebo test, we don't observe this positive correlation when we regress the 2018-2019 import on the 2020-2021 mobility changes.

We then conduct a similar analysis at the exporter city level by regressing the changes

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

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 7 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.

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 it 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^M_{ijk} is equal to $p^X_{ik} + t_{ijk}$, where p^X_{ik} is the export price.

3.1.1 Import Demand

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

$$q_{ijk} = (p^M_{ijk})^{-\eta}(P^M_{jk})^{\eta-1}Z_{jk}, \tag{4}$$

where $P^M_{jk} \equiv [\sum_{i\in\Omega_{jk}}(p^M_{ijk})^{1-\eta}]^{\frac{1}{1-\eta}}$ 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 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, not only because of the price changes but also because of health concerns. These additional furniture and home supplies are likely to be imported.[19]

3.1.2 Export Supply

We assume exporters have a fixed amount of capital over the period we consider. In this case, given their Cobb-Douglas technology, their cost function is:

$$C_{ik} = A_{ik}Q^{\alpha}_{ik}, \tag{5}$$

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

[19] 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 $Z_{jk} = \phi_{jk} \times (P^D_{jk})^{\sigma-\varepsilon} \times (P_j)^{\varepsilon-1} \times f(\text{Income}_j)$, where P^D_{jk} is the composite price index combining the import and domestic price indices, P^M_{jk} and P^{CO}_{jk} respectively, P_j is the aggregate price index of all goods at j, and $f(\text{Income}_j)$ is a positive function of consumer's income. A reduction in income would reduce Z_{jk} and thus lower demand for the variety jk; an increase in P^D_{jk} 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}.

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, the friction of communication induced by this change in work arrangements can lead to a decline in firm productivity. Finally, it can also capture idiosyncratic supply shocks.[20]

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

$$p_{ijk}^{X} = \frac{\eta}{\eta-1}\alpha A_{ik} Q_{ik}^{\frac{\alpha-1}{\alpha}} + \frac{1}{\eta-1} t_{ijk}. \tag{6}$$

This expression captures several features of export prices.[21] First, the price to all importers will increase if there is an increase in demand from any specific importer. Specifically, as exporter i faces a larger demand, the marginal cost of production $\alpha A_{ik} Q_{ik}^{\frac{\alpha-1}{\alpha}}$ increases, raising the average cost of serving any destination. Second, cost shocks to location i also increase prices through A_{ik} (e.g., labor shortages that increase local wages). Finally, an increase in transportation costs also raises export prices because it shifts the demand curve inwards, decreasing marginal revenue.

3.1.3 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:

$$t_{ij} = B_{ij} v_{ij}^{\rho}, \tag{7}$$

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, and $\rho > 1$ is the decreasing returns to scale parameter. For example, labor shortage in exporter country ports, importer country ports, or intermediate shipping ports will lead to an increase in B_{ij}.

3.1.4 Solution in Changes

We are interested in how changes in underlying economic conditions in different locations along the supply chain affect equilibrium import and transport prices and quantities at the

[20] 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.

[21] 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.

exporter-importer-product level. To do so, we first differentiate import prices to get the following expression in changes:

$$\hat{p}^M_{ijk} = \iota_{ijk}\hat{A}_{ik} + \iota_{ik}\frac{\alpha-1}{\alpha}\hat{Q}_{ik} + (1-\iota_{ijk})\hat{B}_{ij} + (1-\iota_{ijk})\beta\hat{v}_{ij}, \tag{8}$$

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.[22]

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

$$\hat{q}^M_{ijk} = -\eta\hat{p}^M_{ijk} - (\eta-1)\hat{P}^M_{jk} + \hat{Z}_{ijk}, \tag{9}$$

and it is evident that on top of the price change effect, an increase in the price index P^M or the demand shifter Z also leads to declines in import quantities.

3.2 Empirical Strategy

Our goal is to estimate Equations (8) and (9), 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 city ($\hat{A}$), importer city ($\hat{Z}$), and during transportation ($\hat{B}$). In Section 4, we focus on the first two terms by controlling for the transportation disruptions using fixed effects, and we further study the role of $\hat{B}$ in Section 5. We do so 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. We then provide evidence that congestion also had a role in shaping trade flows during the pandemic, but including the congestion measures did not affect the estimates of the direct impact.

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

3.2.1 Local Demand and Supply Shocks Measurement

We measure local demand and supply shocks using changes in within-city human mobility from Facebook and Baidu. In Appendix Section B.1, we provide evidence on how the number of new Covid cases and the government containment policies are correlated with our mobility measures. In the model, local disruption shocks during the pandemic can be interpreted as changes in the cost shifter (A) and the demand shifter (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.

$$\hat{A}_{ik} = \gamma_A \hat{x}^I_i + \epsilon_{A,ik}, \tag{10}$$

$$\hat{Z}_{jk} = \gamma_Z \hat{x}^J_j + \epsilon_{Z,ik}, \tag{11}$$

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

3.2.2 Empirical Equations and Identification

To get the final estimating equations, we start by plugging the Equations (10) and (11) into Equations (8) and (9). We then construct two measures to 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^{Tr}_{cut}. 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.[23]

[23]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 endogenous. In Appendix Section B.9 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, quantities demanded at j also depend on the state of competition at that location, captured by the import price index. In order to control for it, we can think of the import price index at location j as having two components. First, the import price index at the entry port, and second, the cost of the internal transportation to location j. Given we do not have data on the latter, we assume that it is absorbed by importer firms and thus is captured by the local importer mobility measure. To control for the former, we include a product-time fixed effect, δ^P_{kt}.

The resulting empirical equations are as follows:

$$\hat{q}^M_{ijkt} = \beta^q_J \hat{x}^J_{jt} + \beta^q_I \hat{x}^I_{it} + \delta^{P,q}_{kt} + \delta^{Tr,q}_{cut} + \varepsilon^q_{ijkt}, \tag{12}$$

$$\hat{p}^M_{ijkt} = \beta^p_J \hat{x}^J_{jt} + \beta^p_I \hat{x}^I_{it} + \delta^{P,p}_{kt} + \delta^{Tr,p}_{cut} + \varepsilon^p_{ijkt}, \tag{13}$$

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. 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 parameters of interest are β^q_J, β^q_I, β^p_J, and β^p_I. In Equation (13), 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. There should be no role for the importer mobility to affect prices, so we expect β^p_I to be zero. In Equation (12), a positive β^q_J indicates that the income effect dominates the domestic substitution effect and the preference change effect; we take the sign of this coefficient as an empirical question, especially since different types of products may have different patterns. We expect β^q_I to be positive since an increase in price will to a reduction in quantity demanded.

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 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 not very likely, since Colombia is a relatively small country in international trade, and the probability that an exporter city's main clients are located in one Colombian city is very small. 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. The mobility change will capture all three scenarios. In other words, the mobility measures are the summary of the Covid disruptions resulting from different sources. In addition, we assume that people who work in the manufacturing sector are subject to the same shocks as people who work in the same city but in other sectors.

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

4 Estimation of the Trade Impact of Disruptions at Exporter and Importer Cities

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) and by product characteristics (i.e., upstreamness, price stickness, inventory intensity, and differentiated or not). We then deviate from the baseline model and investigate (1) the role of production congestion, (2) the interaction effects of exporter and importer mobility changes, and (3) the effects on the extensive margin.

4.1 Baseline Results

We start by estimating the empirical quantity (12) and price (13) equations, plus the sum of the two which corresponds to the impact on total import values (Table 1 Panel A). 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%. 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.[24]

We can recover the elasticity of substitution across exporter cities using these baseline results by taking the ratio of the quantity to price estimates of the export mobility shock, i.e., $-\beta_I^q/\beta_I^p = \eta$. This yields a $\eta = 3.4$, which is in line with the imperfect substitution assumption. Our estimated elasticity of substitution differs from the ones estimated in the literature in two ways. First, we use monthly variations (i.e., a short-run measure) compared to annual variations in the literature (i.e., a long-run measure). As discussed in Anderson and Yotov (2020), our elasticity should be lower than standard values that employed longer horizons given that short-term adjustments are harder to make than long-term ones. Second, our exporter locations (and thus varieties) are identified at the sub-national level, while the literature has focused on cross-country substitution. It is reasonable to think that it is easier to substitute across regions than across countries. All in all, our estimate is similar to the ones obtained in the literature, which has been estimated to be around 4 with country-level data and annual frequency (e.g., Head and Mayer, 2014).[25]

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 import city might be where the regional distributor is located, rather than the actual consumers and firms that use the imported goods. In Appendix Section B.7 we 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. However, given this pattern, we will not be able to distinguish the distributor effects from the actual consumer effects.

4.2 Pre-Trends, Alternative Fixed-Effects, Alternative Standard Error Clustering and Balanced Sample

Mobility shocks may have affected trade flows differently depending on their flow-specific seasonal patterns and pre-trends. In Table 1, Columns (4)-(6) in Panel A, 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

[24]In Appendix Table A3, we show the summary of statistics of the variables used in this section.

[25]We can also recover the empirical elasticity of the demand shifter with respect to local human mobility using these results. The coefficient of the import mobility in the quantity equation exactly pins down γ_Z, suggesting that a decline in importer mobility of 10% induced an average decline in import demand of 4%.

of confounding pre-trends.[26]

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 theory most closely. In the two bottom panels of Table 1, we allow for some flexibility and use alternative fixed effects. Panel B Columns (1)–(3) do not include the product-time fixed effects, which intend to control for the price index. Panel B Columns (4)–(6) exclude the MPOE dimension in the transportation fixed effect, leaving it as an exporter country-time fixed effect. Panel C Columns (1)–(3) include country-time and MPOE-time fixed effects separately. Finally, Panel C Columns (4)–(6) assume that transportation costs are product-specific and include country-MPOE-product-time fixed effects. Most results are very similar to the baseline results.

In Appendix Table B3, we take a more conservative approach by clustering standard errors at higher levels of aggregation. In Columns (1)–(3), we use exporting country-time and importer city-time clusters, and in Columns (4)–(6), we change the latter to importer department-time. Results remain significant.

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 intensive margin definition. In Appendix Table B4, we show that the sign and significance of the estimated coefficients are robust to this restriction.

4.3 Heterogeneity by Type of Good

In this section, we estimate Equations (12) and (13) 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 elasticities 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 Table 2 Panel A. We find that importer mobility shocks affected the three types of goods similarly. Importantly, the theoretical prediction of not having an

[26]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 happened in both the current period and the pre-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.

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.[27] This is not the case in the case of 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 if mobility shocks affected the demand and supply of medical products differently given the nature of the shock.[28] Since the importer mobility changes directly reflect the severity of the Covid outbreak on the demand side, a reduction in mobility should be associated with increased demand for Covid-related medical products. This is what we find in Table 2 Panel B. When we interact the change in log importer mobility with the dummy for medical goods, we see a statistically significant negative coefficient. Note, however, that the overall effects of importer mobility change on medical goods demand are still positive, suggesting that the income effect is still strong with this type of good. We also find a large elasticity of substitution for medical goods compared to non-medical goods, and this is likely to be driven by the fact that medical goods are likely to be homogeneous (within their product category).[29]

4.4 Other Heterogeneous Effects

We explore other potential heterogeneous effects using other important product characteristics in the trade 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 differentiated goods indicator from Rauch (1999).

Results are shown in Table 3. 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

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

[28]We identified Covid-related medical goods based on a list of products put together by the World Customs Organization and World Health Organization. Medical goods can be consumer, intermediate, or capital goods. See Appendix Section A.5 for details.

[29]The elasticity of substitution across varieties for medical goods is 4.1=(0.374+0.349)/(0.106+0.072), and 3.3=0.349/0.106 for non-medical goods.

pandemic, it is unlikely for them to cut back on material input. Second, given the coefficient estimates for the exporter mobility change, we find that the elasticity of substitution across varieties is larger for goods that are more upstream. This is consistent with the fact that upstream goods are more homogeneous. 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.

In sum, we find that the heterogeneous effects by product characteristics are in line with predictions from general trade theories.

4.5 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. 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.[30]

In Appendix Table B5, we estimate the baseline (Table 1 Panel A Columns 1–3) and

[30]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. Please see Appendix Section B.4 for details on how we construct these variables.

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.

4.6 Interaction Between Importer and Exporter Mobility

Exporter and importer mobility shocks may have had a stronger impact if both happened at the same time for a given product. In Appendix Table B6, we replicate Table 2 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.

4.7 Extensive Margin

We focus on the intensive margin in the main analysis. In this section, we explore the impact of exporter and importer mobility changes on the extensive margin, defined at the exporter-importer-product level. Specifically, we estimate the following linear probability model in differences:

$$\hat{I}_{ijkt} \quad = \quad \beta^J \hat{x}^J_{jt} + \beta^I \hat{x}^I_{it} + \delta^{P,E}_{kt} + \delta^{Tr,E}_{cut} + + \varepsilon^E_{ijkt}, \tag{14}$$

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.

Appendix Table B7 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.

One thing to note is that overall the extensive margin adjustments during the pandemic were relatively small, with an average change in trade probability of -1.2%. As shown in Appendix Figure B1, while at the beginning of the pandemic, the changes in Colombian imports were mainly driven by the extensive margin (defined as the number of exporter products at the importer level), since July 2020, the trade dynamics were mostly driven by the intensive margin. 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.

In sum, we presented a battery of results that point towards a robust effect of local 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 study the impact of importer-city mobility and exporter-city mobility on Colombian imports, including total value, quantity, and prices. There, we take 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:

$$\hat{Y}_{cym} = \alpha_0 \hat{x}^{\text{Ports}}_{cym} + \delta_m + \delta_y + \delta_c + \epsilon_{cym}, \tag{15}$$

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:

$$\hat{x}^{\text{Ports}}_{cym} = \sum_{p(c)} \frac{\text{TEU}_{p(c)2020}}{\sum_{p'(c)} \text{TEU}_{p'(c)2020}} \hat{x}_{p(c)ym}, \tag{16}$$

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 a country since in the Colombian trade data, we don't observe the exact city 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 at port cities will lead to fewer port calls being processed.

The set of identification assumptions is very similar to the ones in Section 3.2.2. 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 people who work in the ports are subject to the same shocks as people who work 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.[31]

The cost of shipping can be measured in two ways: the freight cost per unit and the freight cost per weight. We calculate the change in log freight cost using the February 2020 value as the baseline. The regression is as follows:

$$\hat{T}_{kcym} = \beta_0 \hat{x}^{\text{Ports}}_{cym} + \delta_m + \delta_y + \delta_c + \delta_k + \epsilon_{kcym}, \tag{17}$$

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.[32] The parameter β_0 being negative indicates that a decline in port mobility increases the cost of shipment 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.

[31] 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.

[32] We present details of variation in port performance measures and freight costs in Appendix Section B.8. 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.

5.2 Regression Results of Port Mobility Shocks

Table 4 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 16. 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 mean change in mobility (-0.16), there is a 2.1 percent increase in the number of hours in port. This result suggests that labor shortage lowers port productivity and generates 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, 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 discussed in the case of the Los Angeles Port, but the situation can be quite general.[33]

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, and we see an average of 1.4% increase in the number of hours in port for each additional month.

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

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

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.[34]

Then we proceed to investigate the impact of mobility changes on freight costs. Table 5 shows the regression results. Panel A Columns (1)–(4) use the change in log freight cost per unit as the outcome variable. Column (1) follows the specification in Equation (17), 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, and Columns (3)–(4) control for different sets of fixed effects. Columns (5)–(8) find similar results by using freight cost per weight as the outcome variable.

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. We don't find statistically significant effects when we run placebo regression using pre-Covid changes in Panel B.[35]

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.

[34] Appendix Figure B5 shows the residual plots for results in Table 4 Panel A Columns (1) and (3) and Panel B Columns (1) and (3). We also conduct robustness checks by dropping one country at a time and by dropping one period at a time. The corresponding results are shown in Appendix Figures B7, B8, and B9. Overall, we find that the results are not driven by one particular country or period.

[35] 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 regression as in Table 5. The residual plots are shown in Appendix Figure B6. Reassuringly, the country-level regression results are similar to the product-level results.

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. For the first intermediate country $O1$, the average mobility change is

$$\Delta \log(\text{mobility}_{cym}^{O1}) = \sum_{o1} \frac{\text{prob}(o1(c))}{\sum_{o1'} \text{prob}(o1'(c))} \Delta \log(\text{mobility}_{o1(c)ym}^{\text{Ports}}), \tag{18}$$

where $\Delta \log(\text{mobility}_{o1(c)ym}^{Ports})$ 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 $\text{prob}(o1(c))$ 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 ($\Delta \log(\text{mobility}_{cym}^{O2})$), 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 are essentially assuming that in a country, a large port for all container trade is also a large port for trade with Colombia.[36]

Similarly, we can 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 6 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 5 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. 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.

[36] If this assumption is violated, then we will have an attenuation bias.

6 Decomposition of the Disruptions at Exporter, Importer and Transport Locations

In previous sections, we documented the impact of mobility changes at the exporter, importer, and port locations on the quantity and prices of imports by Colombia. In this section, we bring together the evidence and do a decomposition of the relative effects coming from different sources. In particular, we are interested in the decomposition over time (in the 20 months we study).

Method Recall that in Equation (12) and (13), the change in log quantity and import price can be written as a function of the change in log exporter mobility $\hat{x}_{it}$, the change in log importer mobility $\hat{x}_j t$, and a set of fixed effects. Specifically, we can compute the total predicted changes in quantity and prices as

$$q^T \equiv \hat{\beta}_I^{k,q} x_I^T + \hat{\beta}_J^{k,q} x_J^T, \tag{19}$$

$$p^T \equiv \hat{\beta}_I^{k,p} x_I^T + \hat{\beta}_J^{k,p} x_J^T, \tag{20}$$

where we condition on the fixed effects. Note that the fixed effects will incorporate general equilibrium effects that are endogenous. For example, $\delta^{Tr,p}$ will capture the change in exporter-country-importer-port-specific transportation costs.[37]

For maritime trade, we can further decompose the $\delta^{Tr,q}$, where transportation costs are shown to be affected by changes in mobility in ports in exporting countries. Thus, we can write the predicted changes in shipping costs as

$$t^T \equiv \hat{\beta}_0 x_{Port}^T + \hat{\beta}^{trend}\text{time}. \tag{21}$$

As shown in Equation (7), we can write the $\delta^{Tr,p}$ and $\delta^{Tr,q}$ as follows:

$$\hat{\delta}^{Tr,p} = (1 - \bar{\iota})t^T + \epsilon^{Tr,p}, \tag{22}$$

$$\hat{\delta}^{Tr,p} = -\hat{\eta}(1 - \bar{\iota})t^T + \epsilon^{Tr,q}. \tag{23}$$

The average share of transportation cost in import price $\bar{\iota}$ in 2018 and 2019 is 7%. Then

[37]In Appendix Section B.9, we average the log per-unit freight costs in changes to the MPOE-product-month 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 and positively correlated with the fixed effects estimated using the price equation, indicating that the fixed effects capture the disruptions in the transportation sector well. Again, we are only able to provide direct evidence on maritime shipping due to data constraints.

we use the coefficient estimates from the previous sections to conduct the decomposition.

Time series By using the average mobility changes in each time period, we can do the decomposition of the total effects over the 20 months we study, using the intermediate goods as an example, evaluated at the average shock at the exporter city, importer city, and exporter-country ports.[38]

Results are shown in Figure 8. We find that for quantity, importer mobility shocks 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. In terms of import prices, the direct price effect in April 2020 was explained entirely by exporter mobility shocks, but the importance of the transportation sector increased over time as well given its positive linear trend.

Supply Chain Complexity We also want to see which products suffered the most. The size of the impact will depend on (1) the number of suppliers; (2) the average mobility change in each supplier; (3) the correlation of the mobility change across different suppliers. We find similar mean and standard deviation for exporter mobility changes for products with a different number of supplier countries or supplier cities. Thus, the complexity of the supply chain, measured as the number of suppliers, did not predict the severity of the Covid-trade disruptions coming from the producer side. This is consistent with two observations. First, although the epicenters of the pandemic changed rapidly in the first few months of 2020, by the end of 2021, all areas around the world were affected by the pandemic. In addition, over several waves of outbreaks, regions that initially experienced smaller shocks might be affected more severely in later periods, and vice versa for regions with initially larger shocks. Thus, there seemed to be no obvious way of arranging the location of the suppliers in a way that minimized the disruptions. Second, as we have discussed in the section on the extensive margin, the Covid shock seemed to be viewed by both the demand and the supply side as a temporary shock, and there were no substantial changes in the extensive margin.

7 Trade Disruptions and Inflation

In this section, we explore the relationship between international trade disruptions and domestic consumer prices in Colombia. Specifically, we analyze if consumer goods for which its imported varieties were sourced from cities that experienced a negative mobility shock

[38] Results for consumption products are in the Appendix Section B.10.

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).[39]

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).[40] 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).[41,42] We find that on average, 56 sub-classes observe direct positive imports each month.[43]

Figure 9 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.

Import Price Changes at the Consumer Goods Level To study the relationship between consumer and import prices, 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:

$$\hat{p}^M_{\kappa t} \equiv \sum_{ijk \in \Omega_\kappa} \theta_{ijkt} \hat{p}^M_{ijkt}, \tag{24}$$

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

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

[41] We use the available UN concordances between the two and manually concord the ones 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).

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

[43] 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 A5.

where $\theta_{ijk} \equiv \frac{m_{ijk}^{2019}}{\sum_{ijk \in \Omega_\kappa} m_{ijk}^{2019}}$, and Ω_κ is the set of ijk combinations within κ goods that is observed in 2019.[44]

Relationship between CPI Changes and Mobility Shocks To investigate the relationship between consumer price changes and import price changes, we run the following regression:

$$\hat{p}_{\kappa t}^{C} = \mu \hat{p}_{\kappa t}^{M} + \delta_t^T + \zeta_{\kappa t}, \tag{25}$$

where $\hat{p}_{\kappa t}^{C}$ 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 goods variation, and we also present an alternative specification with κ fixed effects.

In Table 7 Columns (1) and (2), we use the actual import price changes ($\hat{p}_{ijkt}^{M}$) to compute $\hat{p}_{\kappa t}^{M}$. In Column (1), we include time fixed effects as in Equation (25), and find a low import price pass-through, of about 1%. In Column (2), we add goods fixed effects (sub-class), and the result is similar. These estimates do not consider any particular exogenous source of import price changes; i.e., import price changes incorporate exogenous shocks along the supply chain and general equilibrium responses. In Columns (3) and (4), we use the *predicted* import price changes from mobility shocks to exporters to compute $\hat{p}_{\kappa t}^{M}$ (i.e., replace $\hat{p}_{ijkt}^{M}$ with $\hat{\beta}_I^p \hat{x}_{it}^I$). The estimated pass-through is $\hat{\mu} = 0.575$ in Column (3), with time-fixed effects. This means that a 10% increase in import prices due to export mobility shocks was related to a consumer price increase close to 6%. Adding goods fixed effects in Column (4) does not change the magnitude of the estimate. In Appendix Figure B12, we plot the relationship between the residualized consumer price changes and the predicted import prices.[45]

In conclusion, this evidence suggests that trade disruptions at exporters' locations propagated through the international supply chain and played an important role in driving domestic inflation in Colombia during the pandemic.

[44]In Appendix Figure A6, 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.

[45]This result is robust to 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.

8 Conclusion

In this paper, we study the impact of disruptive local shocks on international trade during the pandemic. Using Colombian customs data and container ship port call information, we document a sudden decrease in import quantities, a steady increase in export prices and shipping costs, and port congestion with an increased processing time in world ports. We find that local mobility shocks at the exporter and importer locations led to a reduction in import quantity, an increase in prices, and a reduction in trade participation. We also find that mobility shocks at seaports generated port congestion and increased freight costs. Using a simple trade framework, we decompose the impact into an exporter, importer, and transportation shock. We find that most of the impact at the onset of the pandemic was due to adverse demand shocks. Over time, the transportation sector increased its importance in the decrease in import quantities and the rise in import prices. Finally, we show that shocks at exporter locations were related to increases in consumer prices in Colombia.

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.

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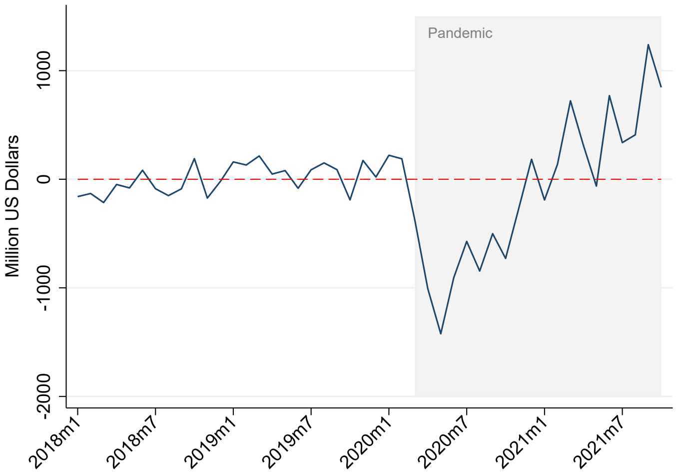
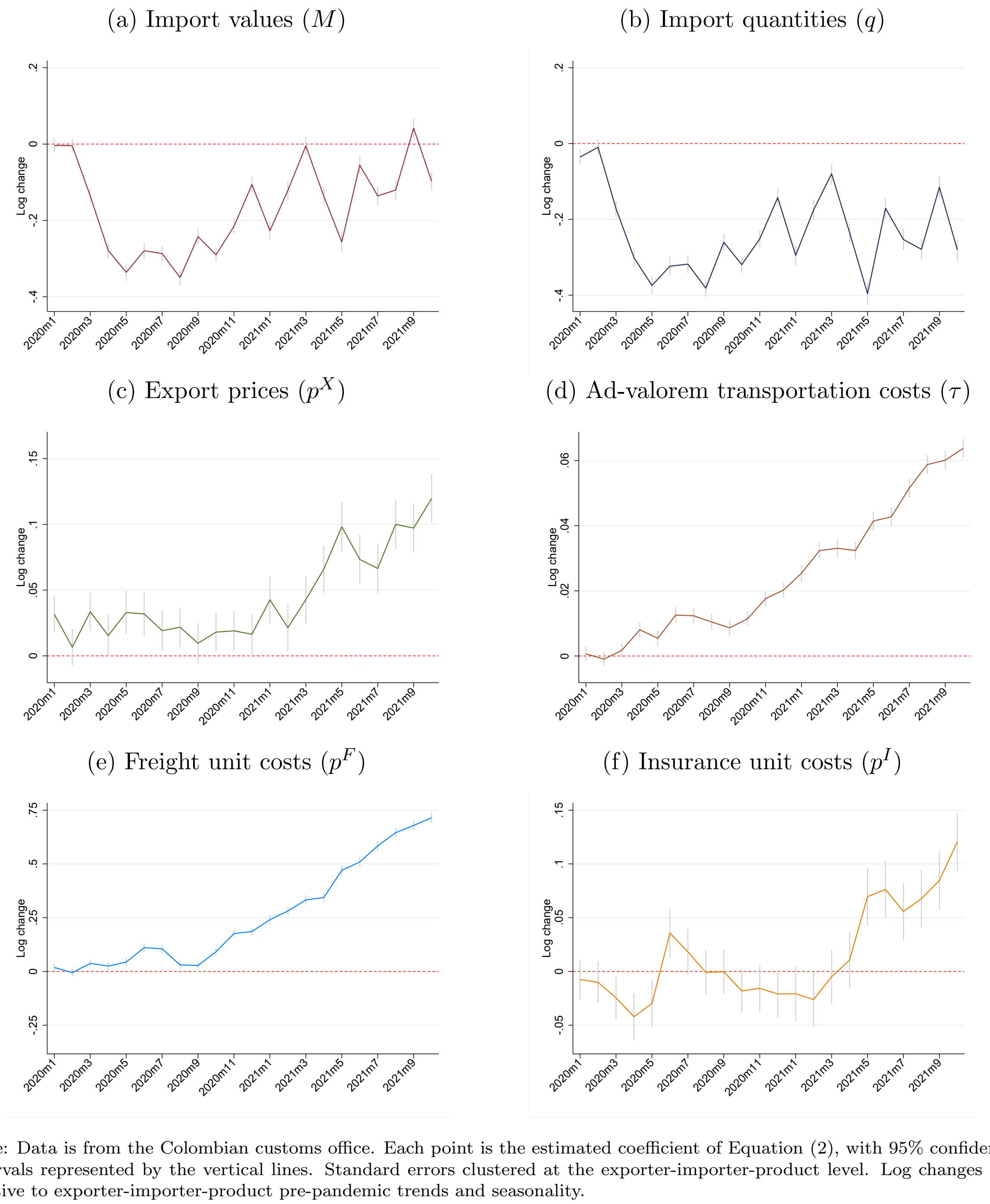
Figures and Tables

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



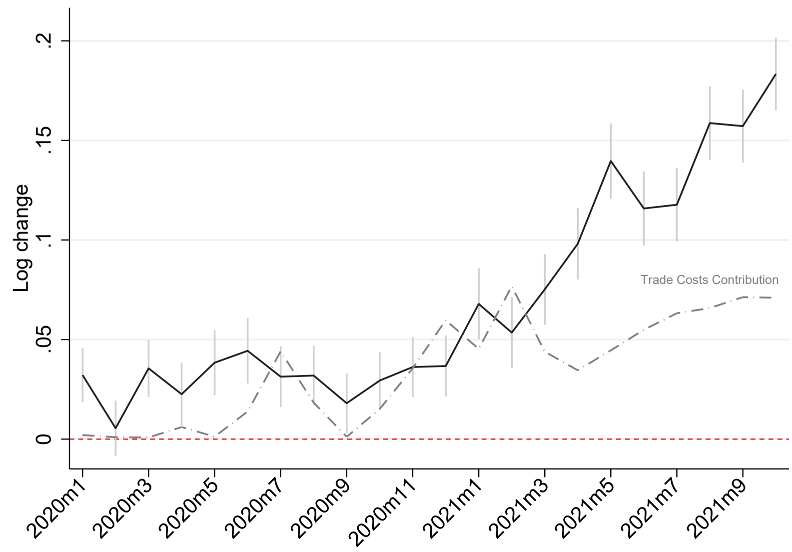
Note: Data is from the Colombian customs office. Each month's value is calculated as the total Colombian imports minus the 2018–2019 month-specific average, covering the twenty-seven major exporters to Colombia.

Figure 2: Average Changes in Trade Outcomes Relative to Pre-Pandemic Trends



Note: Data is from the Colombian customs office. Each point is the estimated coefficient of Equation (2), 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.

Figure 3: Decomposition of the Changes in Import Prices



Note: Each point in the solid line is the estimated coefficient of Equation (2) 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 2.

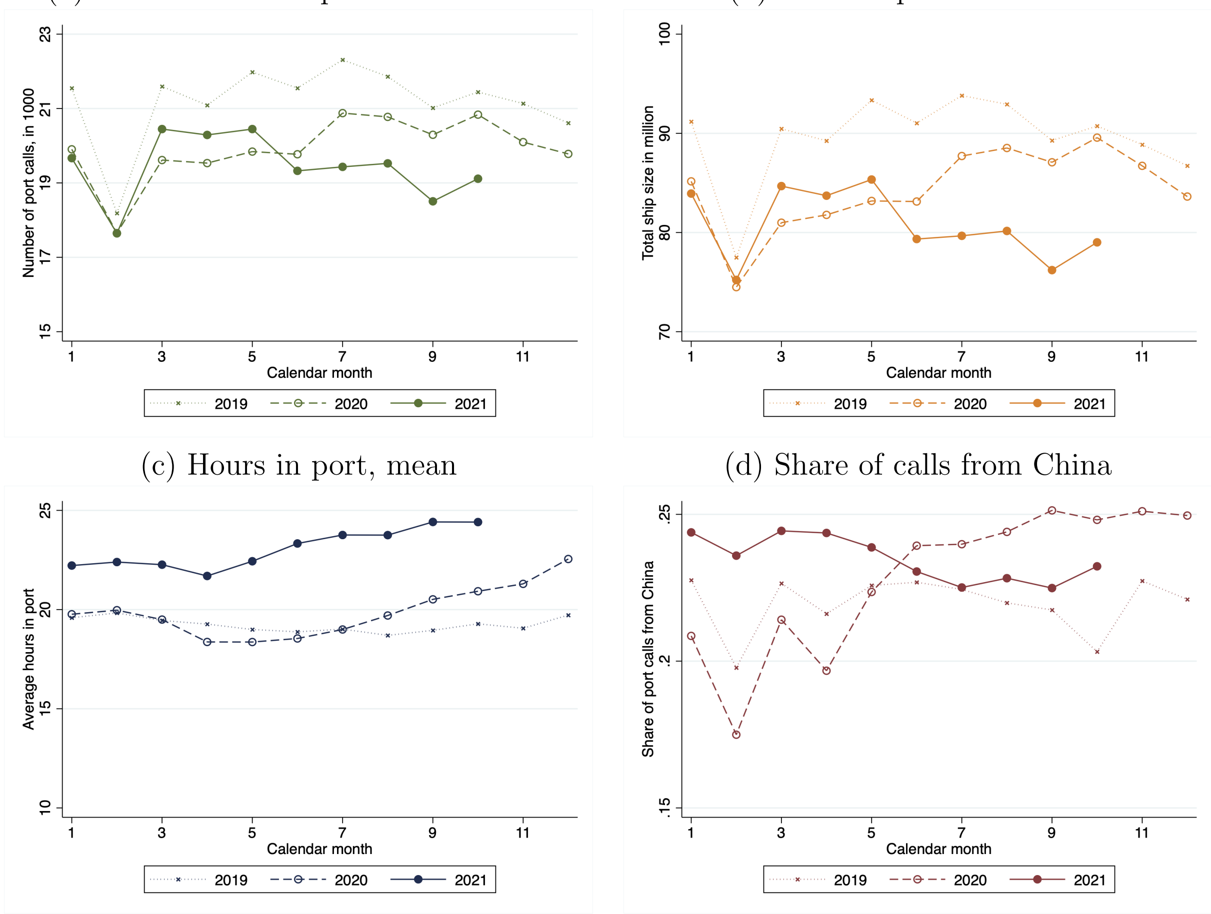
Figure 4: Port Performance From January 2019 to October 2021, 150 Ports in 27 Countries

(a) Total number of port calls in 1000

(b) Total ship size in million

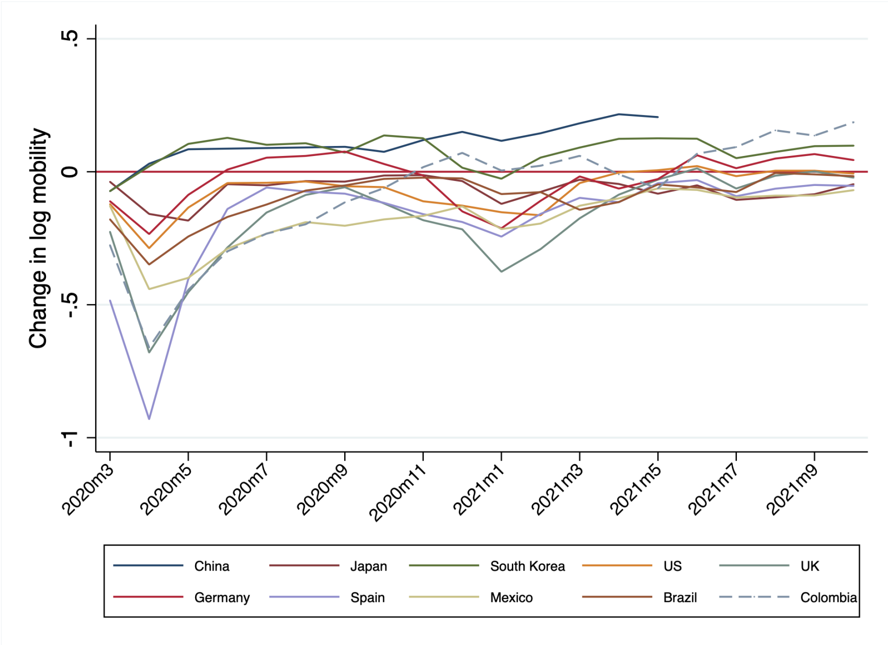
(c) Hours in port, mean

(d) Share of calls from China



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 total number of port calls is in 1000 units, and the total ship size is in millions of twenty-foot equivalent units. The hours in port are measured as the difference between the sailed time and the arrival time at the port. The share of calls from China is measured as the share of port calls whose last port of call was in a Chinese port.

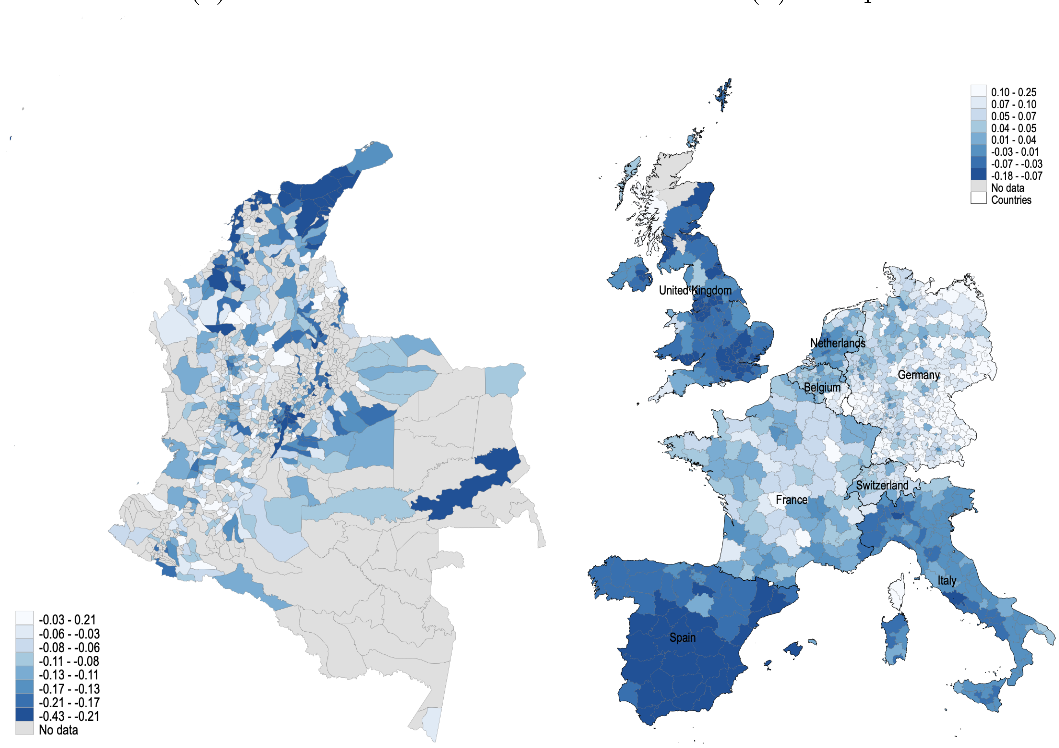
Figure 5: The Trend of Mobility in Exporting Cities Across Countries and in Colombia



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.

Figure 6: The Decline in Mobility Across Municipalities in Colombia and Across NUTS3 Units in Eight European Countries, September 2020 Compared to February 2020

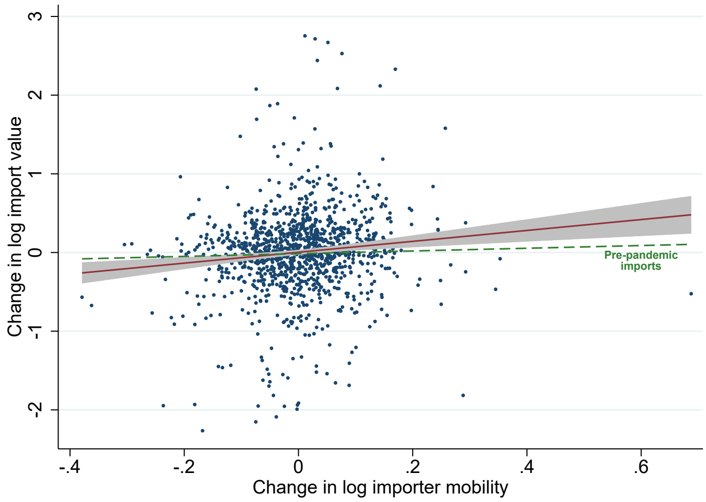
(a) Colombia (b) Europe



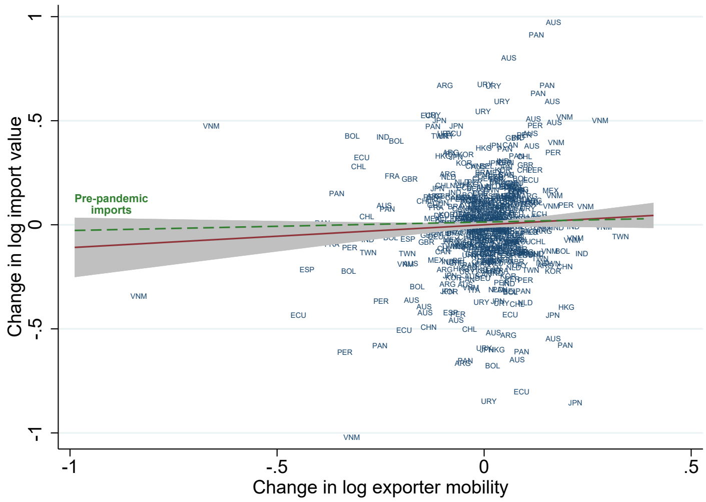
Note: Data is from Facebook. The Colombian data covers 530 municipalities. The European countries include the UK, France, Spain, Italy, Switzerland, Belgium, the Netherlands, and Germany. The NUTS (Nomenclature of territorial units for statistics) classification is a hierarchical system for dividing 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.`

Figure 7: Relationship Between Changes in Log Import Value and Changes in Human Mobility at the Importer City and the Exporter City

(a) Importer mobility



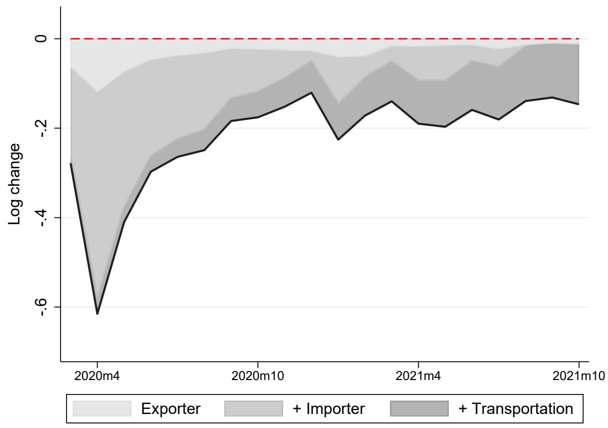
(b) Exporter mobility



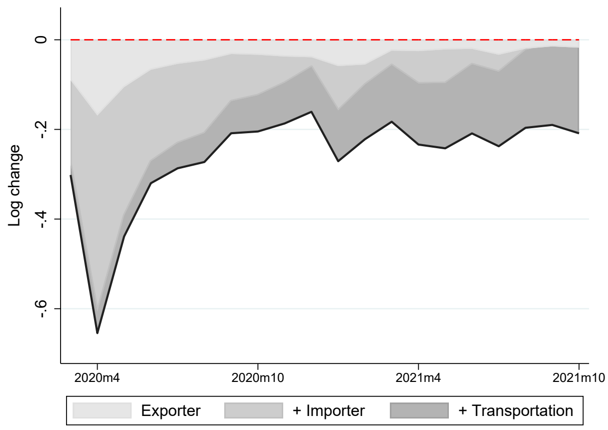
Note: In both figures, each dot represents a city-time pair. Panel (a) is the residual plot of the log change in import value at the importer city regressed on the log change in importer mobility, controlling for time fixed effects. The red solid line is the corresponding fitted line with a slope of 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 $-0.003(0.067)$.

Figure 8: Decomposition of Predicted Changes in Trade Outcomes of Intermediate Goods into Exporter, Importer, and Transportation Shocks

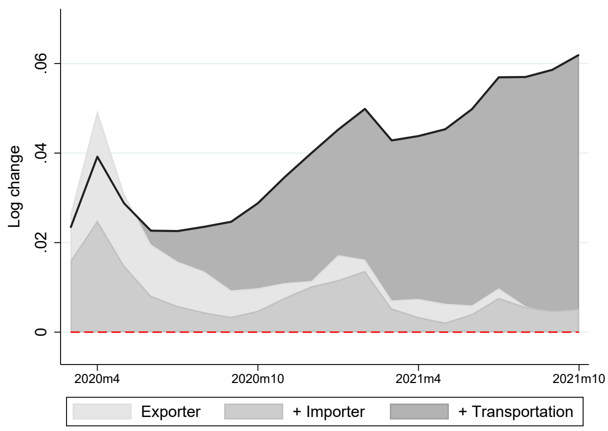
(a) Import value



(b) Import quantity

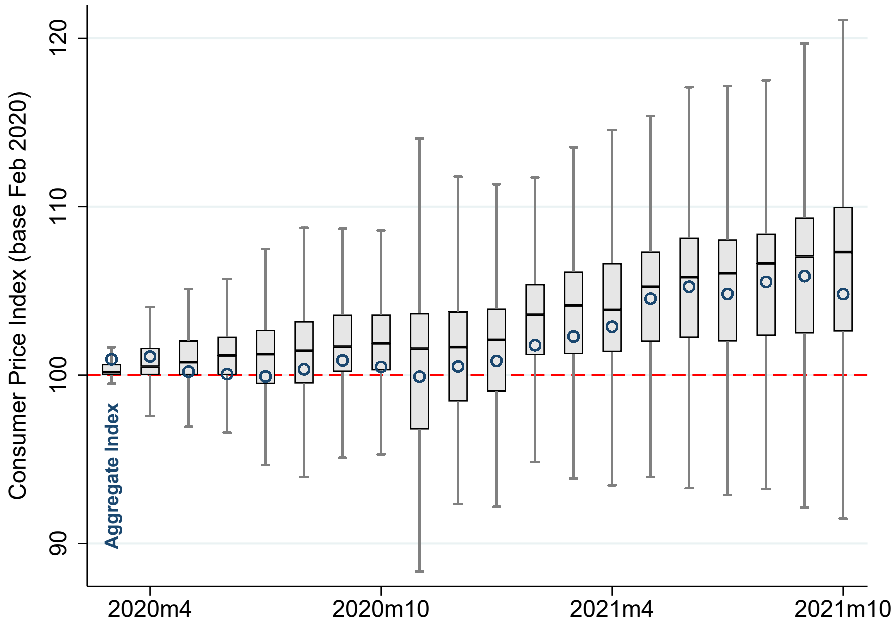


(c) Import price



Note: Each data point is computed using baseline estimates for intermediate goods in Table 2 and for freight costs in Table 5 and month-specific average changes in exporter, importer and port mobility.

Figure 9: 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.

Table 1: The Impact of Exporter and Importer Mobility on Trade Outcomes, Baseline and Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	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
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B	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 C	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 shows the regression results of the price equation (Equation 12), the quantity equation (Equation 13), and the sum of the two, i.e., values. The baseline regressions (Panel A Columns 1–3) follow the equation specifications exactly, while other columns and panels show the robustness results by changing the controls, including fixed effects. 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. For an additional summary of statistics in other specifications, see Appendix Table A3 for details.

Table 2: The Impact of Exporter and Importer Mobility on Trade Outcomes, by Product Categories

Panel A	(1)	(2)	(3)
Dependent variable:	Δ log value	Δ log quantity	Δ log price
Δ log importer mobility $\times$ consumer	0.469***	0.387***	0.082
	(0.139)	(0.149)	(0.081)
Δ log importer mobility $\times$ intermediates	0.420***	0.393***	0.027
	(0.075)	(0.085)	(0.062)
Δ log importer mobility $\times$ capital	0.393***	0.417***	-0.024
	(0.107)	(0.110)	(0.061)
Δ log exporter mobility $\times$ consumer	-0.023	0.074	-0.096**
	(0.126)	(0.148)	(0.048)
Δ log exporter mobility $\times$ intermediates	0.280***	0.398***	-0.118***
	(0.094)	(0.121)	(0.045)
Δ log exporter mobility $\times$ 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 $\times$ 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 $\times$ 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 A3 for details.

Table 3: 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).

Table 4: 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-squared	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).

Table 5: The Impact of Port Mobility in the Exporter Country on Freight Costs

Panel A	(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. 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.

Table 6: The Impact of Port Mobility in the Exporter Country and in the Intermediate Country on Freight Costs

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Δ log freight cost, unit			Δ log freight cost, weight		
Δ log mobility, exporter country	-0.25**			-0.30***		
	(0.11)			(0.10)		
Δ log mobility, first intermediate		-0.53***			-0.59***	
		(0.16)			(0.15)	
Δ log mobility, second intermediate			-0.72***			-0.76***
			(0.20)			(0.20)
I (year=2021)	0.51***	0.57***	0.69***	0.55***	0.62***	0.74***
	(0.08)	(0.08)	(0.11)	(0.07)	(0.08)	(0.11)
Constant	0.02	-0.06	-0.16*	-0.04	-0.12**	-0.23**
	(0.05)	(0.06)	(0.09)	(0.04)	(0.06)	(0.09)
N	245,995	245,995	245,995	245,995	245,995	245,995
R^2	0.11	0.11	0.11	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. All columns control for 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), 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, -0.15 (0.16) for the first intermediate country, and -0.17 (0.20) for the second intermediate country.

Table 7: Relationship Between Observed and Predicted Import Price Increases and Consumer Price Indices

	(1)	(2)	(3)	(4)
	Observed		Predicted	
Δ log import price	0.013**	0.009**	0.575***	0.568**
	(0.006)	(0.005)	(0.168)	(0.226)
Time FE	Yes	Yes	Yes	Yes
Goods FE		Yes		Yes
N	1,126	1,126	1,126	1,126
R^2	0.102	0.667	0.104	0.670

Note: Bootstrapped standard errors (200 reps) are shown in the 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 also aggregated to that level. In Columns (1) and (2), the log import price changes are calculated using the observed prices of imports. In Columns (3) and (4), the log import price changes are calculated using the predicted prices of imports due to changes in the log exporter mobility in Column (3) of Table 2.

Online Appendices

(Not for publication)

A Additional Data Descriptives

A.1 Levels of Aggregation

Table A1: 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 2	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 A1 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.

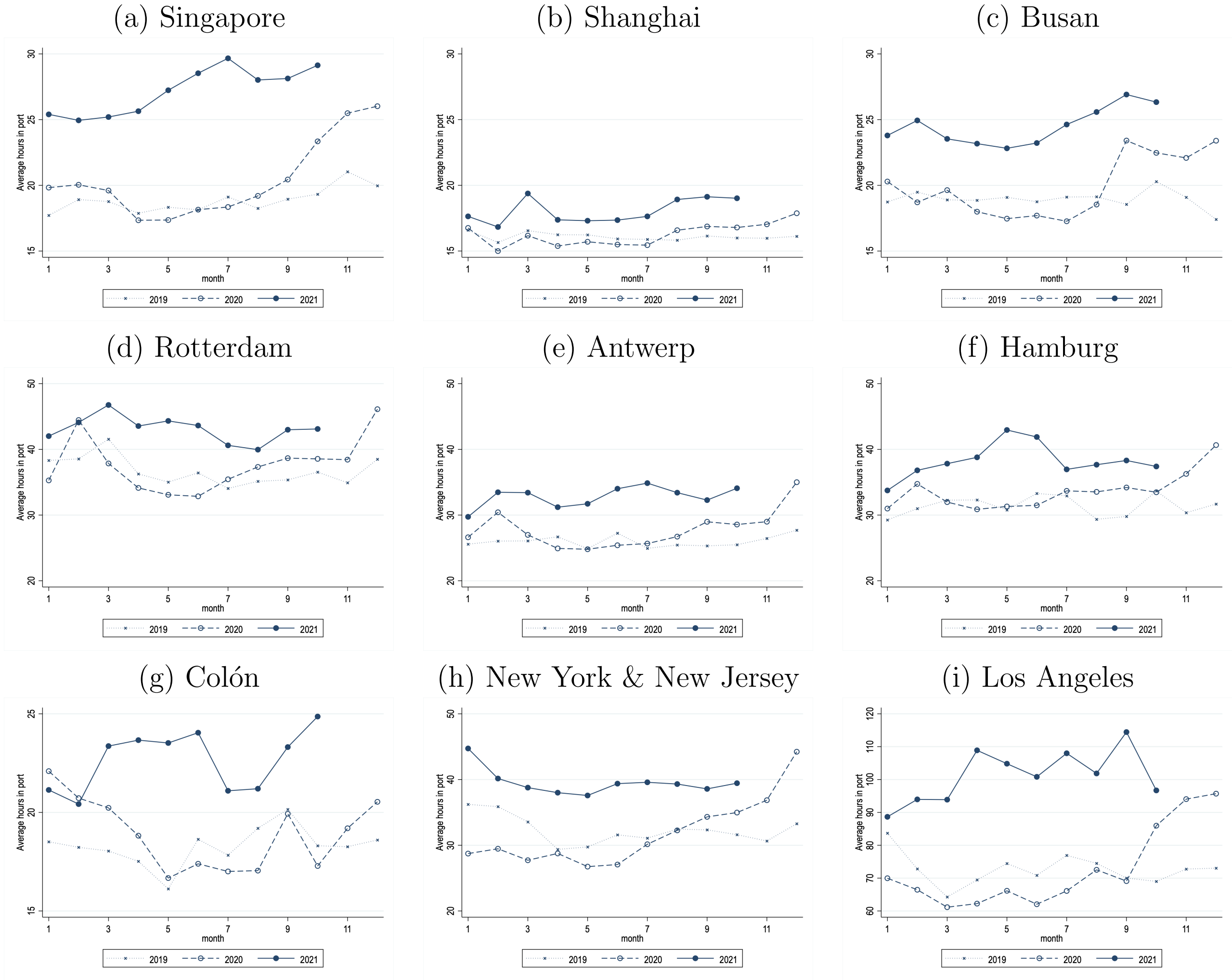
A.2 Ports Included in the Analysis

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.

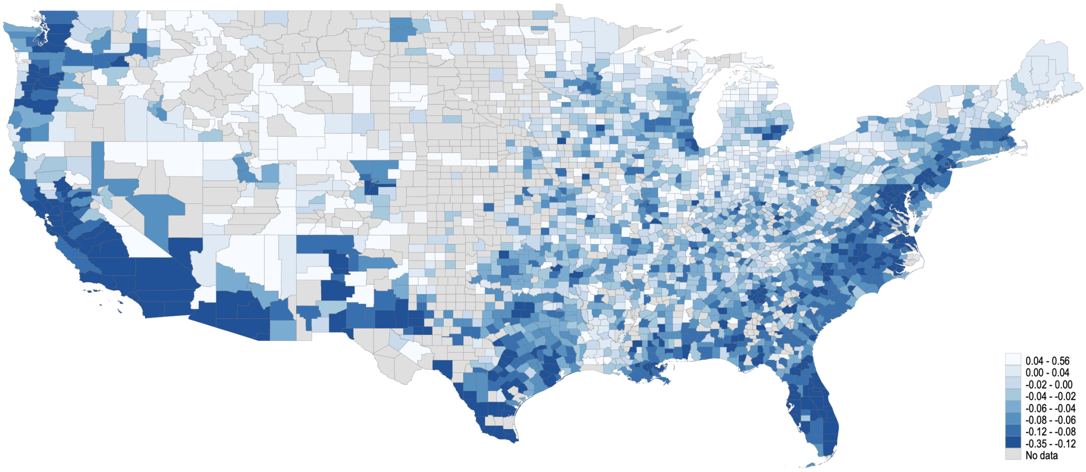
Figure A1: Average Hours in Port, Nine Important Ports



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.

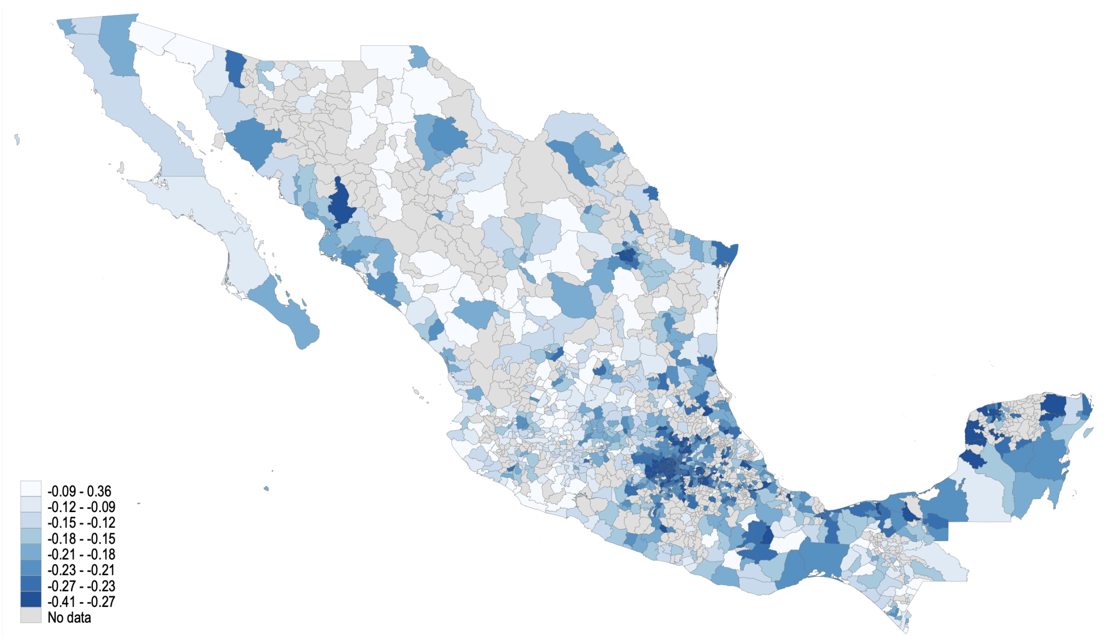
A.3 Mobility Change Maps

Figure A2: The Decline in Mobility Across Counties in the US, September 2020 Compared to February 2020



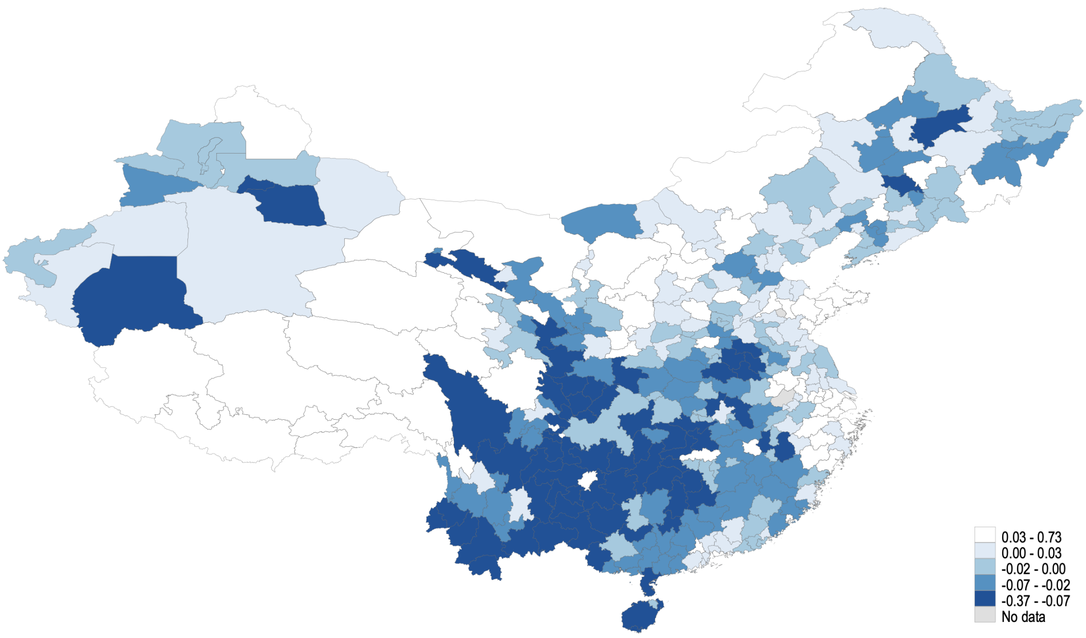
Note: Data is from Facebook.

Figure A3: The Decline in Mobility Across Municipalities in Mexico, September 2020 Compared to February 2020



Note: Data is from Facebook.

Figure A4: The Decline in Mobility Across Prefectures in China, September 2020 Compared to February 2020



Note: Data is from Baidu.

A.4 Descriptive Statistics of Variables Used in Baseline Exporter and Importer Shocks Regressions

Table A3: 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
Extensive margin 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, 2, B5, and B7.

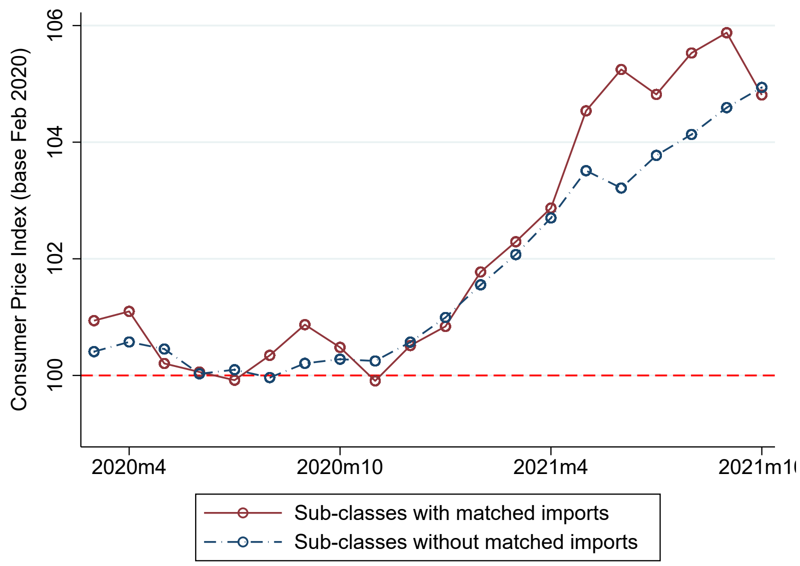
A.5 Covid-Related Medical Goods

A list by World Customs Organization and World Health Organization specifies the list of Covid-related medical goods at the HS6 level.[46] 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).

A.6 Additional Descriptive Statistics of Consumer Price Indices

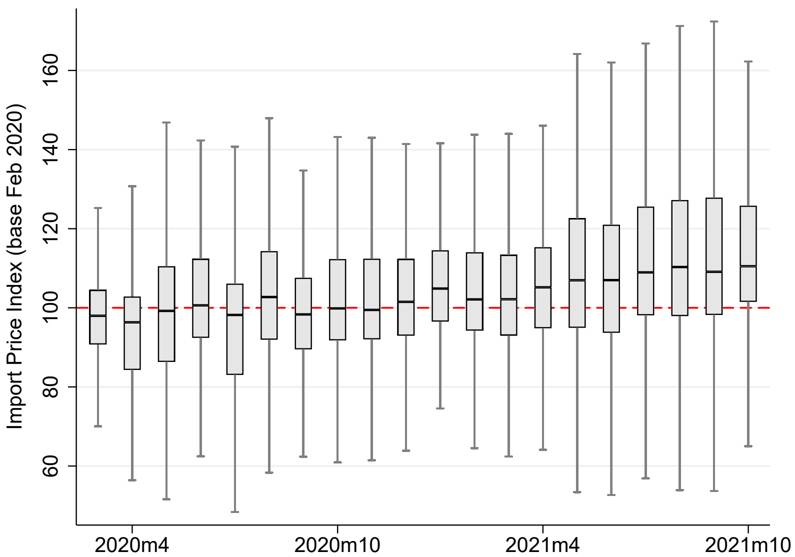
Figure A5: Aggregate Consumer Price Index for Goods Sub-classes With and Without Matched Imports



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.

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

Figure A6: 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 Validation of the Mobility Measure

In this section, we provide evidence of the relationship between mobility changes, local Covid outbreak, 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 B1: 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.

Table B1 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 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 B2 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 B1. 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.

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.

Table B2: 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.

B.2 Alternative Standard Errors Clustering

Table B3: 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
	(0.084)	(0.087)	(0.053)	(0.092)	(0.080)	(0.045)
Δ log exporter mobility	0.249**	0.352**	-0.103**	0.249**	0.352**	-0.103**
	(0.110)	(0.146)	(0.050)	(0.108)	(0.145)	(0.051)
Clustering	Exporting country-time and importer city-time			Exporting country-time and importer department-time		
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.3 Balanced Sample

Table B4: 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.4 Congestion Controls

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:

$$\hat{S}_{ckt} = \sum_{\tilde{c} \in C|c} s^{2018}_{X,\tilde{c}k} \hat{x}_{\tilde{c}t}, \tag{26}$$

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.[47] 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.[48]

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:

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

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

Table B5: 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.

[47] 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.

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

B.5 Interaction of Exporter and Importer Mobility

Table B6: The Impact of Exporter and Importer Mobility on Trade Outcomes, Including the Interaction

	(1)	(2)	(3)
Dependent Variable:	Δ log value	Δ log quantity	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 2 Panel A by interacting the importer mobility and the exporter mobility, by product categories (consumer goods, intermediate goods, and capital goods).

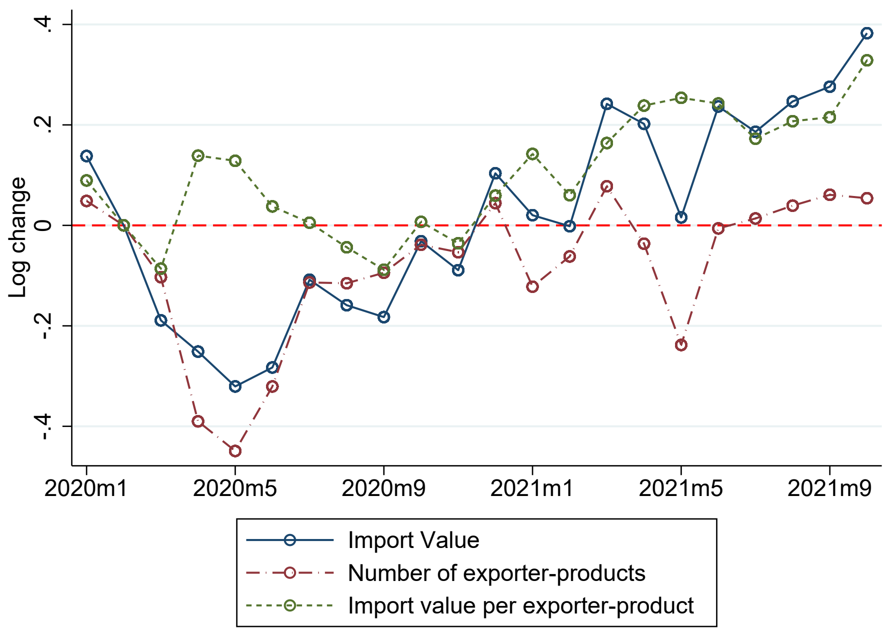
B.6 Extensive Margin

Table B7: The Impact of Importer Mobility and Exporter Mobility on the Extensive Margin

	(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.

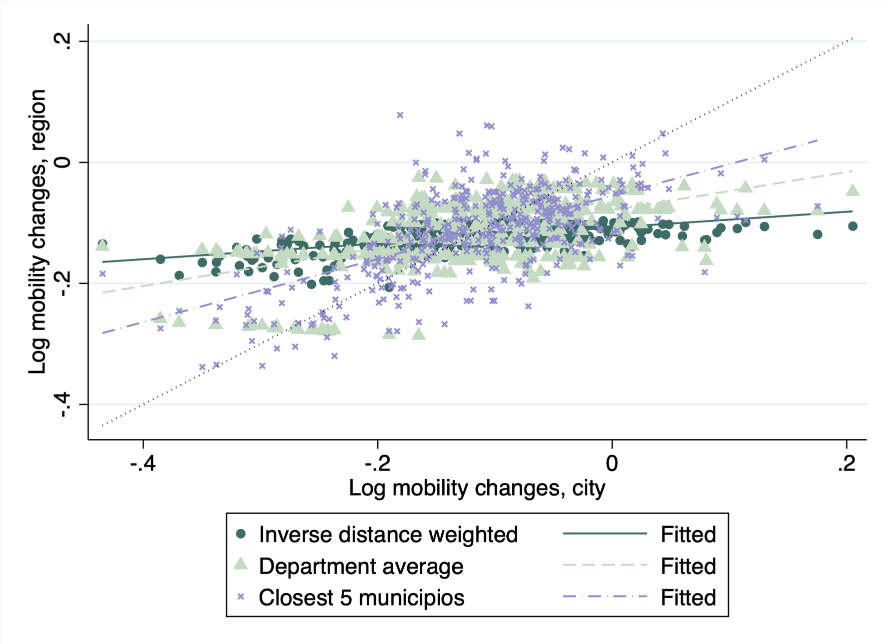
Figure B1: Changes in Log Imports, Log Number of Exporter-products and Log Imports per Exporter-Product Relative to February 2020



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.7 Importer Region vs Importer City

Figure B2: 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.8 Additional Port Performance Results

Figure B3 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 4 Panel (c). In addition, as shown in Figure B3 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 4 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.[49] 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 4 Panel (a), where we observe a decline in the number of port calls since June 2021.

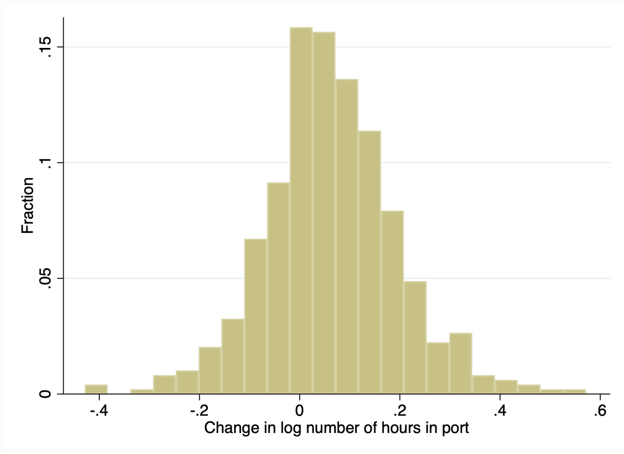
Figure B4 presents the variation in the changes in freight costs. Panels (a) and (c) show the distribution of the change in log freight cost per unit, and (b) and (d) for the change in

[49] 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.

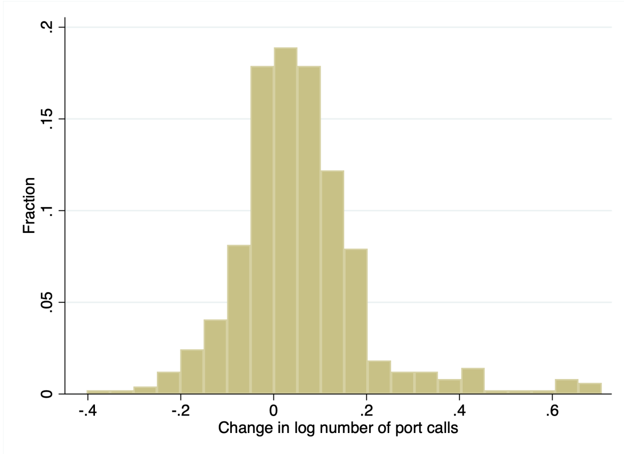
log freight cost per weight. The top and bottom one percent of the N are dropped for both variables.[50] In both cases, there are more N with positive changes, indicating an increase in the freight cost. In addition, the positive changes are more prominent in 2021 than in 2020.

Figure B3: Histograms of Country-Level Port Performance Variations

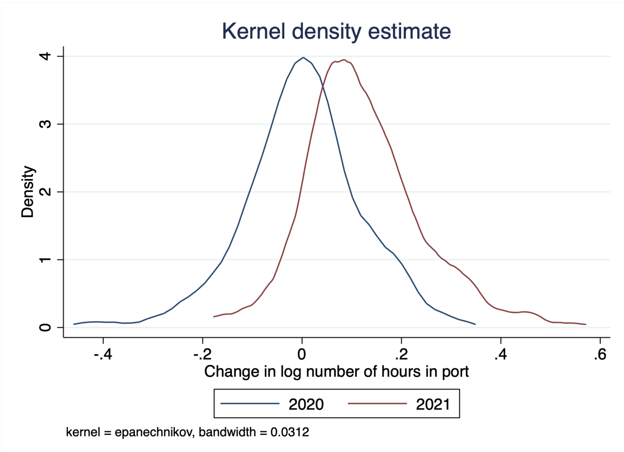
(a) Changes in log number of hours in port
March 2020 to October 20201



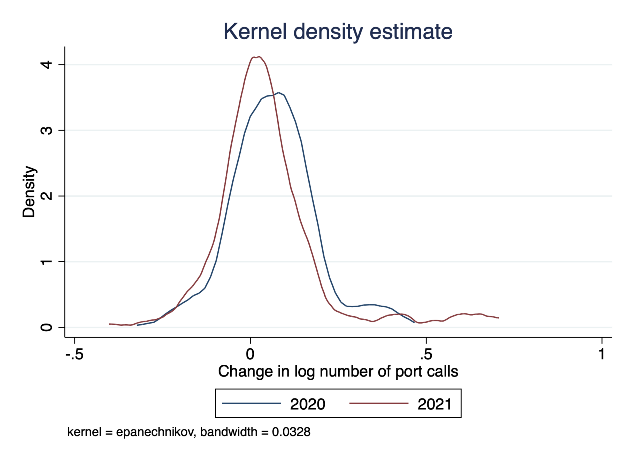
(b) Changes in log number of port calls
March 2020 to October 20201



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



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

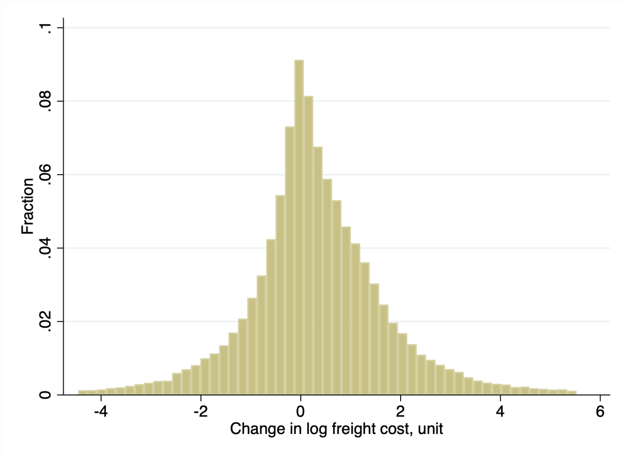


Note: Panels (a) and (b) are the histograms of the changes in port performance in the post-Covid time (March 2020 to October 2021), compared to February 2020. Panels (c) and (d) show the variation in 2020 and 2021 separately, using kernel densities.

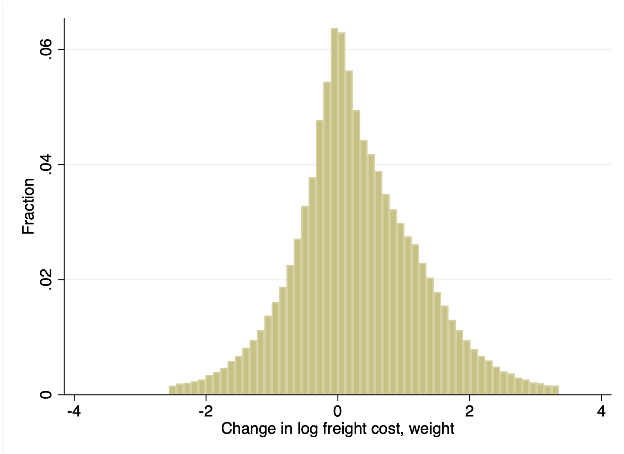
[50] Our regression results are robust to keeping all N.

Figure B4: Histograms of Product-Level Freight Cost Variations

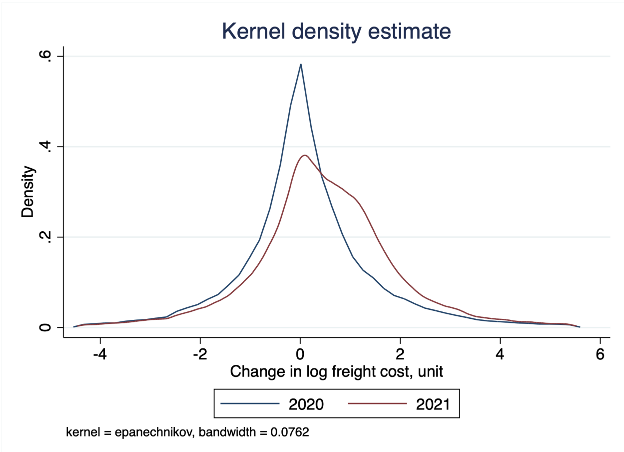
(a) Changes in log freight cost, unit
March 2020 to October 20201



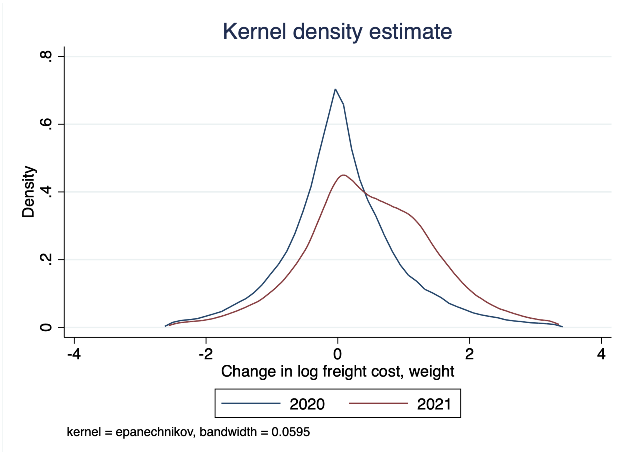
(b) Changes in log freight cost, weight
March 2020 to October 20201



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



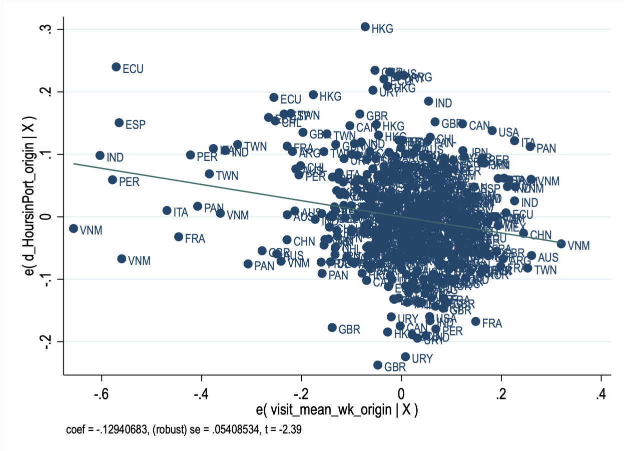
(d) Changes in log freight cost, weight calls
2020 versus 2021



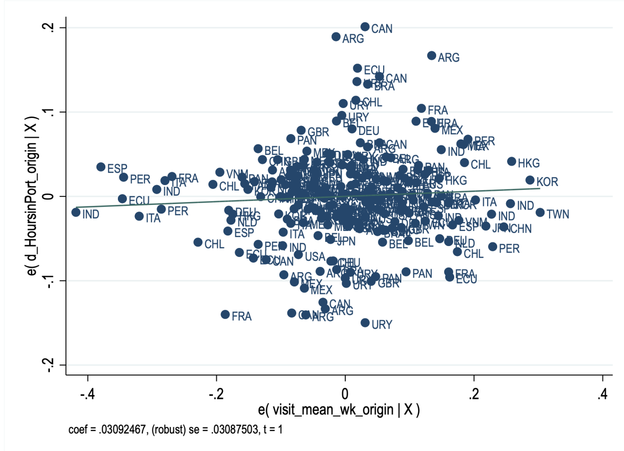
Note: Panels (a) and (b) are the histograms of the changes in log freight cost in the post-Covid time (March 2020 to October 2021), compared to February 2020. Panels (c) and (d) show the variation in 2020 and 2021 separately, using kernel densities. Panels (a) and (c) do not include the changes in log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

Figure B5: 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

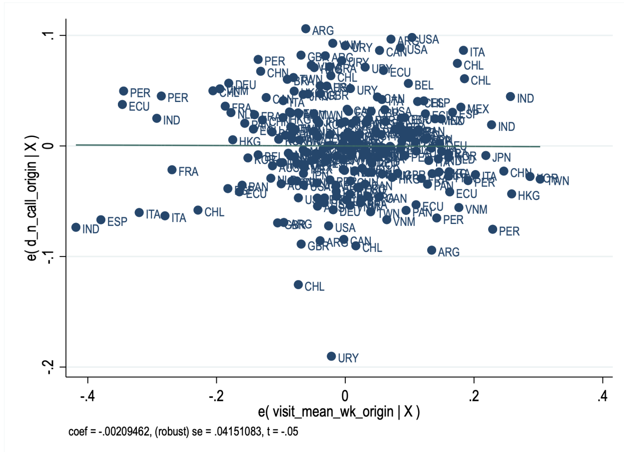


(b) Hours in port, 2018 and 2019



(c) Number of port calls, 2020 and 2021

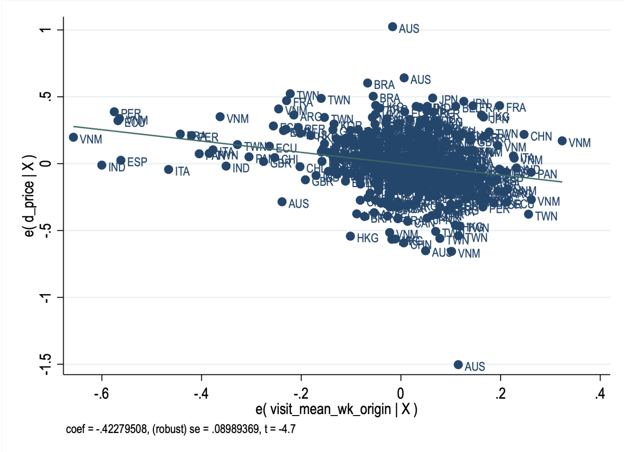
(d) Number of port calls, 2018 and 2019



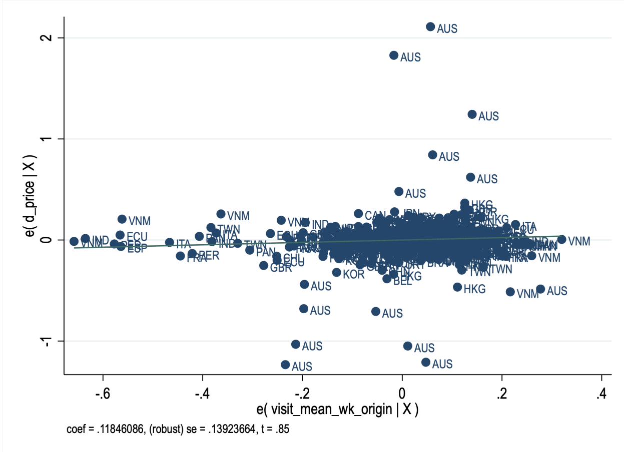
Note: Panel (a) is the residual plot for the results in Table 4 Panel A Column (1), and Panel (b) is the residual plot for Panel B Column (1). Panels (c) and (d) are the residual plots for the results in Table 4 Column (3) in Panels A and B, respectively.

Figure B6: The Impact of Exporter Country Mobility Changes on Freight Costs, Residual Plots for the Post-Covid Time and the Pre-Covid Time

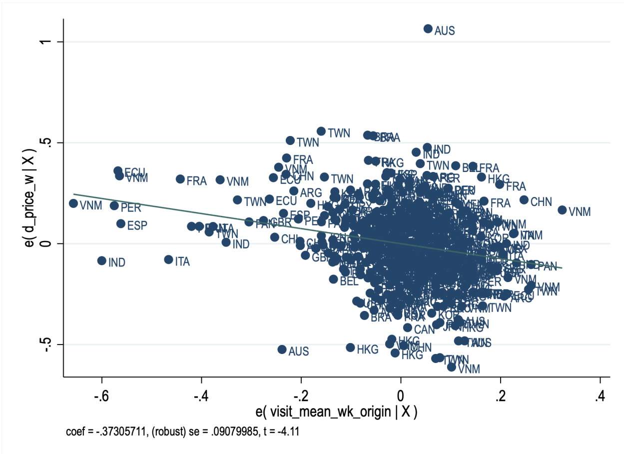
(a) Freight cost, unit, 2020 and 2021



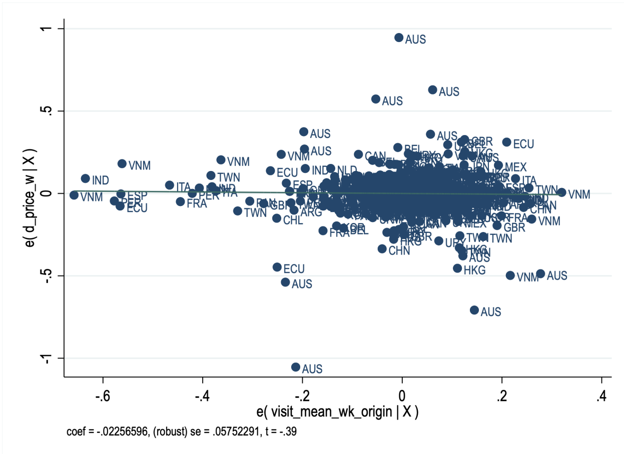
(b) Freight cost, unit, 2018 and 2019



(c) Freight cost, weight, 2020 and 2021



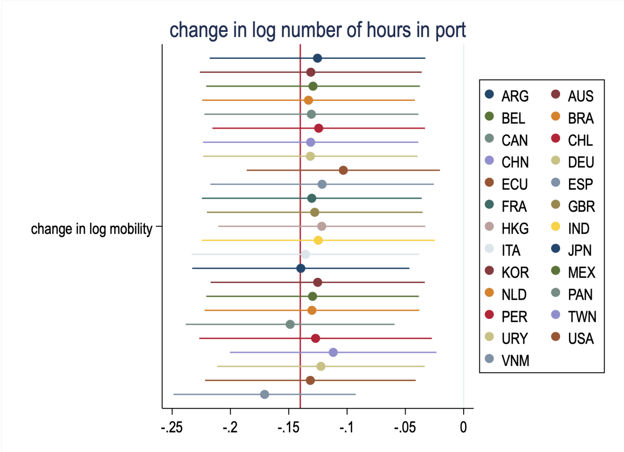
(d) Freight cost, weight, 2018 and 2019



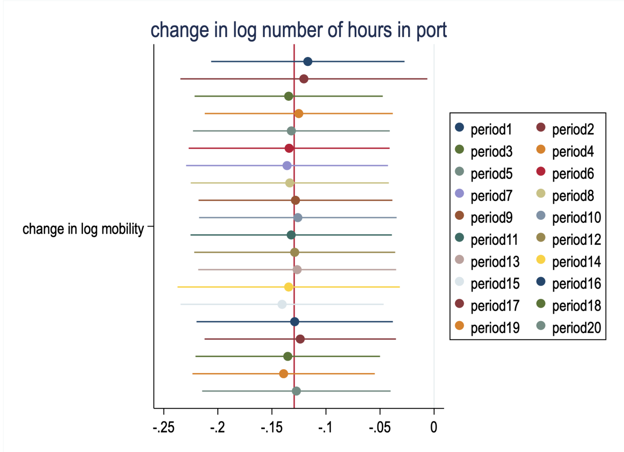
Note: Panel (a) is the residual plot for the results in Table 4 Panel A Column (1), and Panel (b) is the residual plot for Panel B Column (1). Panels (c) and (d) are the residual plots for the results in Table 4 Column (3) in Panels A and B, respectively.

Figure B7: Robustness of Country-Level Results in Table 4, the Impact of Mobility Changes on Port Performance, Dropping One Country at a Time and Dropping One Period at a Time

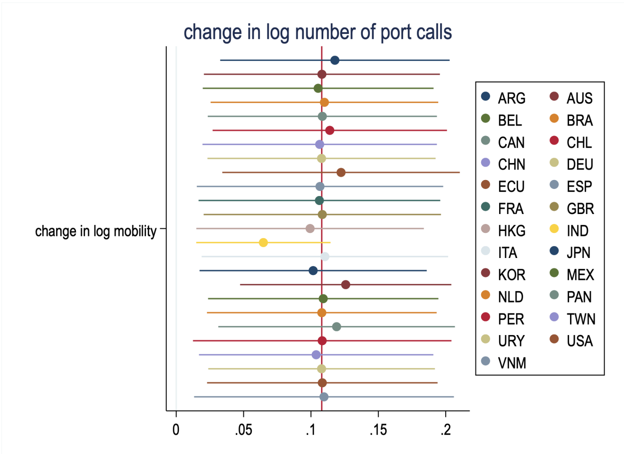
(a) Hours in port, drop country



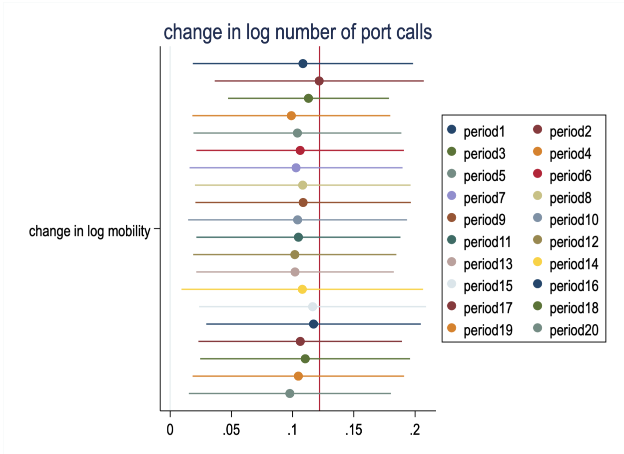
(b) Hours in port, drop period



(c) Number of calls, drop country



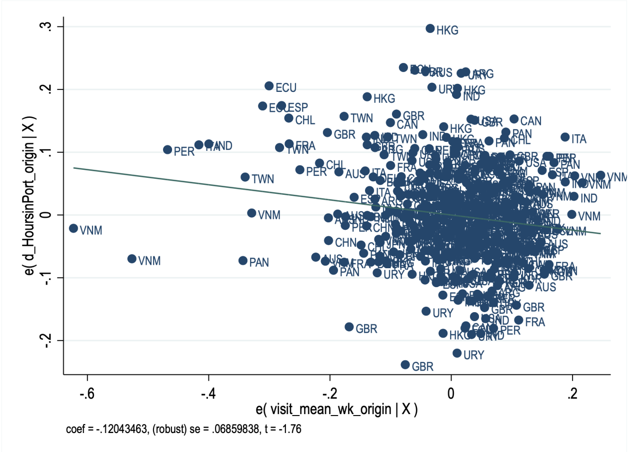
(d) Number of calls, drop period



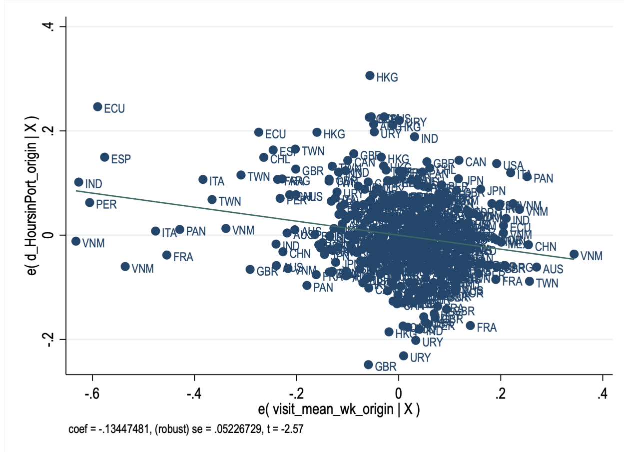
Note: Panel (a) plots the coefficients when replicating results in Table 4 Panel A Column (1) and dropping one country at a time, and Panel (b) plots the coefficients when dropping one time at a time. Panel (c) plots the coefficients when replicating results in Table 4 Panel A Column (3) and dropping one country at a time, and Panel (d) plots the coefficients when dropping one period at a time.

Figure B8: Robustness of Country-Level Results, the Impact of Mobility Changes on the Number of Hours in Port, Residual Plots

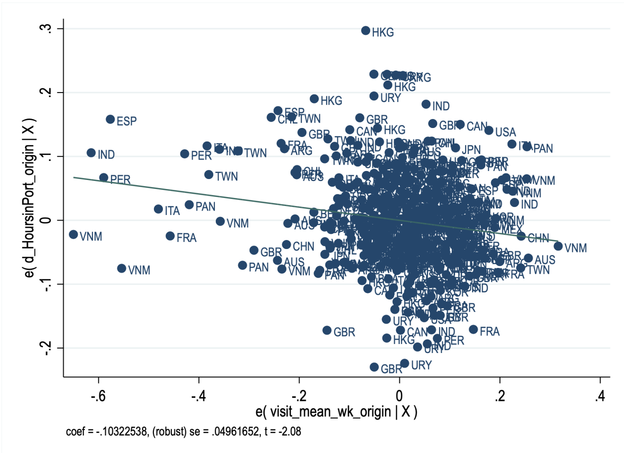
(a) Exclude March 2020



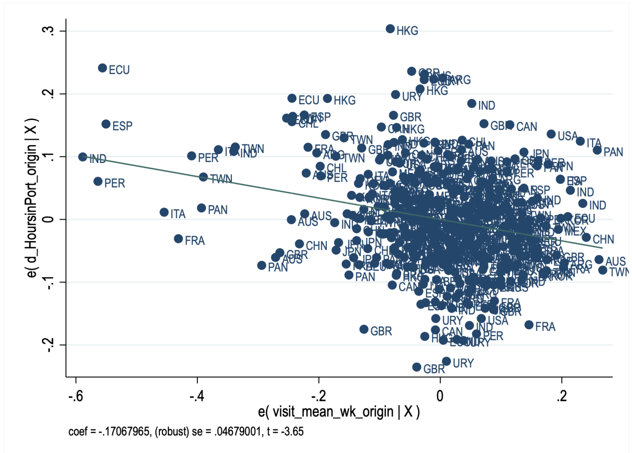
(b) Exclude April 2020



(c) Exclude Ecuador

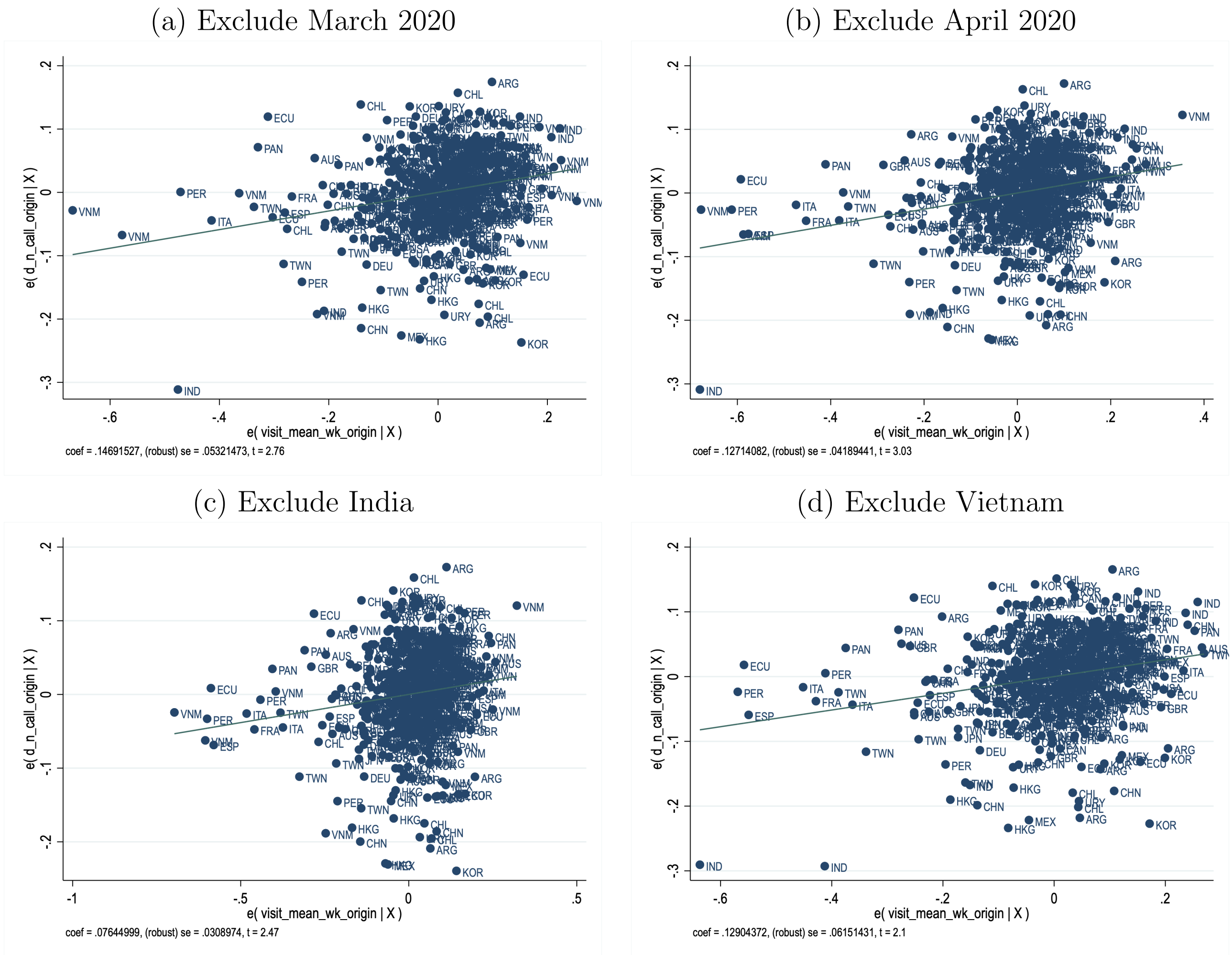


(d) Exclude Vietnam



Note: Panel (a) is the residual plot for replicating results in Table 4 Panel A Column (1) and dropping March 2020. Panel (b) drops April 2020, Panel (c) drops Ecuador and Panel (d) drops Vietnam.

Figure B9: Robustness of Country-Level Results, the Impact of Mobility Changes on the Number of Port Calls, Residual Plots



Note: Panel (a) is the residual plot for replicating results in Table 4 Panel A Column (3) and dropping March 2020. Panel (b) drops April 2020, Panel (c) drops India, and Panel (d) drops Vietnam.

Table B8: The Impact of Port Mobility on Freight Costs, Without Dropping the Top 1% and the Bottom 1%

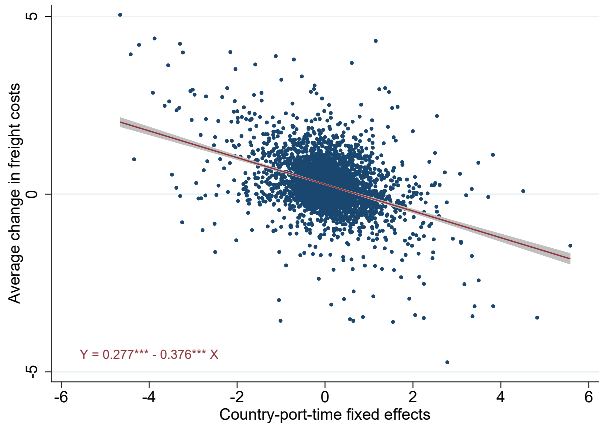
Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome: 2020 and 2021	Δ log freight cost, unit				Δ log freight cost, weight			
Δ log mobility change	-0.31**	-0.31**	-0.35***	-0.62***	-0.34***	-0.34***	-0.37***	-0.63***
	(0.11)	(0.11)	(0.12)	(0.21)	(0.10)	(0.10)	(0.11)	(0.17)
I (year=2021)	0.57***		0.57***	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 5 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.

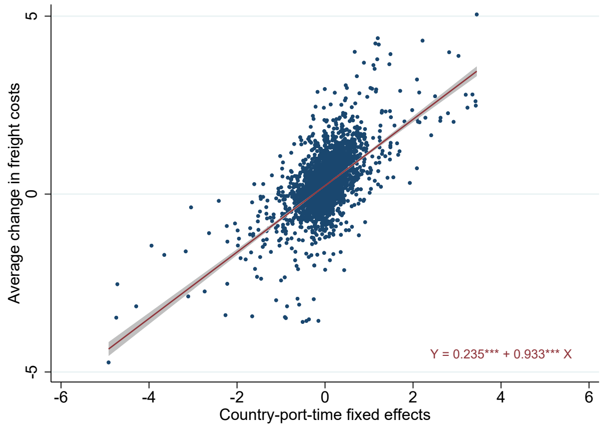
B.9 Freight Unit Values and Country-Port-Time Fixed Effects in Baseline Regression

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

(a) Quantity regression



(b) Price regression

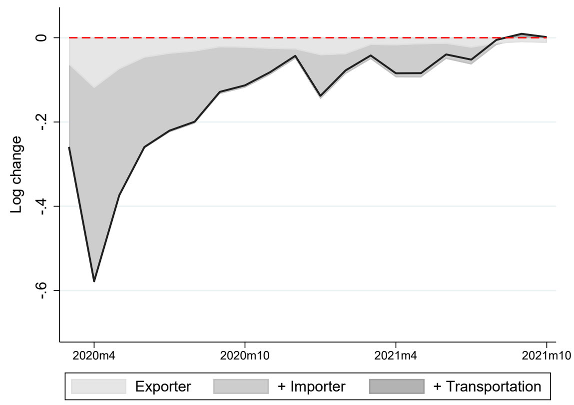


Note: Average changes in freight unit values are computed as averages over log changes in this variable relative to February 2020 in exporter and importer cities observed for each exporting country, product, and time. Country-port-time fixed effect estimates are from Table 1 Panel A Columns (2) (quantity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

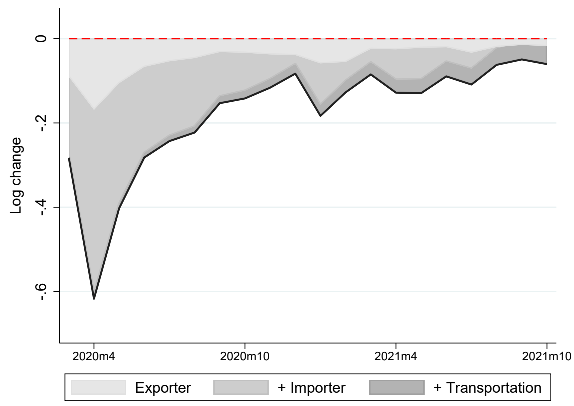
B.10 Additional Decomposition Results

Figure B11: Decomposition: Import Values, Quantities and Prices of Consumer Goods

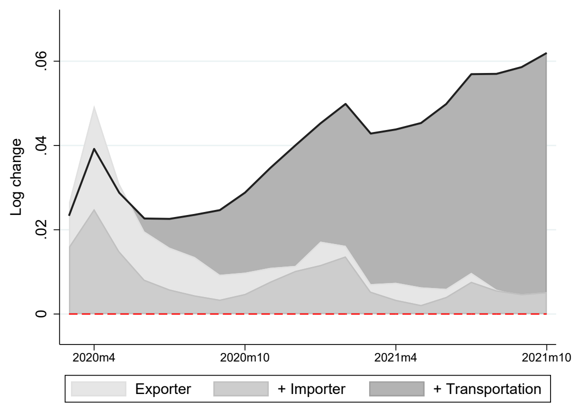
(a) Import value



(b) Import quantity



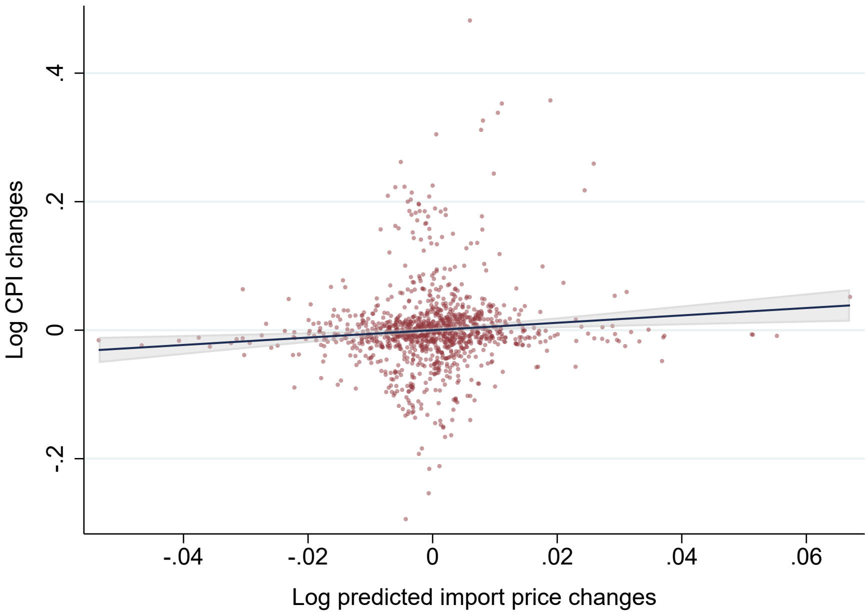
(c) Import price



Note: Each data point is computed using baseline estimates for consumption goods in Table 2 and for freight costs in Table 5 and month-specific average changes in exporter, importer and port mobility.

B.11 Additional Inflation Results

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 7 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:

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