

Trade Disruptions Along the Global Supply Chain*

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Abstract

We study the impact of local disruptive shocks on international trade flows during the pandemic. Using rich product-level import data from Colombia, we show that in aggregate, 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 foreign export prices and shipping costs. We then study the impact of local human mobility declines on imports, including the mobility declines experienced in exporter cities, ports, and importer cities. We find that a 10% decrease in mobility at the importer location lowered imports to that location by 4.8%, and that a 10% decrease in mobility at the exporter location led to a 2.5% decline in imports. Using data on port calls made by container ships, we document a decline in port productivity during the pandemic. We show that mobility change in ports induced a decline in port efficiency and a rise in freight costs, both at the origin country and at the intermediate country. We show that results are consistent with a trade model featuring local labor shocks and short-run production and shipping congestion.

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

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. The Covid-19 pandemic generated disruptions in all three aspects. On the one hand, production capability was compromised by containment efforts, illness, and shifts in workers' preferences. On the other hand, the transportation sector was hit by similar issues, and also suffered from potential congestion when unprecedented volumes of goods needed to pass through ports with limited capacity. Finally, the demand for goods was likely affected by changes in present and future expected income, work modalities, and shifts in consumers' preferences.

In this paper, we study the impact of local disruptions at different points of the supply chain on international trade. We exploit a rich dataset on Colombian monthly imports by 6-digit HS product, exporter location, and importer location with detailed information on import quantities, import prices, export prices, and the wedge between the two, shipping costs. First, we document changes in trade and transportation variables over the pandemic. Second, we use the information on the location of the exporter and importer along with local changes in mobility to estimate the direct impact of disruptive shocks on the quantity and prices of goods imported by Colombia. 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 in terms of congestion. To interpret results, we employ a trade framework featuring firms with short-run decreasing returns to scale, consumers with a love of variety over different locations, and a transportation sector with a limited capacity to ship goods across locations.

Colombia offers a unique opportunity to study the impact of local trade disruptions during the pandemic. First, it is a small economy in world trade. 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 of about 60% before the pandemic. Therefore, Colombia provides an ideal laboratory to study the consequences of the pandemic for international trade.

In addition to the advantage of the Colombian context, our identification relies on different regions across the world experiencing Covid outbreaks and mobility declines differentially across periods. This is likely to be the case since the spread of the disease and behavior responses vary substantially across countries and regions and over time.

Our paper uses highly granular, up-to-date data on mobility, trade flows, and maritime transportation. Our trade outcomes are monthly trade information collected by Colombian customs. The data allows us to identify exporters and importers at the city level (or city-equivalent level). To measure shocks to local producers and consumers, we use changes in human mobility to measure local disruptive shocks during the pandemic. We obtain monthly changes in mobility in Colombia and its 27 major trading partners' cities from Facebook and Baidu and match the exporter and importer cities with their mobility changes. Changes in mobility are measured relative to the pre-Covid period, and we use them to proxy for the decline in local economic activity across regions. Finally, we obtain the universe of port calls made by container ships in these exporting countries from January 2019 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 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. Shipping costs steadily rose over the entire pandemic and reached an increase of 70% in October 2021. Overall, import prices were 18% above pre-trends in October 2021, with shipping costs contributing 40% to that increase.

We find that both reductions in mobility at the exporter and importer locations caused product-level import values and participation to decrease. In our preferred specification, a 10% reduction in importer mobility lowered imports to that location by 4.8%; whereas a 10% reduction in exporter mobility decreased imports to that location by 2.5%. Moreover, such declines in importer and exporter mobility reduced the probability of observing a trade flow at a given exporter-importer-product observation by 3 and 2 percentage points respectively during the pandemic. Therefore, we show that local disruptive shocks likely affected both the intensive and extensive margin of trade.

We also observe salient trends in port performance across the world. In 2020 and 2021, the world trade 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 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 a mean change in mobility induces 2.2% increase in the hours in port at the exporting country. Furthermore, this change in mobility in the exporting country also translated to a 4% increase in freight cost, and the elasticity of mobility to freight cost is even higher for intermediate countries.

In addition, we find that 2021 had a larger number of hours in port and a higher freight cost compared to 2020, even after we control 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.

Our paper contributes to the literature on the impact of local shocks on firms and trade. Researchers have documented the impact of natural disasters on trade, e.g., how an earthquake disrupts domestic roads to ports and affects exporting activities (Volpe and Blyde, 2013). In addition, these effects also propagated along the supply linkages (Barrot and Sauvagnat, 2016; Boehm et al., 2019; Carvalho et al., 2021). There is also direct evidence on how input shortages (e.g., electricity shortages) dampen firm growth (Allcott et al., 2016). We contribute to this literature along several dimensions. First, we study a plausibly exogenous shock that affects regions across the world differentially, and we show how shocks to one country and one region propagate globally through international trade. Second, we have a direct measure of the size of the shock across regions, which allows us to estimate the elasticity of trade with respect to the shocks. Third, we have detailed information on price, quantity, and freight costs to estimate the impact on trade along different margins. Finally, we decompose the overall changes in trade outcomes into the impact of importer shocks, exporter shocks, and port shocks.

Our paper is closely related to the literature on the role of transportation on 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. Related, Cosar and Thomas (2021) find substantial regional welfare losses in the event of the closure of key maritime waterways in Southeast Asia. We contribute to the literature in three ways. First, we focus on a different type of shock to maritime shipping, which is 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, 2018), 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.

Our paper also relates to the literature on the short-run impact of changes in the trading environment. Anderson and Yotov (2020) show that the short-run trade elasticity is one-quarter of the long term due to fixed bilateral capacities. We use this idea to construct the theoretical framework, where production has decreasing returns to scale, and shipping has limited capacity. We also decompose the short-run impact of changes in trading conditions as in Fajgelbaum et al. (2020), which find that the tariffs hikes due to the U.S.-China trade war reduced imports and exports in the short-run entirely through quantities. In our setting, quantities and prices react differentially depending on the location of shocks.

Finally, this paper contributes to recent research studying the impact of the pandemic on trade and economic activity in general. First, a few papers develop quantitative models to simulate the impact of country-level pandemic shocks on supply-chain disruptions (Guan et al., 2020; Bonadio et al., 2021; Liu et al., 2021). Second, several papers document the impact of the pandemic on labor markets and on income and consumption (Chetty et al., 2020; Coibion et al., 2020a,b). Third, some papers develop general frameworks to study the impact of globalization where trade also spreads diseases through human interactions (Antràs et al., 2020), and the impact of an increase in trade in services due to the offshorability of remote work (Baldwin and Freeman, 2021). One exception is Martin et al. (2021), where the authors show how French firms sourcing from Chinese experienced declines in exports in the early period of the pandemic. To the best of our knowledge, we are the first to use detailed measures of *actual* trade outcomes, port performances, and human mobility at the sub-national level to causally estimate the impact of local pandemic shocks on international trade.

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 outlines a simple trade model to interpret the subsequent results. In Section 4, we study the relationship

between exporter and importer local mobility shocks and Colombian imports. In Section 5, we study the impact of mobility and congestion in world ports on freight unit values. In Section 6, we present some preliminary results on the decomposition of the effects over time. Section 7 concludes.

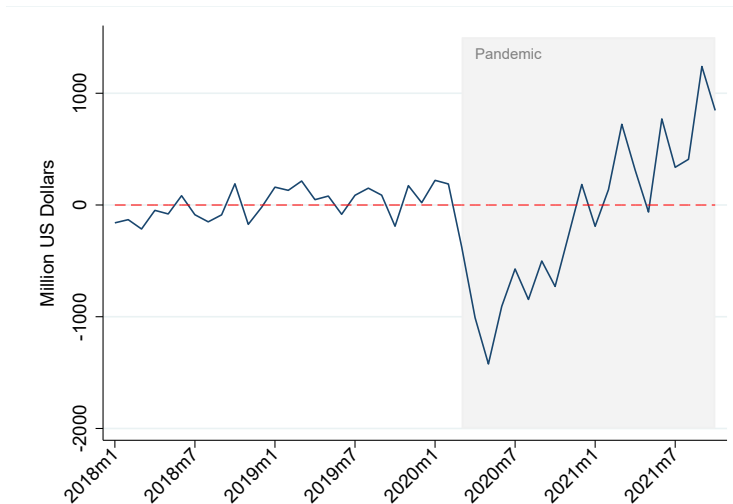
2 Data and Motivating Facts

2.1 Trade Data

In this section, we characterize monthly changes in Colombian import trade variables from 2018 to 2021.

To do so, we employ data collected by the Colombian customs office and made available by DANE (the National Administrative Statistical Office by the Spanish acronym). This dataset includes monthly information about the importer location, exporter location, 6-digit HS products, import values, quantities and weights, and freight and insurance costs. We select 27 major trade partners for the analysis, which account for about 90% of total 2018 imports.¹

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



Note: Each month's value is calculated as the total Colombian imports minus the 2018–2019 month-specific average. Twenty-eight selected countries (90% of total Colombian imports (2018)).

We start by documenting total monthly imports over the 2018–2021 period in terms of

¹We do not use all exporting countries because within-country exporter locations required extensive cleaning.

pre-pandemic averages. To do so, we take the month-specific average total import value of 2018 and 2019 in US dollars and use them to demean 2018-2021 imports. Figure 1 plots the demeaned values in million US dollars.

Before the pandemic, aggregate imports did not show large monthly swings, with changes always lower than 6% relative to the month-specific 2018–2019 average. Aggregate imports to the selected countries declined by almost 40% — 1.4 billion US dollars — at the beginning of the pandemic, and they increased by as much as 35% — 1.2 billion US dollars — during 2021.

These values mask the different 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 location, importer location, product, and month level to accurately define quantities and prices and reduce compositional changes.

We decompose log import values $\hat{m}$ as follows:

$$m \equiv q + p^X + \tau \quad (1)$$

where q is quantities, p^X is export prices, measured in free on board (FOB) terms, and τ is the ad-valorem trade costs, defined as the sum of the freight and insurance costs. By definition, log import prices is $p^M \equiv p^X + \tau$, i.e. it is measured in cost, insurance and freight (CIF) terms.

We calculate each variable in Equation 1 at the exporter location (i), importer location (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:

$$m_{ijkt} = \sum_{r=01/2020}^{10/2021} \delta^r \times \mathbb{1}\{t = r\} + \delta_{ijk}^{seas} + \delta_{ijk}^{trend} \times t + \varepsilon_{ijkt} \quad (2)$$

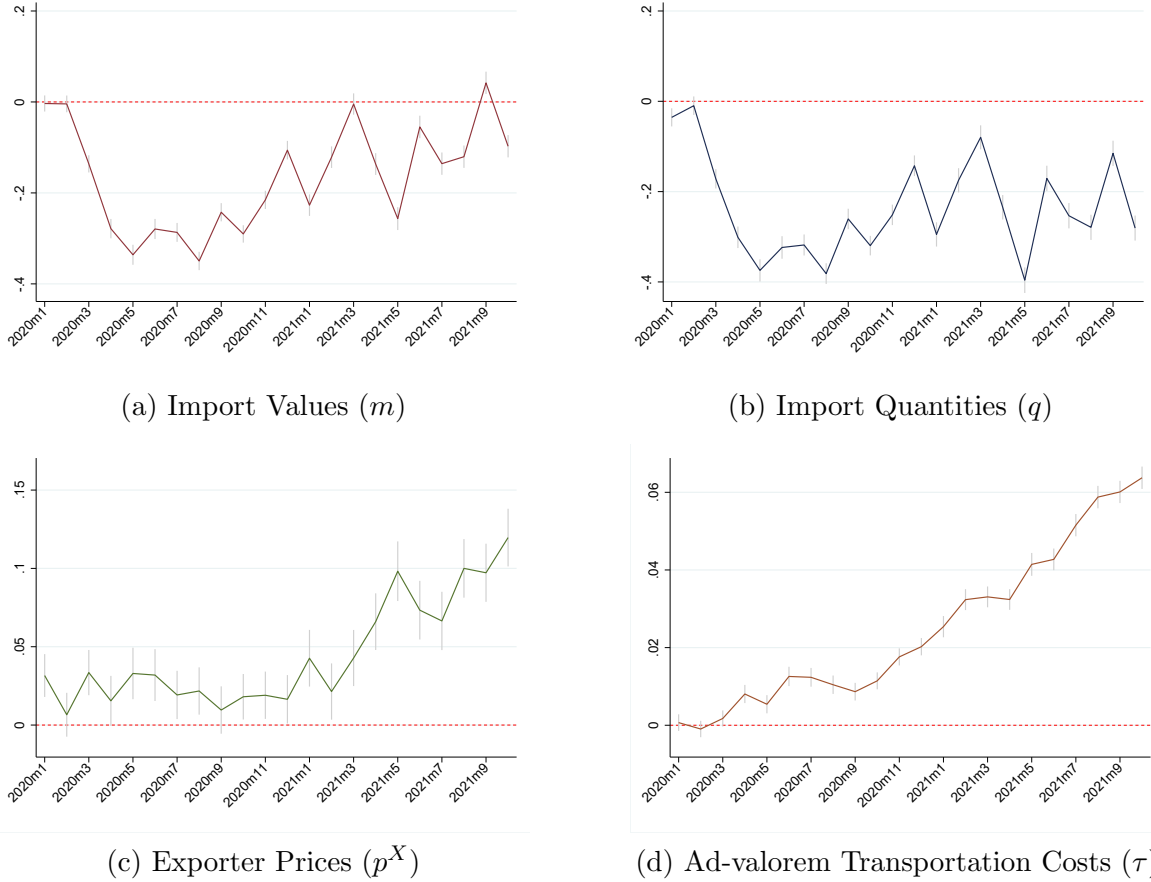
where m can be imports or any of the other variables in Equation 1. We include an exporter-importer-product-month fixed effect δ^{seas} to control for seasonality, and an exporter-importer-product-specific linear time trends δ^{trend} . The coefficients of interest are the δ^r , with r ranging from January 2020 to October 2021. We interpret each of these coefficients as the average deviation from pre-pandemic trends at month r .

Figure 2a shows that the average impact on import values had a similar dynamic pattern as the aggregate: a sharp decrease at the beginning of the pandemic and a slow, non-monotonic recovery. This pattern is mostly explained by changes in the quantities imported, as seen in Figure 2b.²

²Import quantities are defined at the 6-digit HS level and do not change over the sample period, which

Export prices had a different dynamic. They remained relatively unchanged during 2020 and the first quarter of 2021 but started rising in the second quarter (Figure 2c). Ad-valorem transport costs increased steadily since the beginning of the pandemic (Figure 2d). 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.

Figure 2: Average Change in Import Variables Relative to Pre-Pandemic Trends



Note: Each point is the estimated coefficient of Equation 2 with 95% confidence intervals. Standard errors clustered at the exporter-importer-product level.

Trade costs in ad-valorem terms are the standard approach in the trade literature, but we can actually construct freight and insurance unit values with the Colombian data. In Figure 3 we show the their dynamics also using Equation 2 specification.³

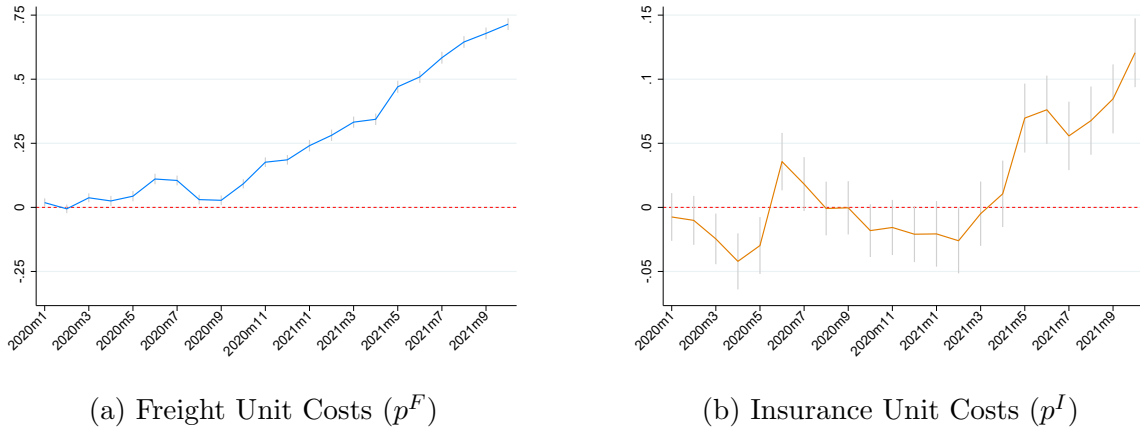
Figure 3a shows that freight unit values increased more than 10% during the June-July means that, given the fixed effects in equation 2, coefficient estimates are well-defined.

³Specifically, we construct freight unit costs as $p^F \equiv \frac{\text{Freight total costs}}{\text{Quantity shipped}}$, and insurance costs p^I similarly.

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 the last month available (October 2021).

Insurance unit values show a different pattern. As showed in Figure 3b, 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 2021.⁴

Figure 3: Average Change in Freight and Insurance Unit Costs Relative to Pre-Pandemic Trends



Note: Each point is the estimated coefficient of Equation 2 with 95% confidence intervals. Standard errors clustered at the exporter-importer-product level.

Export, transportation and insurance prices showed an increase over the 2020–2021 period, which means that import prices also increased, as shown in Figure 4.

What was the contribution of transportation costs to such an increase over time? We employ the following decomposition to measure it:

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

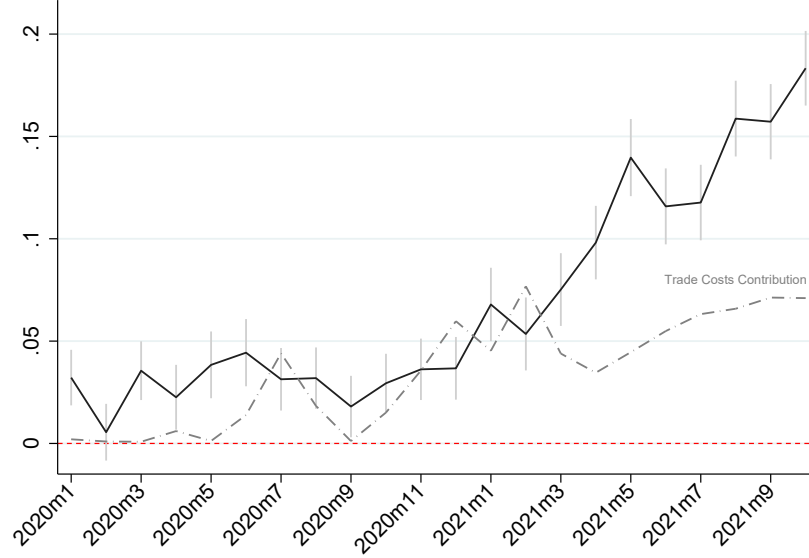
where $\hat{\cdot}$ are differences with respect to pre-pandemic trends, and θ^X , θ^F and θ^I are the average pre-pandemic share of export prices, freight, and insurance unit costs respectively.⁵ We then replace each term by the corresponding estimated deviation from pre-trends estimated in

⁴Note 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.

⁵The average pre-pandemic export prices share in import prices were 92%, freight unit costs were 8% and insurance costs were 1%.

equation 2. Figure 4 shows that freight and insurance cost contribution to the increase in import prices was close to 50% towards the end of 2021.⁶

Figure 4: Average Change in Import Prices Relative to Pre-Pandemic Trends



Note: Each point is the estimated coefficient of Equation 2 with 95% confidence intervals. Standard errors clustered at the exporter-importer-product level. 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 3.

In conclusion, import variables experienced large swings 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 a different timing.

2.2 Container ship port call data

We use port call data on 150 ports in 27 countries and regions from January 2019 to October 2021 to measure port performance. The data on container ship movement is from IHS Markit's Maritime & Trade Platform.⁷ 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, and Venezuela for which there is no mobility data), Colombia, and Singapore (as an important intermediate port). We include the most important ports in these countries. The 150 ports

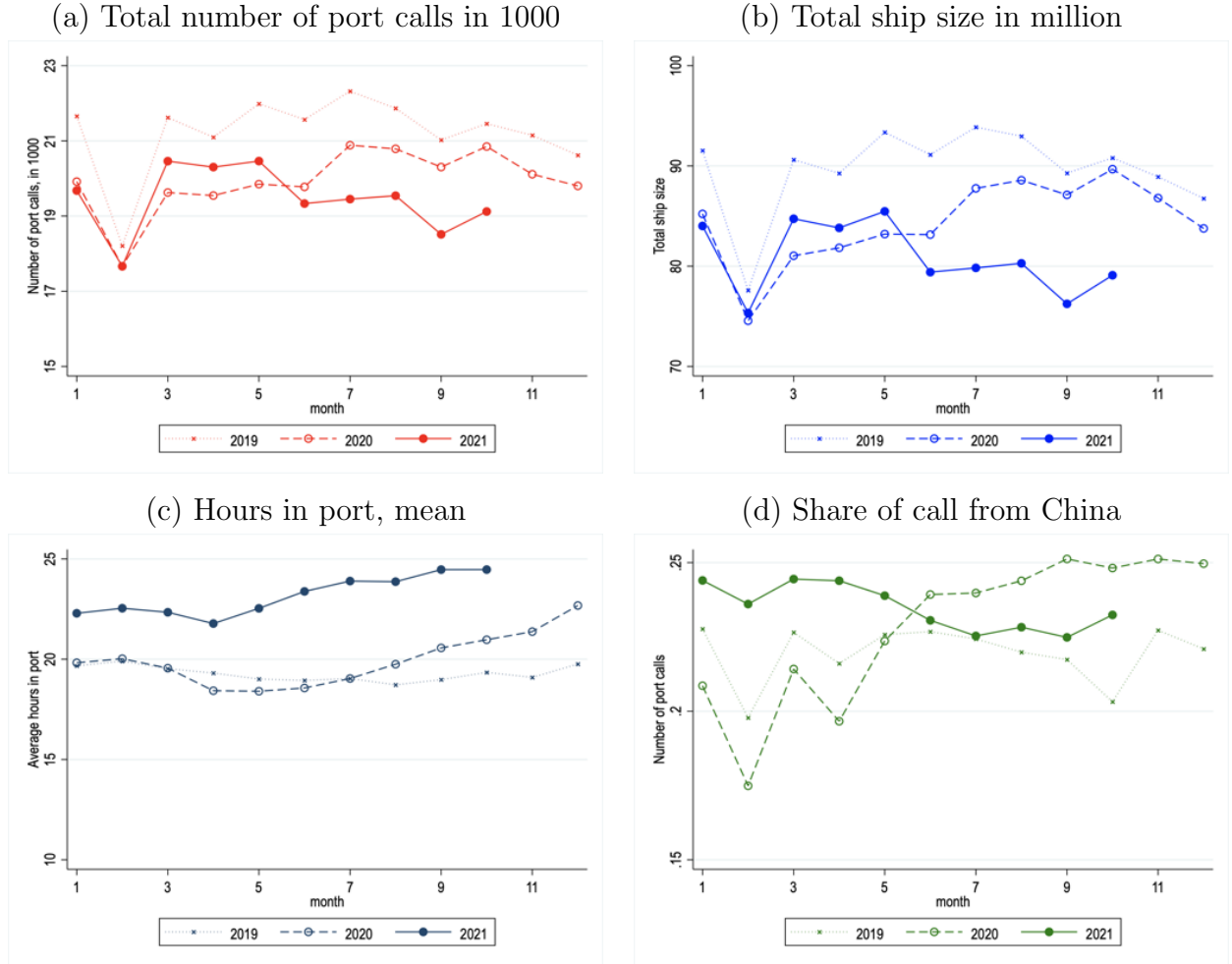
⁶Contribution is calculated as $(\theta^F \hat{p}^F + \theta^I \hat{p}^I) / \hat{p}^M$.

⁷See <https://ihsmarkit.com/industry/maritime.html>.

have at least 10 port calls made by container ships per month in 2019, and at least 5 port calls in each month in 2019. 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 A3.

Figure 5 presents the important trends in port performance from 2019 to 2021. Panel (a) shows the total number of port calls. We can see that the container ship trade was at a lower level in 2020 and 2021 than in 2019. The first half of 2020 had an about 10% decline, and the second half of 2020 experienced some recovery. The recovery continued until May 2021, and since June 2021, the number of port calls was even below the 2020 level. Panel (b) presents a similar trend, by measuring trade volume using the total twenty-foot-equivalent units of the ships that made port calls.

Figure 5: Port performance from January 2019 to October 2021, 150 ports in 27 countries



Note: Data is from the IHS Markit Maritime & Trade Platform. The figures use port calls made by container ships at 150 ports in 27 countries. The 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.

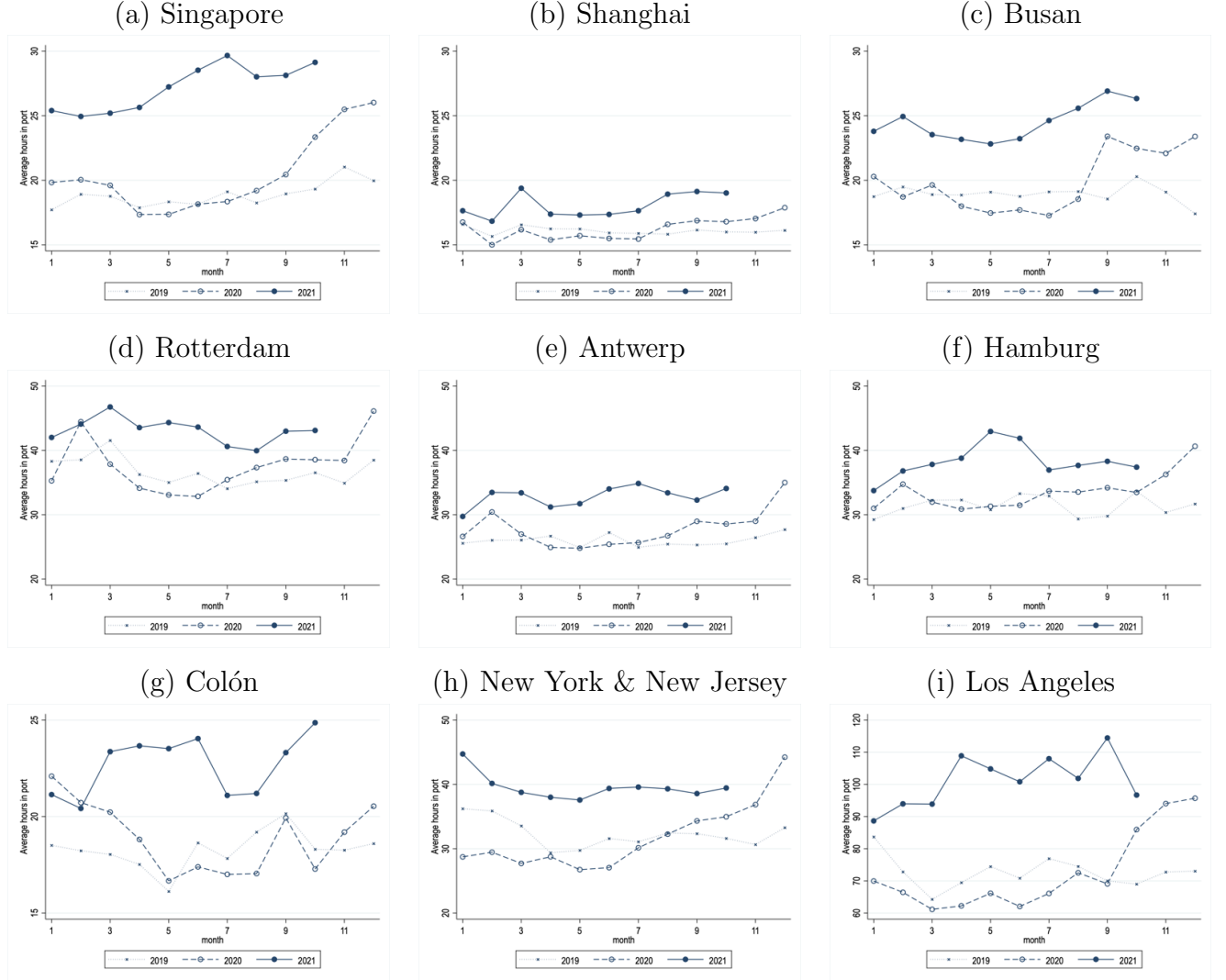
Panel (c) presents the trend in the average hours in port. The number of hours in port is measured using the difference between the sailed time and the arrival time for the port call. Arrival time is the first AIS position that appears within the designated port zone, and sailed time is the first AIS 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 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, Figure 6 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 2021.⁸

⁸See more about the Los Angeles port congestion here: www.wsj.com/articles/why-container-ships-cant-sail-around-the-california-ports-bottleneck-11632216603?mod=article_inline.

Figure 6: Average Hours in Port, 9 Important Ports



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

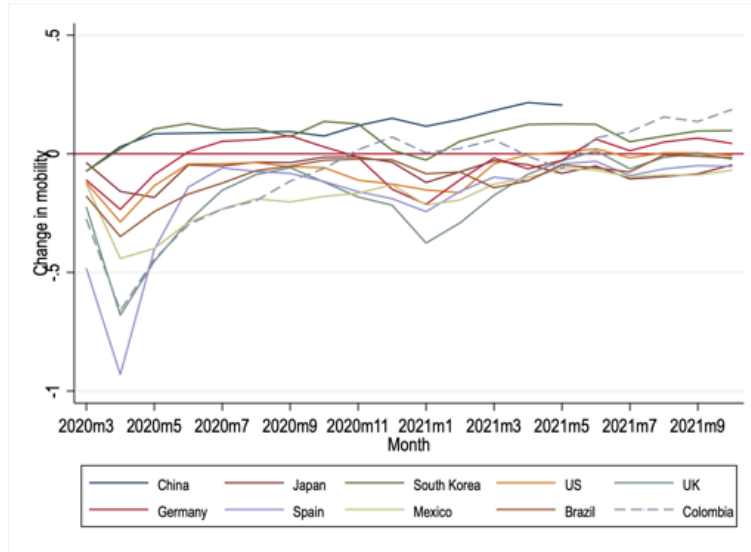
2.3 Mobility Data

Countries around the world experienced declines in mobility during the pandemic, because of government restrictions, sickness, and voluntary containment efforts. We measure the shock to labor in cities using the change in daily log 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 baseline period is the first two weeks in January.⁹ 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. For Colombia and its 27

⁹Source: Baidu Mobility Map at <https://qianxi.baidu.com/>.

major trade partners, the data is from Facebook, and the baseline period is February 2020. Venezuela does not have Facebook data.¹⁰ 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 administrative level, so we refer to the regions as "cities." Only cities with more than 300 users are included. Then we average across the working days in a month (i.e., Monday to Friday) to measure the mobility change in a month.

Figure 7: The Trend of Mobility in Exporting Cities Across Countries and in Colombia

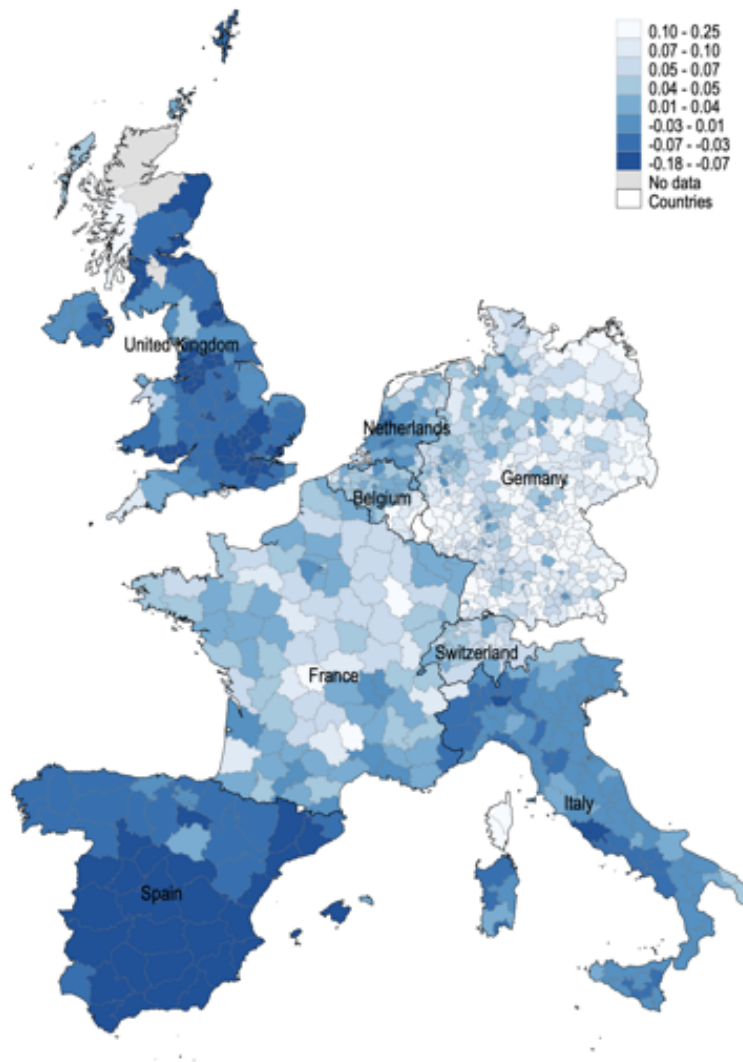


Note: Include only cities that export to Colombia and have mobility data. Data on Chinese mobility is from Baidu, and for other countries, comes from Facebook.

Figure 7 presents the changes in mobility in Colombia and some of its major 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 lockdown. 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.

¹⁰See <https://dataforgood.facebook.com/dfg/tools/movement-range-maps>.

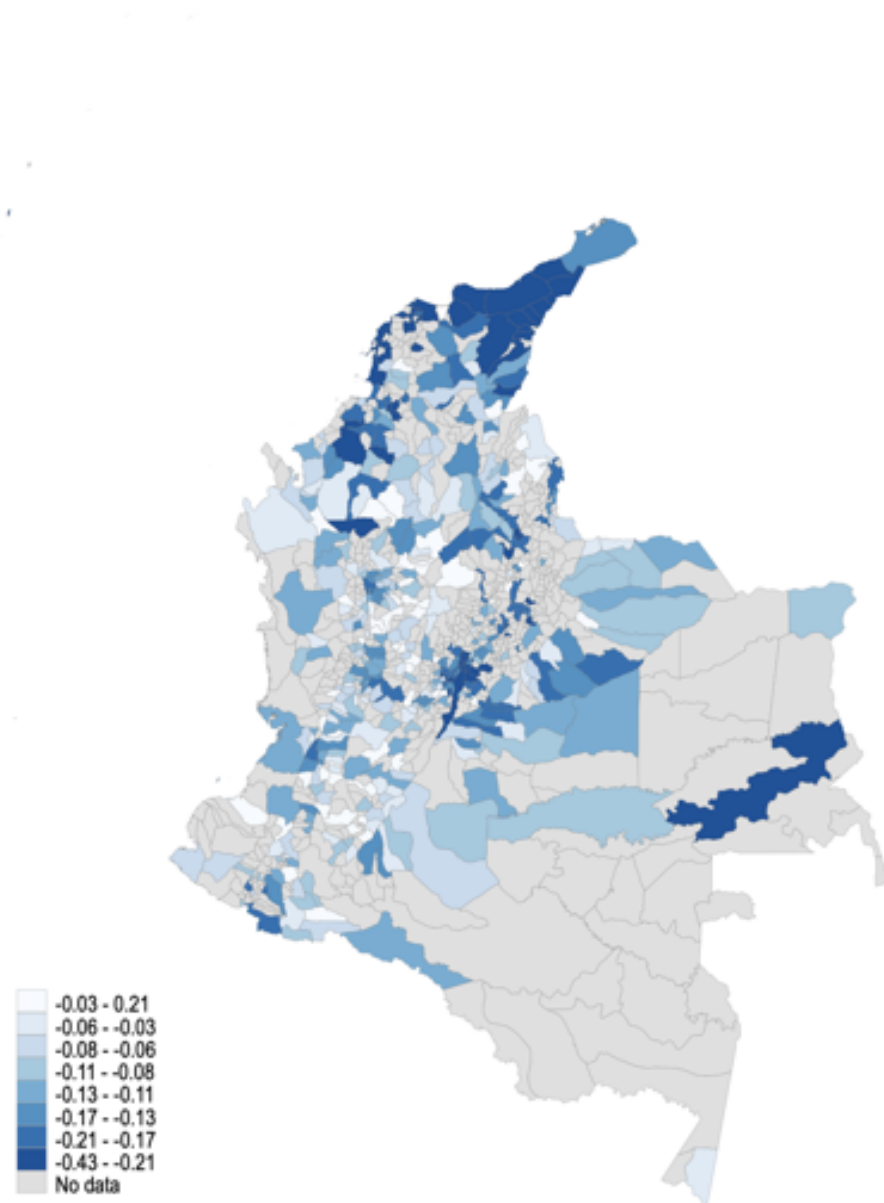
Figure 8: The Decline in Mobility Across NUTS3 Units in 8 European Countries, September 2020



Note: Data is from Facebook. Countries include the UK, France, Spain, Italy, Switzerland, Belgium, the Netherlands, and Germany.

In addition, there is substantial within-country variation in mobility. Take Europe as an example, Figure 8 shows the distribution of mobility declines across eight European countries that are the major trading partners with Colombia 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.2.

Figure 9: The Decline in Mobility Across *Municipios* in Colombia, September 2020



Note: Data is from Facebook.

Figure 9 presents the local mobility variations in Colombia in September 2020. Note that Facebook covers only 530 out of 1,065 *municipios* in Colombia. In Appendix A.3, we present the level of aggregation in each country and the number of units per country.

3 Theoretical Framework

In this section, we construct a simple trade model to have a conceptual framework to guide our empirical strategy.

3.1 Environment

We assume there are I locations in the world located in countries indexed by C . Each location i has two type of firms. The first one produce products indexed by $k \in K$, where K is the industry. The second set of firms are competitive bundlers that sell industry goods domestically to either consumers or domestic firms.

Producing firms combine local labor and capital with a Cobb-Douglas technology to produce, where $\tilde{\alpha}_L^K$ 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 $i \in C$ exporting product $k \in K$.

Bundlers’ technology is also Cobb-Douglas and combine labor and the sourced product k to domestically sell it. They can source product k from locations in a pre-determined set Ω_{jk}^K , where j indexes the location of this firm as a buyer importing product k . Importantly, we assume that bundlers cannot perfectly substitute across locations, and thus model their technology as CES with elasticity of substitution η^K . We call bundlers importers given that we focus on international sourcing.

International trade is subject to a per-unit international transport cost t_{ijk} . Therefore, the import price p_{ijk}^M is equal to $p_{ik}^X + t_{ijk}$, where p_{ik}^X is the export price.¹¹

3.2 Local Import Demand

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

$$q_{ijk} = (p_{ijk}^M)^{-\eta^K} (P_{jk}^M)^{\eta^K-1} Z_{ijk}^K \quad (4)$$

where $P_{jk}^M \equiv [\sum_{\Omega_j^K} (p_{ijk}^M)^{1-\eta^K}]^{\frac{1}{1-\eta^K}}$ is the CES price index over locations, and Z_{ijk}^K is a good K -specific demand shifter. This term can include a variety of factors. First, it can capture a decline in current and future expected income. For instance, we would expect a decline in quantities imported if a local disruption increases layoffs because the bundler would see the demand for its goods reduced. We call this an “income effect”. Second, it can capture

¹¹We interpret t_{ijk} as including both freight and insurance costs.

a “substitution effect” to or from other goods —e.g. non-tradable goods. In this case, the impact of the pandemic can be either positive or negative depending on substitution patterns. Finally, it can also capture idiosyncratic shocks.

3.3 Local Export Technology

We assume exporters have a fixed amount of capital over the period we consider, which means that, given their Cobb-Douglas technology, their cost function is:

$$C_{ik} = A_{ik}^K Q_{ik}^{\alpha^K} \quad (5)$$

where A_{ik}^K is a cost-shifter specific to good K , $Q_{ik} \equiv \left[\int_{\Omega_{ik}^{IK}} q(j)_{ik} dj \right]$ is total production, Ω_{ik}^{IK} is the set of locations served by i , and $\alpha^K \equiv 1/\tilde{\alpha}_L^K > 1$ captures the degree of decreasing returns to scale in the short run due to fixed capital. The cost-shifter A_{ik}^K can capture different factors, as in the case of demand. First, it can capture local changes in wages, which may be increased by a reduced labor supply during the pandemic. Second, it can capture changes in productivity, for instance due to work-from-home patterns induced by the pandemic. Finally, it can also capture idiosyncratic supply shocks.¹²

3.4 Export Prices

Exporters maximize profits by choosing export prices given the CES importer demand and their technology.¹³ Therefore, they charge the following optimal export price:¹⁴

$$p_{ijk}^X = \frac{\eta^K}{\eta^K - 1} \alpha^K A_{ik}^K Q_{ik}^{\frac{\alpha^K - 1}{\alpha^K}} + \frac{1}{\eta^K - 1} t_{ijk} \quad (6)$$

This expression captures different features of export prices. First, they increase to all exporters in the short-run if there is an increase in demand from any importer. Specifically, as exporter i faces more demand, the marginal cost of production $\alpha^K A_{ik}^K Q_{ik}^{\frac{\alpha^K - 1}{\alpha^K}}$ increases, raising the average cost of serving any destination. Second, cost shocks to location i also increase prices through A_{ik}^K (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.

¹²Given the technology assumptions, $A_{ik}^K \equiv \left[\frac{w_j}{a_j^K \hat{H}^{1-\tilde{\alpha}_L^K}} \right]^{\frac{1}{\tilde{\alpha}_L^K}}$, where a_{jk} is a Hicks-neutral productivity parameter and $\hat{H}$ is the fixed amount of capital.

¹³Exporters maximize $\Pi_{ik} = \sum_{\Omega_{ik}^{IK}} p_{ijk}^X q_{ijk} - C_{ik}$

¹⁴See derivation in the Appendix C.1.

3.5 Transport Prices

We assume the transportation sector is operated by a global firm that faces local decreasing returns to scale. The supply curve to ship products from i to j is given by:

$$t_{ij} = B_{ij}v_{ij}^\beta \quad (7)$$

where v_{ij} is the total volume of goods transported from i and j and $\beta > 1$ is the local decreasing returns to scale parameter.

Depending on their volume, different products face different per-unit transport costs. For instance, large products such as cars face a higher per-unit cost than smaller products such as shirts. To capture these differences, we employ a constant product-specific factor κ_k , which adjusts differences in size: $t_{ijk} \equiv t_{ij}\kappa_k$.

3.6 Solution in Changes

We are interested in how changes in underlying conditions affect equilibrium import and transport prices and quantities at the exporter-importer-product level.

Local import prices changes are as follows:

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

where $\hat{\cdot}$ means the log-change of variable x with respect to the equilibrium value, and $\iota_{ijk} \equiv \frac{p_{ik}^D}{p_{ijk}^M}$, assuming that transport costs of shipping to the domestic market —where the exporter is located— are zero and thus the domestic price p_{ijk}^D is determined only by the local marginal cost of production and producer markups. As expected, import prices increase when exogenous production costs rise, but also when the total production increases, given that the marginal cost increases through congestion in the short run. Finally, an increase in transportation costs due to exogenous or general equilibrium shocks ($\hat{B}$) or an increased the volume shipped ($\hat{v}$) also rise import prices.¹⁵

The impact on import demand takes into account local competition and exogenous demand shocks:

$$\hat{q}_{ijk}^M = -\eta^K\hat{p}_{ijk}^M - (\eta^K - 1)\hat{P}_{jk}^M + \hat{Z}_{ijk}^K \quad (9)$$

On top of the price change determinants, an increase in the the price index P^M or the demand shifter Z^K also rise local domestic prices.

¹⁵The impact of transport prices on import prices comes from both their accounting relationship and the optimal export price set by the exporter.

The above price (8) and quantity equations (9) will guide our empirical strategy at the exporter-importer-product, which we explore in the next section.

4 Trade Disruptions at the Importer City and the Exporter City

In this Section, we estimate the impact of demand and supply local trade disruption shocks on import variables. We start by documenting the impact of shocks at the importer and exporter location level. Then, we characterize the impact at the bilateral-product level, where we can map results to the theoretical framework in Section 3 and disentangle the impact on prices and quantities.

4.1 Effects of Mobility Changes at the Importer City

Colombia is divided into 32 departments and about 1,100 municipalities. We employ the top 60 municipalities in terms of 2018–2019 imports for the analysis, which explain about 99% of total imports. In Appendix Figure A4, we plot the distribution of mobility shocks relative to February 2020 in April 2020 — the month with the highest reduction in mobility — and in April 2021, by the department of those included. As observed, there is a variation within departments and over time.

In order to explore the relationship between importer mobility and import values, we estimate the following equation at the monthly frequency:

$$\hat{m}_{jt} = \beta^J \hat{x}_{jt}^J + \tilde{\Theta}^J + \varepsilon_{jt}, \quad (10)$$

where $\hat{m}_{jt}$ is the log change in imports in location j at t relative to February 2020, and $\hat{x}_{jt}^J$ is the log change in importer mobility in j at t relative to February 2020. The term $\tilde{\Theta}^J$ is a vector of fixed effects, specified below, and ε_{jt} is an idiosyncratic error term. The sample period runs from March 2020 to October 2021.

The coefficient of interest is β^J , which we interpret as the correlation between importer mobility and import values at the importer-level. It is reasonable to expect β^J to be positive, since a reduction in mobility during the pandemic can be associated with a local covid shock —either through a lockdown or self-isolation due to an increase in covid cases—, which can reduce consumer and firms’ demand for imported goods through a decline in economic activity.

In the top panel of Table 1, we estimate Equation 10 for different fixed effects specifications. In column (1), we include month fixed effects to control for seasonal demand factors. The impact of changes in mobility is positive and significant as expected. A 10% decrease in local mobility relative to February 2020 is related to a 8.8% decrease in import values. Including year fixed effect in column (2) reduces the effect to about 4.3%, suggesting a higher elasticity for inter-annual changes in mobility during the pandemic. In column (3), we introduce time (i.e., month-year) fixed effects, to see if variation in mobility across locations at a given time also affects import values. The impact is positive and significant. In columns (4) to (6), we replicate Columns (1) to (3) but also add department fixed effects. Estimates remain positive but become noisier when we include year or time fixed effects. Figure 10 presents the residual plot corresponding to Column (3) in Table 1 and shows that the result is not driven by outliers in either the mobility or the import variables.

Table 1: The Relationship Between Importer Local Mobility and Import Values

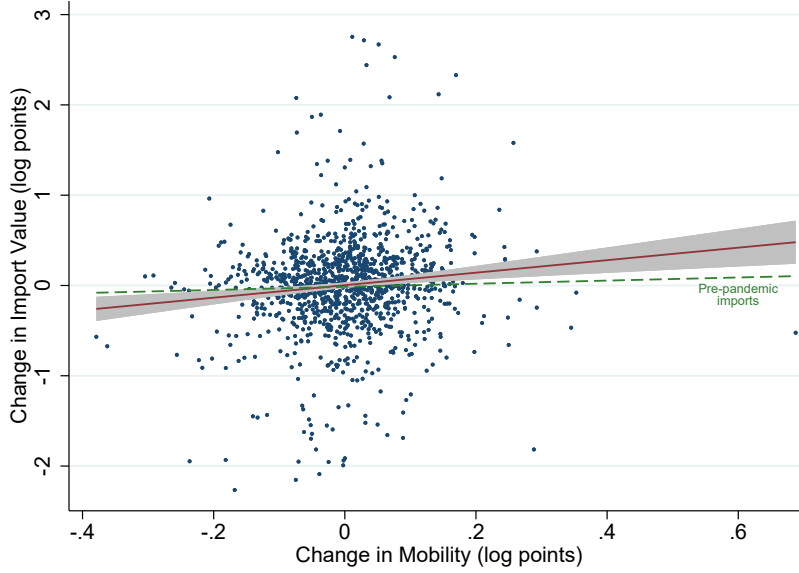
	(1)	(2)	(3)	(4)	(5)	(6)
Imports in the Pandemic period (2020-2021)						
Importer Mobility (2020-2021)	0.879*** (0.079)	0.429*** (0.129)	0.692*** (0.197)	0.837*** (0.074)	0.208 (0.129)	0.349 (0.228)
Department F.E.	No	No	No	Yes	Yes	Yes
Month F.E.	Yes	Yes	No	Yes	Yes	No
Year F.E.	No	Yes	No	No	Yes	No
Time F.E.	No	No	Yes	No	No	Yes
Observations	1,155	1,155	1,155	1,155	1,155	1,155
R^2	0.120	0.132	0.139	0.255	0.274	0.278
Imports in the Pre-pandemic period (2018-2019)						
Importer Mobility (2020-2021)	0.029 (0.061)	0.072 (0.105)	0.173 (0.153)	0.015 (0.051)	0.021 (0.103)	0.110 (0.169)
Department F.E.	No	No	No	Yes	Yes	Yes
Month F.E.	Yes	Yes	No	Yes	Yes	No
Year F.E.	No	Yes	No	No	Yes	No
Time F.E.	No	No	Yes	No	No	Yes
Observations	1,155	1,155	1,155	1,155	1,155	1,155
R^2	0.016	0.016	0.020	0.348	0.348	0.352

Note: OLS regressions at importer location-time level, where time is at the monthly frequency. Fixed effects are included as indicated in each column. Robust standard errors clustered at the importer-time level in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In the bottom panel of Table 1, we explore whether changes in mobility can be associated

to the existence pre-pandemic trends. To do so, we regress changes in import values for 2018–2019 period relative to February 2018, i.e., before the pandemic, on changes in mobility during the pandemic. We estimate the same specifications as in the top panel and all estimates are insignificant. We interpret this as providing support to the exogeneity of the variation we employ during the baseline period. In Figure 10 we also include the residual linear fit of Column (3) specification in the bottom panel of Table 1.

Figure 10: Residual Plot for the Impact of Importer Mobility on Import Values



Note: Residual plot of equation 10 with period fixed effects (Column (3) of Table 1). Pandemic period fit (red solid line):

$$\hat{m}_{ct}^{resid} = 0.003 + 0.692 *** \times \hat{x}_{ct}^{I,resid}. \text{ Pre-pandemic period (green dash line): } \hat{m}_{jt}^{resid} = -0.015 + 0.173 \times \hat{x}_{jt}^{J,resid}.$$

In sum, mobility declines at the importer location during the pandemic are associated with lower imports from that location as expected. Those declines are not observed when we employ pre-pandemic import changes.

4.2 Effects of Mobility Changes at the Exporter City

We analyze the impact of local exporter mobility on Colombian imports using the 26 main partners of Colombia, excluding Venezuela.¹⁶ In total, these countries provide about 4,200 locations where we can identify local mobility shocks. In Appendix Figure A5, we plot the distribution of mobility shocks in April 2020 and in April 2021 by country, both relative

¹⁶We do not include Venezuela, one of the main Colombian partners, due to the lack of mobility data.

to February 2020. The figure shows that there is variation over time and within countries in exporter mobility shocks.

We estimate the correlation of exporter mobility and imports originating at that location using the following empirical equation:

$$\hat{m}_{it} = \beta^I \hat{x}_{it}^I + \tilde{\Theta}^I + \varepsilon_{it}, \quad (11)$$

where $\hat{m}_{it}$ is the log change in Colombian imports from i at t relative to February 2020, and $\hat{x}_{it}^I$ is the log change in exporter mobility in i at t relative to February 2020. The term $\tilde{\Theta}^I$ is a vector of fixed effects, specified below, and ε_{it} is an idiosyncratic error term. The sample period runs from March 2020 to October 2021, with the exception of Chinese locations, which runs from March 2020 to May 2020 and from September 2020 to May 2021 due to mobility data availability.

The coefficient of interest is β^I , which reflects the effect of exporter mobility changes on the value of imports. We expect β^I to be positive, since a reduction in mobility in an exporter city can reflect a local covid shock and likely higher costs of production and shipping.

We estimate Equation 11 for different fixed effect specifications in the top panel of Table 2. In column (1), we include month fixed effects to control for seasonal supply factors. The impact of changes in mobility is positive and significant as expected. A decrease of 10% in exporter mobility is related to a decrease of 3.4% in imports from that location. This estimate is lower than what we observed on the importer mobility side. Including year or time fixed effects in Columns (2) and (3) make the estimate insignificant, suggesting that time variation is a key driver of the impact.

The definition of a location differ across countries and thus cross-countries comparisons can capture differences in sizes.¹⁷ Therefore, we replicate estimations in columns 1 to 3 and add country fixed effects. Estimates show in columns (4) to (6) show results are qualitatively the same, but relatively less noisy. When we include country and month fixed effects, a decrease of 10% in exporter mobility is related to a decrease of 4.7% in import values from there. Figure 11 shows the residual plot corresponding to Column (4) in Table 2.

We show the residual plot associated to specification in column (4) of the top panel in Table 2 in Figure 11. We average residuals to the exporting country and time level to improve readability. In contrast to importer mobility shocks, we use time-series variation in this case, given the not inclusion of time fixed effects. Reductions in exporter mobility are associated

¹⁷For instance, we use a 1-digit GADM (Database of Global Administrative Areas) classification for Argentina, but a 2-digit GADM classification for Australia. We chose the level of aggregation based on how the exporter location was declared in the Colombian imports data. See details in Table A1.

Table 2: The Relationship Between Exporter Local Mobility and Import Values

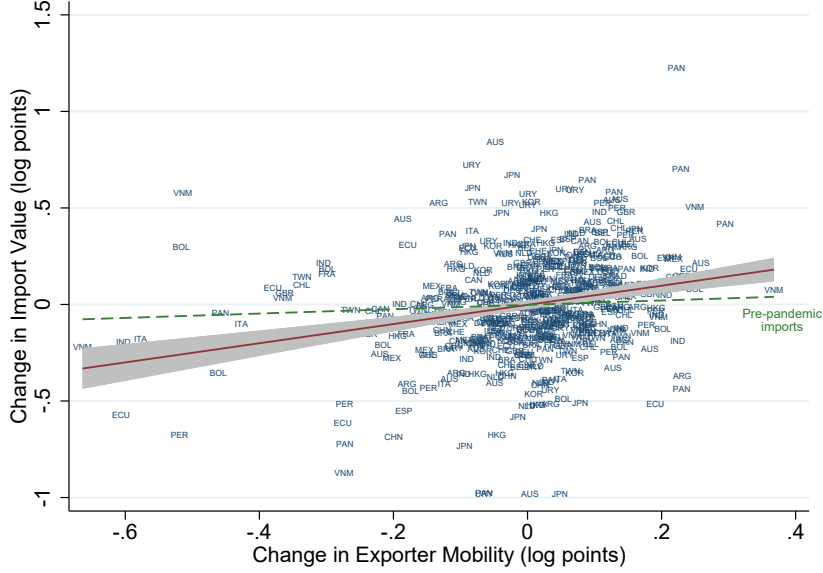
	(1)	(2)	(3)	(4)	(5)	(6)
Imports in the Pandemic period (2020-2021)						
Exporter Mobility (2020-2021)	0.337*** (0.050)	0.041 (0.053)	0.051 (0.056)	0.468*** (0.058)	0.081 (0.063)	0.101 (0.068)
Country F.E.	No	No	No	Yes	Yes	Yes
Month F.E.	Yes	Yes	No	Yes	Yes	No
Year F.E.	No	Yes	No	No	Yes	No
Time F.E.	No	No	Yes	No	No	Yes
Observations	32,380	32,380	32,380	32,380	32,380	32,380
R^2	0.004	0.010	0.011	0.018	0.023	0.024
Imports in the Pre-pandemic period (2018-2019)						
Exporter Mobility (2020-2021)	0.013 (0.046)	-0.031 (0.050)	-0.036 (0.053)	0.053 (0.055)	-0.003 (0.061)	-0.003 (0.067)
Country F.E.	No	No	No	Yes	Yes	Yes
Month F.E.	Yes	Yes	No	Yes	Yes	No
Year F.E.	No	Yes	No	No	Yes	No
Time F.E.	No	No	Yes	No	No	Yes
Observations	33,498	33,498	33,498	33,498	33,498	33,498
R^2	0.002	0.002	0.002	0.008	0.008	0.008

Note: OLS regressions at exporter location-time level, where time is at the monthly frequency. Fixed effects are included as indicated in each column. Robust standard errors clustered at the exporter-time level in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

with a reduction on exports to Colombia as expected.

In the bottom panel of Table 1, we conduct the same exercise as in the importer level section and regress changes in import values for 2018–2019 period relative to February 2018, i.e. before the pandemic, on changes in exporter mobility during the pandemic. We then estimate the same specifications as in the top panel. Reassuringly, all estimations are insignificant, which help us rule out the existence of pre-trends. Moreover, estimates that are insignificant in both cases —using either pre-pandemic or pandemic import changes as a dependent variable— are noisier when we use pre-pandemic import changes. In Figure 11 we also include the residual linear fit corresponding to Column (4) in the bottom panel of Table 2.

Figure 11: The Impact of Exporter Mobility on Import Values. Residual Plot



Note: Residual plot of equation 11 with country and month fixed effects (Column (4) of Table 2). Each observation is a country-time average of the residuals. Pandemic period fit (red solid line): $\hat{m}_{ct}^{resid} = -0.002 + 0.497 *** \times \hat{x}_{ct}^{I, resid}$. Pre-pandemic period (green dash line): $\hat{m}_{ct}^{resid} = -0.002 + 0.113 \times \hat{x}_{ct}^{I, resid}$.

In conclusion, mobility declines at the exporter location during the pandemic are associated with lower exports to Colombia as expected. Results are noisy when we only rely on cross-sectional variation, but still point in the same direction. Importantly, pre-pandemic changes are not associated with pandemic mobility shocks.

4.3 Effects at the Product Level, Combining the Importer Mobility Shocks and the Exporter Mobility Shocks

So far, we have estimated the impact of exporter and importer mobility on aggregate import values. In this section, we exploit the highly detailed information in the data to explore the average impact at the bilateral-product level. Doing so has multiple advantages. First, we can employ the theoretical framework as a guide for the estimation strategy. Second, it allows us to estimate the impact on prices and quantities separately for well-defined goods categories. Third, it helps us characterise the impact on the extensive margin. Finally, it will help us decompose the impact of the pandemic into exporter, importer and transportation sources in Section 6.

4.3.1 Empirical Strategy

The goal is to estimate equations 8 and 9, the structural price and quantity equations in changes, and check whether empirical results are in line with the theory. If so, then we can study the importance of each type of disruption on trade flows to Colombia.

We initially assume that there is no congestion to focus on the direct channels, which in the theory implies assuming that $\alpha^K = 1$, and later provide evidence that it had also role in shaping trade flows during the pandemic. Given that, the three main direct sources of trade disruptions in the model are at the exporter location, importer location and during transportation. In these equations, they are captured by $\hat{A}$, $\hat{Z}$, and $\hat{B}$ respectively. In this section, we focus on the first two terms, and leave the impact of $\hat{B}$ for the following section, where we study disruptions at ports. This implies two things. First, we need to measure the demand and cost shifters. We go into the details of how the demand and cost shifters can be proxied by the mobility shocks next. Second, we need to indicate how we control for the transportation terms. We cover that and derive the empirical equations subsequently.

4.3.2 Local Demand and Supply Shocks Measurement

We measure local demand and supply shocks using changes in human mobility from Facebook and Baidu, in the case of China. In the model, local disruption shocks during the pandemic can be interpreted as changes in the cost and demand shifters, A^K and Z^K respectively. For instance, a regional lockdown may suddenly reduce labor supply, increasing wages and thus A^K in products within the good K . Moreover, a local pandemic shock may affect demand of products in good K through income and substitution effects, as captured by Z^K .

In order to map these changes to the data, we assume the following empirical relationships.

$$\hat{A}_{ik}^K = \gamma_A^K \hat{x}_i^I + \epsilon_{A,ik} \quad (12)$$

$$\hat{Z}_{jk}^K = \gamma_Z^K \hat{x}_j^J + \epsilon_{Z,ik} \quad (13)$$

where γ_A^K and γ_Z^K are the shifters elasticities with respect to local mobility, and $\epsilon_{A,ik}$ and $\epsilon_{Z,ik}$ are idiosyncratic mobility changes. We index the elasticities with K to indicate that changes in mobility may have different effects on different goods.

4.3.3 Empirical Equations

In order to get the empirical equations, we do the following. First, we replace $\hat{A}_{ik}^K$ and $\hat{Z}_{jk}^K$ by expressions 12 and 13 into equations 8 and 9. Second, we do two identification assumptions to deal with (a) changes in transportation costs $\hat{t}$, and (b) the import price index in the quantity equation.

To control for international transport costs, we include an exporting country (c)-main port of entry (u)-time fixed effect δ_{cut}^{Tr} , where we calculate the main entry port for each exporter, importer, product and time observation.¹⁸¹⁹ Most of the observations in our baseline sample use only a single entry port to Colombia, and in a 70% of them the main entry port accounts for the 90% imports.

In the model, the price exporters charge do 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 ad-valorem internal transportation to location j . We assume that the later is absorbed by importer firms and thus is captured by the local importer mobility indicator. To control for the former, we include a product-time fixed effect, δ_{kt}^P .

The resulting empirical equations are as follows:

$$\hat{q}_{ijkt} = \beta_I^{K,q} \hat{x}_{it}^I + \beta_J^{K,q} \hat{x}_{jt}^J + \delta_{kt}^{P,q} + \delta_{cut}^{Tr,q} + \varepsilon_{ijkt}^q \quad (14)$$

$$\hat{p}_{ijk}^M = \beta_I^{K,p} \hat{x}_{it}^I + \beta_J^{K,p} \hat{x}_{jt}^J + \delta_{kt}^{P,p} + \delta_{cut}^{Tr,p} + \varepsilon_{ijk}^p \quad (15)$$

where the error terms ε_{ijkt}^q and ε_{ijk}^p 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, $\delta_{kt}^{P,p}$, to both equations 15 for symmetry and comparability, but the model only predicts it to be relevant for the quantity equation. Therefore, the inclusion of it should not have a substantial impact on results if the model is an accurate depiction of the underlying data generating process.

¹⁸Note that we call “port” to any entry point of entry to Colombia in this section, including land customs and airports.

¹⁹We observe transportation costs at this level but we do not include the specific transport variable as a control to avoid including an endogenous variable as a control that is not our main object of interest in this section. We provide robustness to this decision.

4.3.4 Estimating Samples

In the model, the set of exporting locations that serve importers is fixed, and therefore it only accounts for the intensive margin effect of trade shocks. However, the data at the exporter-importer-product level is unbalanced. If the absent observations within exporter-importer-product are explained by these shocks, then not accounting for selection would bias the coefficient estimates. For that reason, we focus on a sample of balanced flows for the baseline estimations —the ones we use to interpret the theory.²⁰ However, we also provide results for the entire sample to corroborate that the main results hold. Finally, we also consider the impact of local mobility shocks on the extensive margin by employing a linear probability model in changes.

4.3.5 Regression Results

Baseline Results with No Congestion. We start by estimating the empirical price (14) and quantity (14) equations, plus one where we use import values as a dependent variable. We do so for both the balanced and entire sample. In Table 3, we include these estimates. We cluster standard errors at the level of the mobility variables —exporter-time and importer-time.

Table 3: Local Importer and Exporter Mobility and Import Variables. Baseline Results.

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Dependent Variable:</i>	Import Value	Import Quantity	Import Price	Import Value	Import Quantity	Import Price
Importer Mobility	0.357** (0.168)	0.400** (0.183)	-0.043 (0.063)	0.433*** (0.068)	0.410*** (0.073)	0.023 (0.053)
Exporter Mobility	1.372*** (0.228)	1.632*** (0.323)	-0.260** (0.120)	0.249*** (0.094)	0.352*** (0.124)	-0.103** (0.044)
Sample	Balanced	Balanced	Balanced	Full	Full	Full
N	77,351	77,351	77,351	537,100	537,100	537,100
R ²	0.219	0.216	0.152	0.100	0.101	0.076

Note: OLS regressions at exporter, importer, product (6-digit HS) and time level, where time is at the monthly frequency. Dependent variable indicated at the top in each column. Exporting country-main port of entry-time, and product-time fixed effects included. Robust standard errors clustered at the exporter-time and importer-time level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

In columns 1 to 3, we include the estimates for the balanced sample. Exporter and importer negative mobility shocks reduced import values as shown in column 1. These effects

²⁰This sample consists of the exporter-importer-products present in the data on the 20 continuous months between March 2020 and October 2021. It accounts for 30% of total imports from the selected countries over this time period.

are explained by a reduction of the imported quantities, as observed in column 2. In column 3 we estimate the impact on import prices, and show that only the export mobility shock had an effect, being negative. A decrease in exporter mobility of 10% induced a decrease in import quantities from that location of 16% with prices 2.6% higher, whereas a decrease in importer mobility of 10% is related to a decrease in import quantities of 3.6%.

In columns 4 to 6, we present estimates for the entire sample — i.e. including exporter-importer-products that are not present over the entire sample. Results are in line with the balanced sample: both exporter and importer mobility declines reduced import values, with the former being related to a decline in quantities and an increase in prices, and the later only with a decline in quantities. The main difference is in the magnitude of the export mobility coefficients. In the quantity equation, this coefficient is more than four times larger in the balanced sample, whereas in the price equation, it is more than twice larger. This suggests that a selection mechanism played a role in shaping the impact of the pandemic on trade flows.

We can map these estimated coefficients into the model as follows. First, we can recover the elasticity of substitution across locations from the export mobility coefficients in the balanced sample by noting that $-\text{beta}_I^{K,q}/\text{beta}_I^{K,p} = \eta^K$. This yields a $\eta^K = 6.3$, indicating that varieties produced at different locations are substitutable by importers. Importantly, this value is within the range of values attributed to the elasticity of substitution across varieties. Second, note that the demand shifter enters directly and only into the quantity equation. This means that we can infer that $\gamma_Z^K = 0.4$, —a decline in importer mobility of 10% induced an average decline in import demand of 4%.

Robustness. Mobility shocks may have affected trade flows differently depending on their flow-specific seasonal patterns and pre-trends at this level of aggregation. In Appendix Table B3, we control for the corresponding value during the 2018-2019 period.²¹ Results do not change qualitatively and remain similar to the baseline both in terms of magnitudes and significance. The main difference is that the impact of importer mobility becomes borderline significant at 10% level.

In Table B4, we estimate these regressions for two alternative specifications. In columns 1 to 3, we do not include the product-time fixed effect. This set of fixed effect controls for import competition at a given product and only enters into the quantity equation. Not including these fixed effects do not change substantially the results, only turns the effect of import mobility on prices negative and significant. In columns 4 to 6, we add the importer

²¹Specifically, we add $\hat{m}_{ijk,t-24}$, the respective dependent variable, to the right-hand side of the equation (we add $\hat{p}_{ijk,t-24}$ in the quantity equation and $\hat{p}_{ijk,t-24}$ in the price equation).

department level to the exporting country-main entry port-time fixed effect to control for internal transport costs potentially also priced in by the exporter. Exporter mobility has the same impact on all import variables, but importer mobility turns insignificant for all of them, suggesting that department-time controls may be absorbing most of the variation.

In Table B5, we cluster standard errors at higher levels of aggregation. In columns 1 to 3, we employ exporting country-time and importer location-time clusters, and in columns 1 to 3, we change the later to importer department-time. Results remain significant under this more conservative approach.

Heterogeneity by Type of Good. In this section, we estimate equations 14 and 15 allowing for goods heterogeneity. We employ the Broad Economic Categories (BEC) classification to identify products falling into the consumer, intermediate and capital goods categories, and estimate the baseline specification for these three sub-samples. We present results in Table 4.

Table 4: Local Importer and Exporter Mobility and Import Variables. Results by Types of Goods.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Goods			Intermediate Goods			Capital Goods		
\textit{Dependent Variable:}	Import Value	Import Quantity	Import Price	Import Value	Import Quantity	Import Price	Import Value	Import Quantity	Import Price
Importer Mobility	-0.375 (0.301)	-0.596* (0.330)	0.221 (0.211)	0.720*** (0.193)	0.803*** (0.205)	-0.083 (0.074)	-0.287 (0.233)	-0.146 (0.250)	-0.142 (0.122)
Exporter Mobility	0.159 (0.325)	0.925*** (0.350)	-0.765*** (0.200)	1.510*** (0.298)	1.975*** (0.379)	-0.465*** (0.133)	2.049*** (0.237)	1.424*** (0.353)	0.625*** (0.221)
N	10,723	10,723	10,723	50,044	50,044	50,044	15,511	15,511	15,511
R ²	0.400	0.351	0.217	0.224	0.220	0.163	0.228	0.231	0.188

Note: OLS regressions at exporter, importer, product (6-digit HS) and time level, where time is at the monthly frequency.

Dependent variable and sample indicated at the top in each column. Exporting country-main port of entry-time, and product-time fixed effects included. Robust standard errors clustered at the exporter-time and importer-time level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

The left panel correspond to consumer goods. The exporter mobility coefficients have the same sign as the baseline: a decrease in exporter mobility increases prices and lowers quantities from that location. The implied elasticity of substitution in this case is lower than on the full sample, with a value of $\eta^{cons} = 1.2$. In terms of the model, this value suggests that consumers have stronger love-of-variety than the average importer. Contrary to the baseline, the importer mobility coefficient on the quantity equation is negative, with $\gamma_Z^{cons} = -0.6$. This suggests, that consumers in locations that experienced negative mobility shocks during the pandemic period increased import demand, possible through a substitution effect.

The mid panel shows the results for intermediate goods. They are qualitatively the same as the baseline, with negative export mobility shocks increasing prices and declining imported quantities from that location; and negative import mobility shocks lowering quantities and

not affecting prices. The implied elasticity of substitution in this case is $\eta^{inter} = 4.2$, which is higher than for consumer goods. Moreover, the importer mobility coefficient is also higher in magnitude, at $\gamma^{Z,int} = 0.8$. Given that firms are most likely to be importing these goods, this coefficient suggests that negative shocks during the pandemic made costlier to produce, declining intermediate factors demand.

The right panel presents results for capital goods. There is no evidence of import mobility affecting imported quantities and prices in this case. On the contrary, exporter mobility declines lead to a decline on the quantity of imported capital goods. This shock also lead to lower prices, conflicting with the predicted sign for this effect. Note, however, that demand for capital goods depends on future profitability and thus this model may not be well-suited to estimate these short-run impacts.

Congestion. So far, we have assumed that there was no congestion in production — $\alpha^K = 1$. In order to identify congestion we employ two proxy variables.

In the model, we allow for the possibility of short-run decreasing returns to scale when there is a short-run fixed production factor such as capital. For instance, 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 and proxy it as follows:

$$\hat{S}_{ckt} = \sum_{\tilde{c} \in C|c} s_{X,\tilde{c}k}^{2018} \hat{x}_{\tilde{c}t}, \quad (16)$$

where $s_{X,\tilde{c}k}^{2018}$ 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 .²² 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.²³

The second source of congestion is related to the demand side. Suppose only two locations import a given product and one of them experience 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 if the income or substitution effect dominate. We proxy for this mechanism as follows:

²²Mobility data at country level from Google.

²³In terms of the model, the degree at which demand shifts due to congestion shocks depends on η^K .

$$\hat{D}_{ckt} = \sum_{\tilde{c} \in C|c} s_{M,\tilde{c}k}^{2018} \hat{x}_{\tilde{c}t}, \quad (17)$$

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

In Appendix Table B6, we estimate the same specifications as in the baseline for the three types of goods including the demand and supply congestion proxies for the balanced sample. In the left panel, we include results for consumer goods. There are two main things to stress. First, exporter and importer mobility coefficients do not significantly change from the case without congestion. Second, the theory predicts the estimated price and quantity coefficients to have opposite signs, and that is what we find. In fact, these results suggests that exporters producing goods for which the main importers experienced lower declines had higher prices. In addition, exporters producing goods for which the main competitors also experienced lower mobility shocks saw lower total demand and thus lower prices. In the former case, Colombian locations ended up importing less from those locations, and in the later case, more, given the change in prices.

The impact on intermediate goods in the mid panel are also in line with the previous results, with congestion variables being insignificant except for the impact of demand congestion on quantities (which have the same sign as for consumer goods). The effect of mobility shocks on imported quantities and prices of capital goods also remain the same as in the baseline.

Interaction Between Importer and Exporter Mobility. Exporter and importer mobility shocks may have had an stronger impact if both happened at the same time for a given product. Specifically, some trade activities may be taken over by the either the exporter or the importer if only one shock happened. In Appendix Table B7, we replicate the baseline table with goods heterogeneity and include an interaction term between the exporter and mobility shock.

In columns 1-3, we show that the interaction term did not play a role for consumer goods. It does, however, make results noisier on the quantity equation, but we still observe a negative and significant impact of importer mobility. In columns 4-6, we show that the exporter and importer mobility shocks interacted in the case of intermediate goods both in the quantity and price equations. In columns 7-9, only the price equation saw the interaction term significant for capital goods.

4.3.6 Extensive Margin

In this Section, we explore the impact of exporter and importer mobility changes on the extensive margin, defined at the exporter-importer-product level, by means of a linear probability model in differences. Specifically, we estimate the following equation:

$$\hat{I}_{ijkt} = \beta^J \hat{x}_{jt}^J + \beta^I \hat{x}_{it}^I + \varepsilon_{ijkt}, \quad (18)$$

where $\hat{I}_{ijkt} = I_{ijk,t} - I_{ijk, Feb20}$ is the difference of an indicator taking the value of 1 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.

In Table 5, we show the results for the baseline estimations. Both exporter and importer mobility changes positively affect the extensive margin — i.e., both exporter and importer declines in mobility reduced the export participation in Colombian import markets at the product level. When we include the interaction between exporter and importer mobility changes, the estimate is negative, meaning that declines at both sides of international transactions further decrease trade participation.

In contrast to the intensive margin results, exporter mobility has a robust impact on trade, suggesting that this was the main mechanism through which the pandemic affected the supply side.

Table 5: Exporter and Importer Local Mobility and Trade Participation. Linear Probability Model

	(1)	(2)	(3)	(4)
$\Delta \log$ Importer Mobility (1)	0.035*** (0.006)	0.035*** (0.006)	0.029*** (0.007)	0.029*** (0.006)
$\Delta \log$ Exporter Mobility (2)	0.029*** (0.006)	0.035*** (0.006)	0.014* (0.008)	0.020** (0.008)
Interaction (1) x (2)			-0.047* (0.028)	-0.041* (0.022)
N	8,877,606	8,876,178	8,877,606	8,876,178
R^2	0.007	0.010	0.007	0.010

Note: OLS regressions at exporter location-importer location-product (HS6)-time level. Exporting country-month, product-month, and time fixed effects are included. The dependent variable is the difference of an indicator that takes the value of 1 if an import flow is observed. Robust standard errors clustered at the exporter-time and importer-time level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

5 Trade Disruptions at the Sea Ports

In this Section, we investigate the impact of trade disruptions on the price of transportation. Trade disruptions include direct labor mobility changes and cumulative effects of the pandemic-induced congestion in the transportation network. We focus on the exporter country and discuss briefly the role of intermediate countries.

5.1 Econometric specification

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

$$\hat{Y}_{cym} = \alpha_0 \hat{x}_{cym}^{\text{Ports}} + \delta_m + \delta_y + \delta_c + \epsilon_{cym}, \quad (19)$$

where $\hat{Y}_{cym}$ can be the change in 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:

$$\hat{x}_{cym}^{\text{Ports}} = \sum_{p(c)} \frac{\text{TEU}_{p(c)2020}}{\sum_{p'(i)} \text{TEU}_{p'(c)2020}} \hat{x}_{p(c)ym}, \quad (20)$$

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 spend 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 perfor-

mances 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 less 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 opposite, since labor shortage at port cities will lead to fewer port calls being processed.

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, in terms of reverse causality, the assumption is that changes in port productivity do not lead to changes in human mobility locally. For example, if the ports that receive more port calls made by container ships lead to more infections of Covid-19, the assumption is violated. We think that this situation is not very likely, 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. 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 terms of port productivity, we assume that people who work in the ports are subject to the same shocks as people who work in the same city but in other industries.

Our second set of analysis is to investigate the impact of the port mobility declines on freight costs using product-country level data. We keep the trade flows with sea as the method of transportation and also drop "fuel and lubricants" since they are not likely to be transported by containerized ships.²⁴

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:

$$\hat{T}_{kcy m} = \beta_0 \hat{x}_{cym}^{\text{Ports}} + \delta_m + \delta_y + \delta_c + \delta_k + \epsilon_{kcy m}, \quad (21)$$

where $\hat{T}_{kcy m}$ 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

²⁴We use the mapping between HS codes and Broad Economic Categories (BEC) codes as in Staff and Division (2003) and drop goods that have a BEC code of 31, 32, and 322.

origin country fixed effects.

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. Specifically, we use the outcome variables where the changes are calculated using the months starting from March 2018 until October 2019, compared to February 2020, instead of using March 2020 to October 2021.

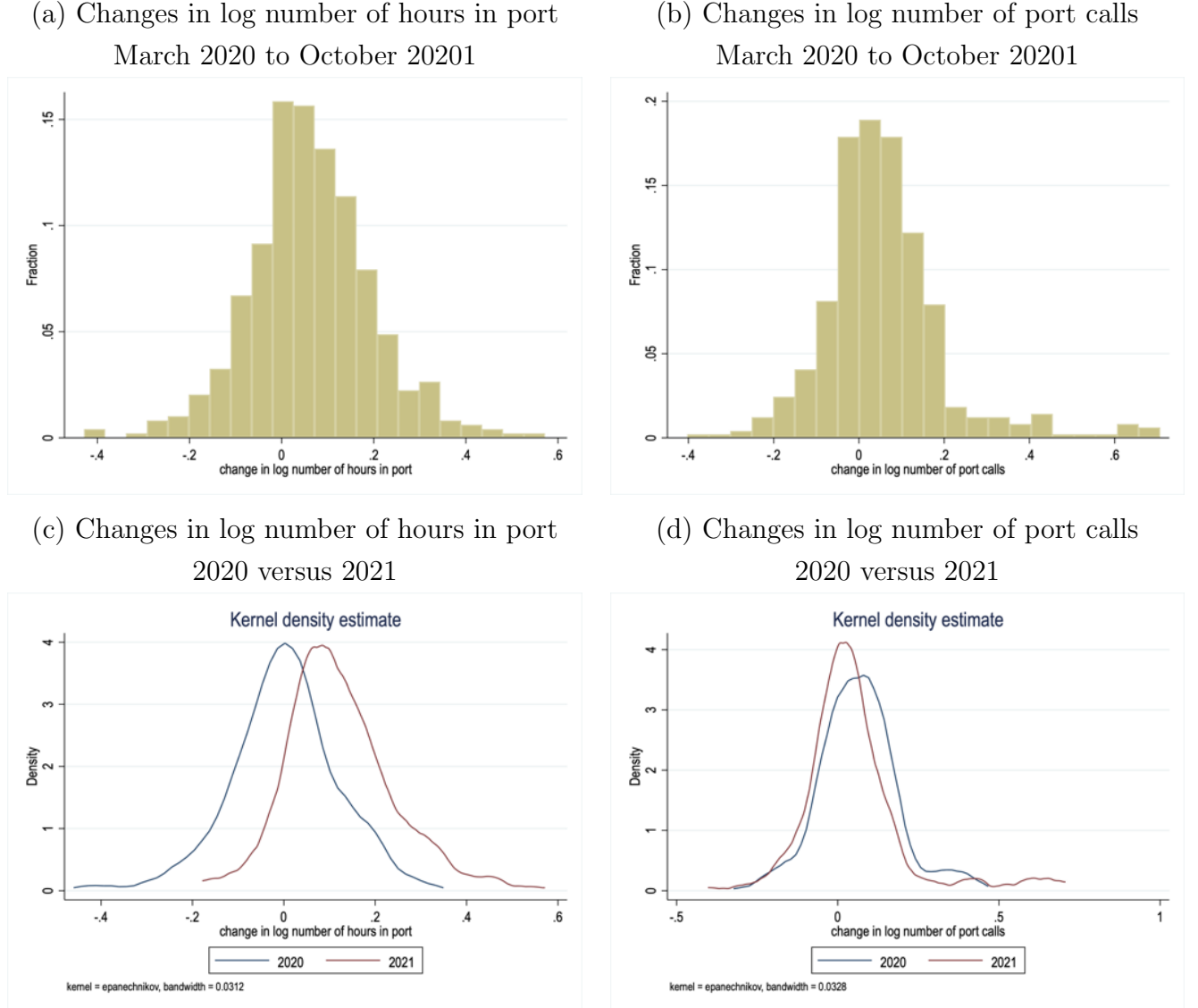
5.2 Variation in the port performance and freight costs

This Section presents the variation in the outcome variables of interest. Figure 12 Panel (a) shows the distribution of country-level changes in the log number of hours each ship spend in port in the post-Covid period (March 2020 to October 2021). The distribution is spread out, ranging from -0.4 to 0.6, and more observations are having a positive change than negative changes. This is consistent with the aggregate trend in Figure 5 Panel (c). In addition, as shown in Figure 12 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 period. Note that the baseline period is February 2020. As noted in Figure 5 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 period.²⁵ 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 5 Panel (a), where we observe a decline in the number of port calls since June 2021.

²⁵An 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.

Figure 12: The Histogram of Country-Level Port Performance Variation

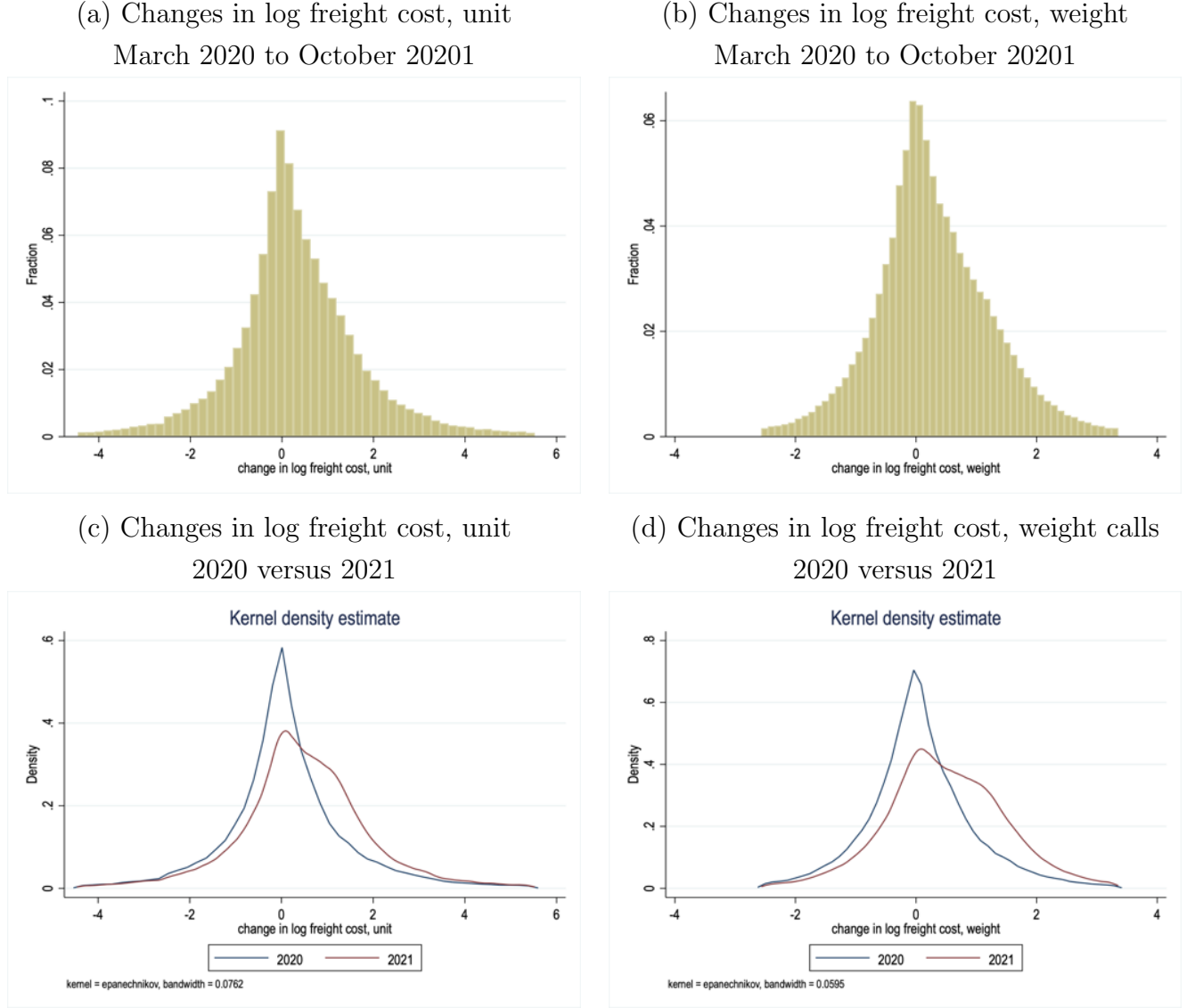


Note: Panels (a) and (b) are the histograms of the changes in port performance in the post-Covid period (March 2020 to October 2021), compared to February 2020. Panels (c) and (d) show the variation in 2020 and in 2021 separately, using kernel densities.

Figure 13 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 log freight cost per weight. The top and bottom one percent of the observations are dropped for both variables.²⁶ In both cases, there are more observations with positive changes, indicating an increase in the freight cost. In addition, the positive changes are more prominent in 2021 than in 2020.

²⁶Our regression results are robust to keeping all observations.

Figure 13: The Histogram of Product-Level Freight Cost Variation



Note: Panels (a) and (b) are the histograms of the changes in log freight cost in the post-Covid period (March 2020 to October 2021), compared to February 2020. Panels (c) and (d) show the variation in 2020 and in 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.

5.3 Regression Results

Table 6 presents the regression results for the country-level regression on port performance. Panel A presents the main results where the port performance measures are changes in the post-Covid period (March 2020 to October 2021), and Panel B presents placebo results where the port performance measures are changed in the pre-Covid period (March 2018 to October 2019). In both cases, the baselines are February 2020.

In Panel A Column (1), the change in the log number of hours each ship spends in port is regressed on the change in human mobility, and we control for year fixed effects, month fixed effects, and origin country fixed effects. 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. 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.²⁷

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 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. 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

²⁷See news reports: www.wsj.com/articles/truckers-steer-clear-of-24-hour-operations-at-southern-california-ports-11637173872.

Table 6: The Relationship Between the Log Number of Port Calls, log Number of the Hours in Port, and Mobility, in the Post-Covid Period (Panel A) and the pre-Covid Period (Panel B)

Panel A.	(1)	(2)	(3)	(4)	(5)	(6)
Outcome: 2020 and 2021	Δ log hours		Δ log number of calls		Δ log hours	
Δ log mobility	-0.129** (0.053)	-0.129** (0.053)	0.108** (0.049)	0.108** (0.049)		
Δ log number of calls					-0.268*** (0.090)	-0.268*** (0.090)
I (Year=2021)	0.169*** (0.021)		-0.021 (0.020)		0.149*** (0.018)	
Time trend		0.014*** (0.002)		-0.002 (0.002)		0.012*** (0.002)
Constant	-0.042** (0.016)	-0.106*** (0.023)	0.084*** (0.011)	0.092*** (0.017)	0.003 (0.010)	-0.052*** (0.016)
Observations	492	492	492	492	492	492
R-squared	0.654	0.654	0.727	0.727	0.661	0.661
Panel B.	(1)	(2)	(3)	(4)	(5)	(6)
Outcome: 2018 and 2019	Δ log hours		Δ log number of calls		Δ log hours	
Δ log mobility	0.018 (0.020)	0.018 (0.020)	-0.022 (0.023)	-0.022 (0.023)		
Δ log number of calls					-0.072 (0.087)	-0.072 (0.087)
I (Year=2019)	0.025** (0.009)		0.005 (0.009)		0.028*** (0.009)	
Time trend		0.002** (0.001)		0.000 (0.001)		0.002*** (0.001)
Constant	0.014** (0.006)	0.005 (0.009)	-0.157*** (0.007)	-0.159*** (0.010)	-0.001 (0.016)	-0.011 (0.018)
Observations	492	492	492	492	492	492
R-squared	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 changes in the log number of hours in ports and the log number of port calls 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, which is Feb 2020 for most countries and Jan 1-14, 2020 for China. 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 changes in the log number of hours in ports and the log number of port calls 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 log number of calls is -0.15 (0.14).

port performances in the pre-Covid period. In addition, there is not a 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.

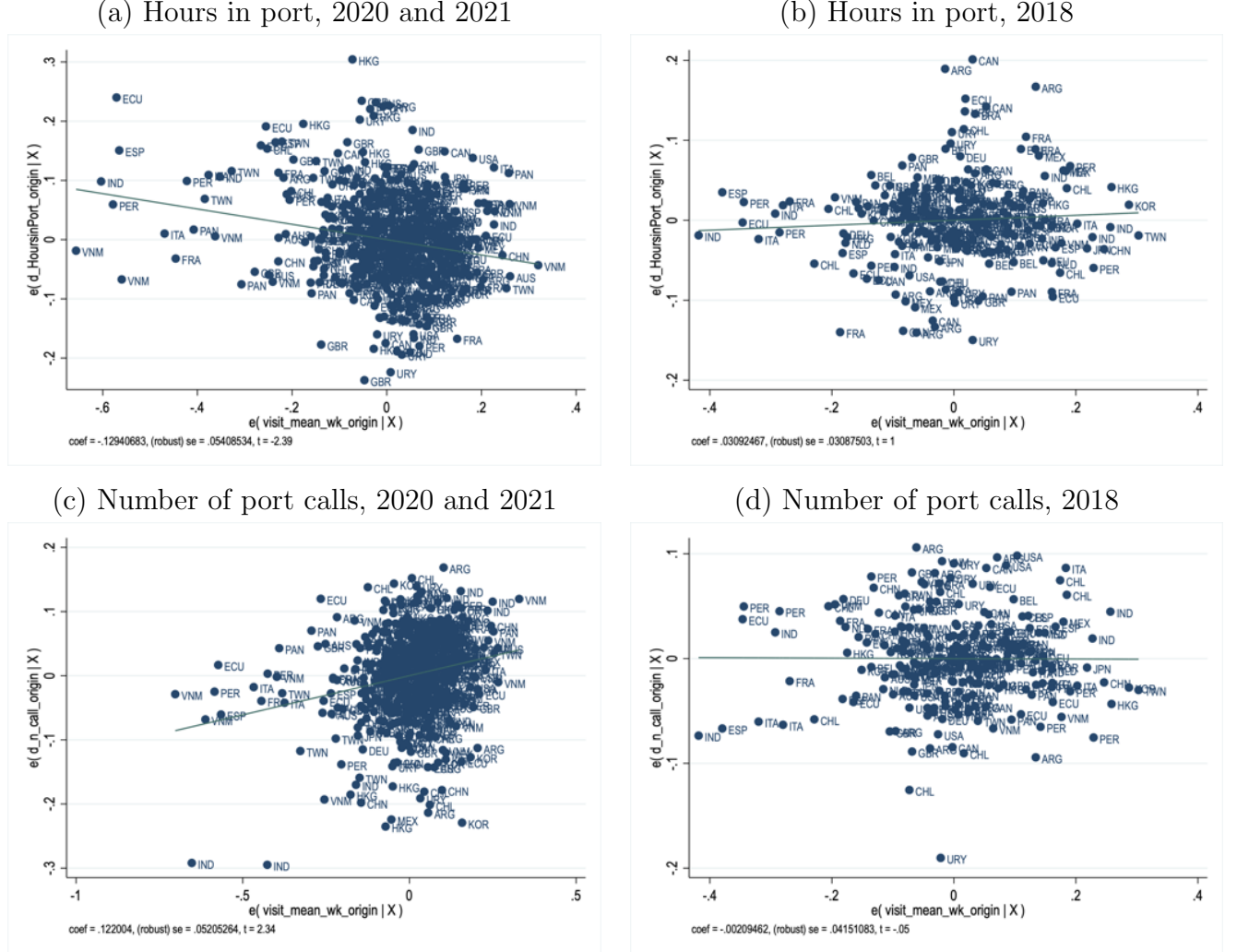
Figure 14 shows the residual plots for results in Table 6 Panel A Columns (1) and (3) and Panel B Columns (1) and (3). We also conduct robustness checks by dropping one country at a time and by dropping one period at a time. The corresponding results are shown in Appendix Figures B11, B12, and B13. Overall, we find that the results are not driven by one particular country or period.

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.

Then we proceed to investigate the impact of mobility changes on freight costs. Table 7 shows the regression results. Panel A presents the main results with post-Covid price changes, and Panel B presents placebo results using the pre-Covid period price changes. In both cases, the baselines are February 2020.

Panel A Columns (1)–(4) use the change in log freight cost per unit as the outcome variable. Column (1) controls for year fixed effects, calendar month fixed effects, product fixed effects, and exporter country fixed effects. 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 the 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, 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.

Figure 14: The Impact of Mobility Changes on the Number of Hours in Port, Residual Plot for the Post-Covid period and the pre-Covid Period



Note: Panel (a) is the residual plot for the results in Table 6 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 6 Column (3) in Panels A and in Panel B, respectively.

Again, the fixed effect for year 2021 has a large and significant coefficient, indicating that the 2021 level is 51% higher than the 2020 level (Column 1). Similarly, the monthly increase in freight cost is 4% (Column 2). 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.

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 7. The residual plots

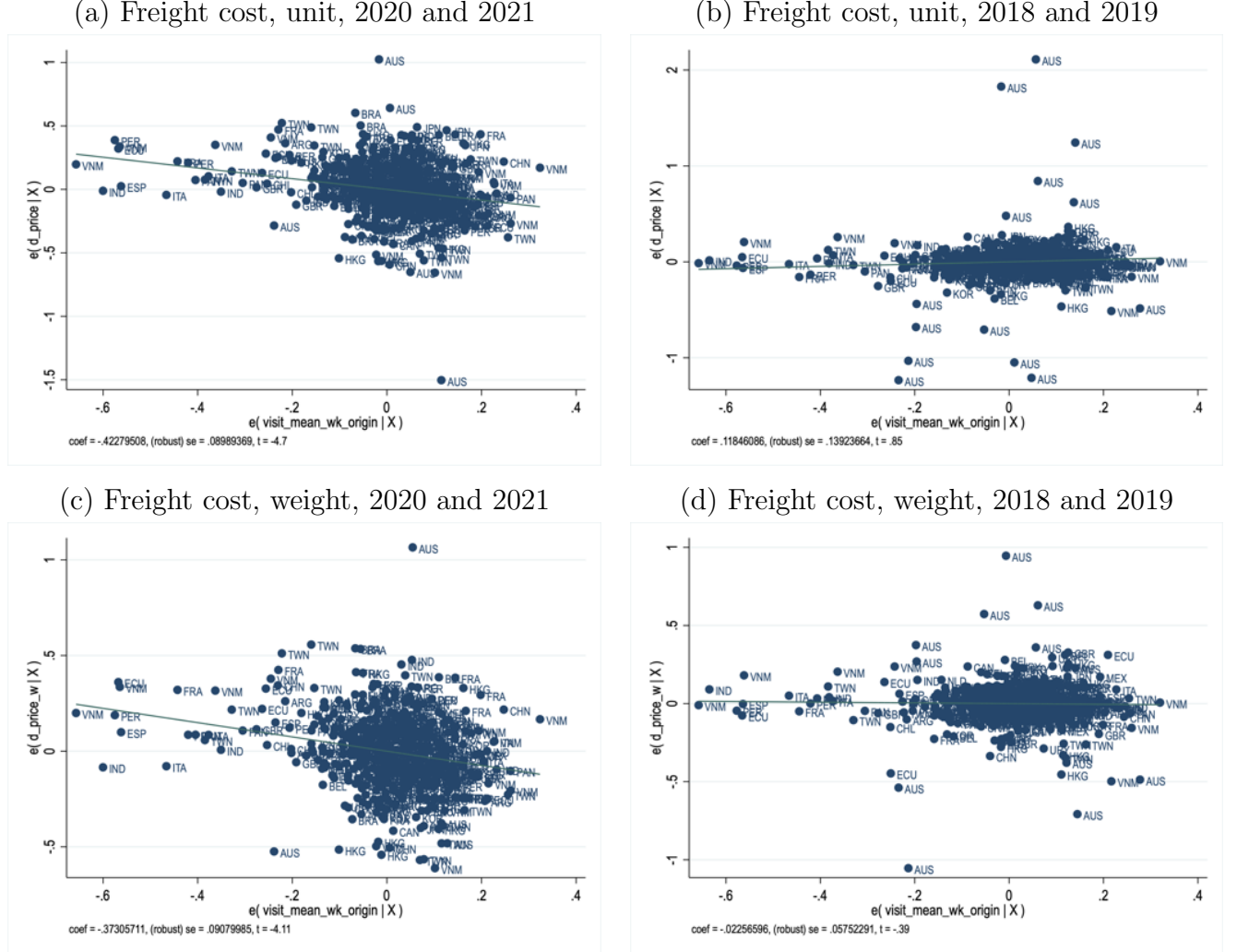
are shown in Figure 15. Reassuringly, the country-level regression results are similar to the product-level results.

Table 7: The Relationship Between Freight Costs and Port Mobility in the Exporter Country

Panel A.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome: 2020 and 2021	$\Delta \log \text{ freight cost, unit}$				$\Delta \log \text{ freight cost, weight}$			
$\Delta \log \text{ mobility change}$	-0.25** (0.11)	-0.25** (0.11)	-0.29** (0.12)	-0.53** (0.20)	-0.30*** (0.10)	-0.30*** (0.10)	-0.34*** (0.11)	-0.57*** (0.18)
I (year=2021)	0.51*** (0.08)		0.51*** (0.08)	0.54*** (0.08)	0.55*** (0.07)		0.55*** (0.07)	0.58*** (0.07)
Time trend		0.04*** (0.01)				0.05*** (0.01)		
Constant	0.02 (0.05)	-0.17** (0.07)	0.01 (0.05)	-0.04 (0.06)	-0.04 (0.04)	-0.25*** (0.07)	-0.05 (0.04)	-0.09* (0.05)
Observations	245,995	245,995	239,425	245,991	245,995	245,995	239,425	245,991
R-squared	0.11	0.11	0.16	0.11	0.15	0.15	0.20	0.16
Panel B.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome: 2018 and 2019	$\Delta \log \text{ freight cost, unit}$				$\Delta \log \text{ freight cost, weight}$			
$\Delta \log \text{ mobility change}$	0.04 (0.03)	0.02 (0.04)	0.03 (0.04)	0.03 (0.04)	-0.01 (0.03)	0.00 (0.03)	-0.02 (0.03)	-0.04 (0.04)
I (year=2019)	0.02** (0.01)		0.03** (0.01)	0.03** (0.01)	0.03** (0.01)		0.03** (0.01)	0.04** (0.01)
Time trend		0.00 (0.00)				0.00* (0.00)		
Constant	0.04*** (0.00)	0.03*** (0.01)	0.04*** (0.01)	0.03*** (0.01)	-0.03*** (0.01)	-0.03** (0.01)	-0.03*** (0.01)	-0.03*** (0.01)
Observations	261,967	261,967	255,881	261,966	261,967	261,967	255,881	261,966
R-squared	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.

Figure 15: The Impact of Mobility Changes on the Freight Costs, Residual Plot for the Post-Covid Period and the Pre-Covid Period



Note: Panel (a) is the residual plot for the results in Table 6 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 6 Column (3) in Panels A and in Panel B, respectively.

Overall, we find that mobility declines in port had significant impacts on the price of the transportation sector.

5.4 Intermediate Ports

The cost of shipping not only depends on the exporter country ports but also 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 K , the average mobility change is

$$\Delta \log(\text{mobility}_{iy m}^K) = \sum_k \frac{\text{prob}(k(i))}{\sum_{k'} \text{prob}(k'(i))} \Delta \log(\text{mobility}_{k(i)ym}^{\text{Ports}}), \quad (22)$$

where $\Delta \log(\text{mobility}_{k(ir)ym})$ is the change in mobility in country k , year y , and month m , compared to the pre-Covid period, and $\text{prob}(k(i))$ is the probability that the optimal route from country i to Colombia uses country k as the first intermediate stop. We compute the second intermediate country's mobility change similarly ($\Delta \log(\text{mobility}_{iy m}^L)$), 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.

Table 8: The Relationship Between Freight Costs and Port Mobility in the Exporter Country and in the Intermediate Country

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	$\Delta \log$ freight cost, unit			$\Delta \log$ freight cost, weight		
$\Delta \log$ mobility, exporter country	-0.25** (0.11)			-0.30*** (0.10)		
$\Delta \log$ mobility, first intermediate		-0.53*** (0.16)			-0.59*** (0.15)	
$\Delta \log$ mobility, second intermediate			-0.72*** (0.20)			-0.76*** (0.20)
I (year=2021)	0.51*** (0.08)	0.57*** (0.08)	0.69*** (0.11)	0.55*** (0.07)	0.62*** (0.08)	0.74*** (0.11)
Constant	0.02 (0.05)	-0.06 (0.06)	-0.16* (0.09)	-0.04 (0.04)	-0.12** (0.06)	-0.23** (0.09)
Observations	245,995	245,995	245,995	245,995	245,995	245,995
R-squared	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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 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.

Note that we use the country-level port averages since the Colombian trade data does not report the exporting and intermediate ports, but only the 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.

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 8 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 7 Panel A Column (1), 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 the entrepôt as discussed in Ganapati et al. (2021), and the reduction in mobility in those transportation hubs is more costly than in individual export countries.

6 Decomposition of the Disruptions

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), across products depending on supply chain features (e.g. how diverse the suppliers are), and by the mode of transportation (e.g., sea shipping versus land and air). Finally, we will do a simple projection of the following scenarios: (1) the lockdown in China; (2) with the update share of transportation cost and insurance cost in the importer prices; (3) Omicron and forward.

6.1 Method

Recall that in Equation 14 and 15, the change in log quantity and import price can be written as a function of the change in log exporter mobility $\hat{x}_i t$, 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

$$q^T \equiv \hat{\beta}_I^{k,q} x_I^T + \hat{\beta}_J^{k,q} x_J^T, \quad (23)$$

$$p^T \equiv \hat{\beta}_I^{k,p} x_I^T + \hat{\beta}_J^{k,p} x_J^T, \quad (24)$$

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.

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

$$t^T \equiv \hat{\beta}_0 x_{Port}^T + \hat{\beta}^{trend} \text{time}. \quad (25)$$

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

$$\hat{\delta}^{Tr,p} = (1 - \bar{\iota})t^T + \epsilon^{Tr,p}, \quad (26)$$

$$\hat{\delta}^{Tr,p} = -\hat{\eta}(1 - \bar{\iota})t^T + \epsilon^{Tr,q}. \quad (27)$$

The average share of transportation cost in import price $\bar{\iota}$ in 2018 and 2019 is 7%. Then we use the coefficient estimates from the previous sections to conduct the decomposition.

6.2 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. The results are as follows:

We find that for quantity, exporter mobility shocks explained 55%, importer shocks 42% and port shocks 2% at the onset of the pandemic (April 2020). Direct price effect in April 2020 explained mostly by exporter mobility (72%), but the importance of the transportation sector increased over time. Transportation effects explained 66% in October 2021.

6.3 By product

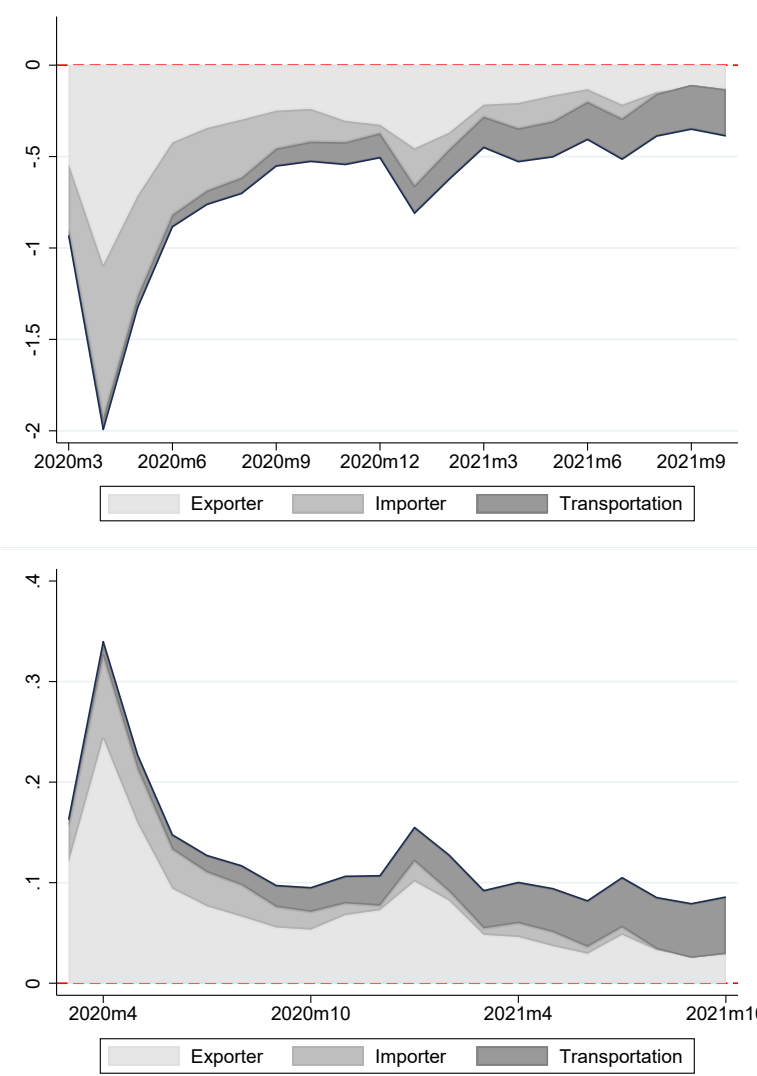
We also want to see which products suffered most. The size of the impact will depend on (1) how many suppliers; (2) the average mobility change in each supplier; (3) the correlation of the mobility change across different suppliers.

Did products with larger numbers of supplier countries or larger numbers of supplier cities experience differential shocks? We find similar mean and standard deviation for exporter mobility changes.

7 Conclusion

We studied the impact of local disruptive shocks on international trade during the pandemic. Using Colombian' customs data, we first documented the sudden decrease in import

Figure 16: Decomposition: Import Quantities and Prices of Intermediate Goods



quantities and the steady increase in export prices and shipping costs. We then documented port congestion by showing that the average hours in world port increased throughout the pandemic.

We found that local mobility shocks at the exporter and importer locations reduced product import values and trade participation. We then documented that country-level average port congestion and mobility shocks at ports increased freight unit values.

References

- Allcott, Hunt, Allan Collard-Wexler, and Stephen D O’Connell, “How do electricity shortages affect industry? Evidence from India,” *American Economic Review*, 2016, 106 (3), 587–624.
- Anderson, James E and Yoto V Yotov, “Short run gravity,” *Journal of International Economics*, 2020, 126, 103341.
- Antràs, Pol, Stephen J Redding, and Esteban Rossi-Hansberg, “Globalization and pandemics,” Technical Report, National Bureau of Economic Research 2020.
- Asjad, Naqvi, “COVID-19 European Regional Tracker,” *Scientific Data*, 2021, 8 (1).
- Baldwin, Richard and Rebecca Freeman, “Risks and global supply chains: What we know and what we need to know,” Technical Report, National Bureau of Economic Research 2021.
- Barrot, Jean-Noël and Julien Sauvagnat, “Input specificity and the propagation of idiosyncratic shocks in production networks,” *The Quarterly Journal of Economics*, 2016, 131 (3), 1543–1592.
- Boehm, Christoph E, Aaron Flaaen, and Nitya Pandalai-Nayar, “Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Tōhoku earthquake,” *Review of Economics and Statistics*, 2019, 101 (1), 60–75.
- Bonadio, Barthélémy, Zhen Huo, Andrei A Levchenko, and Nitya Pandalai-Nayar, “Global supply chains in the pandemic,” *Journal of international economics*, 2021, 133, 103534.
- Brancaccio, Giulia, Myrto Kalouptsi, and Theodore Papageorgiou, “Geography, transportation, and endogenous trade costs,” *Econometrica*, 2020, 88 (2), 657–691.
- Carvalho, Vasco M, Makoto Nirei, Yukiko U Saito, and Alireza Tahbaz-Salehi, “Supply chain disruptions: Evidence from the great east japan earthquake,” *The Quarterly Journal of Economics*, 2021, 136 (2), 1255–1321.
- Chetty, Raj, John N Friedman, Nathaniel Hendren, Michael Stepner, and The Opportunity Insights Team, *How did COVID-19 and stabilization policies affect spending and employment? A new real-time economic tracker based on private sector data*, Vol. 27431, National Bureau of Economic Research Cambridge, MA, 2020.
- Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber, “The cost of the covid-19 crisis: Lockdowns, macroeconomic expectations, and consumer spending,” Technical Report, National Bureau of Economic Research 2020.
- , —, and —, “Labor markets during the COVID-19 crisis: A preliminary view,” Technical Report, National Bureau of economic research 2020.

- Cosar, Kerem and Benjamin Thomas**, “The geopolitics of international trade in South-east Asia,” *Review of World Economics*, 2021, 157 (1), 207–219.
- Fajgelbaum, Pablo D, Pinelopi K Goldberg, Patrick J Kennedy, and Amit K Khandelwal**, “The return to protectionism,” *The Quarterly Journal of Economics*, 2020, 135 (1), 1–55.
- Ganapati, Sharat, Woan Foong Wong, and Oren Ziv**, “Entrepot: Hubs, scale, and trade costs,” Technical Report, National Bureau of Economic Research 2021.
- Guan, Dabo, Daoping Wang, Stephane Hallegatte, Steven J Davis, Jingwen Huo, Shuping Li, Yangchun Bai, Tianyang Lei, Qianyu Xue, Di-Maris Coffman et al.**, “Global supply-chain effects of COVID-19 control measures,” *Nature human behaviour*, 2020, pp. 1–11.
- Hale, Thomas, Noam Angrist, Rafael Goldszmidt, Beatriz Kira, Anna Petherick, Toby Phillips, Samuel Webster, Emily Cameron-Blake, Laura Hallas, Saptarshi Majumdar et al.**, “A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker),” *Nature Human Behaviour*, 2021, 5 (4), 529–538.
- Heiland, Inga, Andreas Moxnes, Karen Helene Ulltveit-Moe, and Yuan Zi**, “Trade from space: Shipping networks and the global implications of local shocks,” 2019.
- Hummels, David and Alexandre Skiba**, “Shipping the good apples out? An empirical confirmation of the Alchian-Allen conjecture,” *Journal of political Economy*, 2004, 112 (6), 1384–1402.
- Ignatenko, Anna**, “Price Discrimination and Competition in International Trade.” PhD dissertation, University of California, Davis 2020.
- Liu, Xuepeng, Emanuel Ornelas, and Huimin Shi**, “The Trade Impact of the Covid-19 Pandemic,” 2021.
- Martin, Julien, Raphael Lafrogne-Joussier, and Isabelle Mejean**, “Supply shocks in supply chains: Evidence from the early lockdown in China,” 2021.
- Staff, Statistical Division and United Nations. Statistical Division**, *Classification by Broad Economic Categories: Defined in Terms of the Standard International Trade Classification, Revision 3, and the Harmonized Commodity Description and Coding System (2002)* number 53, United Nations Publications, 2003.
- Volpe, Christian and Juan Blyde**, “Shaky roads and trembling exports: Assessing the trade effects of domestic infrastructure using a natural experiment,” *Journal of International Economics*, 2013, 90 (1), 148–161.
- Wong, Woan Foong**, “The round trip effect: Endogenous transport costs and international trade,” 2018.

Online Appendices

(Not for publication)

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A Additional Data Descriptives

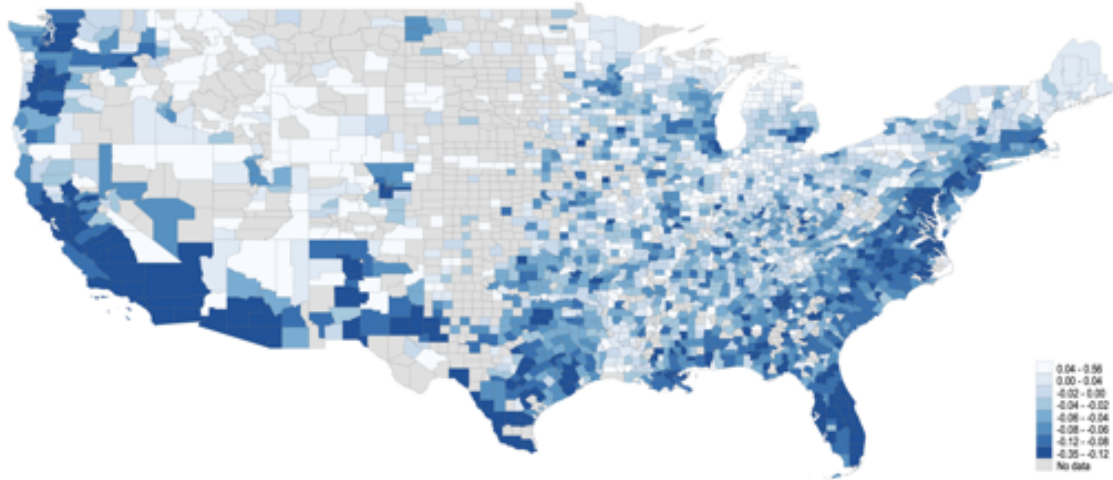
A.1 Levels of Aggregation

Table A1: Levels of aggregation and the matching results between the Facebook data and the Colombian trade data

Country	Unit of geo divisions		Number of divisions						% trade
	Colombian trade data		FB level 1	FB Level 2	Map level 1	Map Level 2	Merged	% merged	
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%

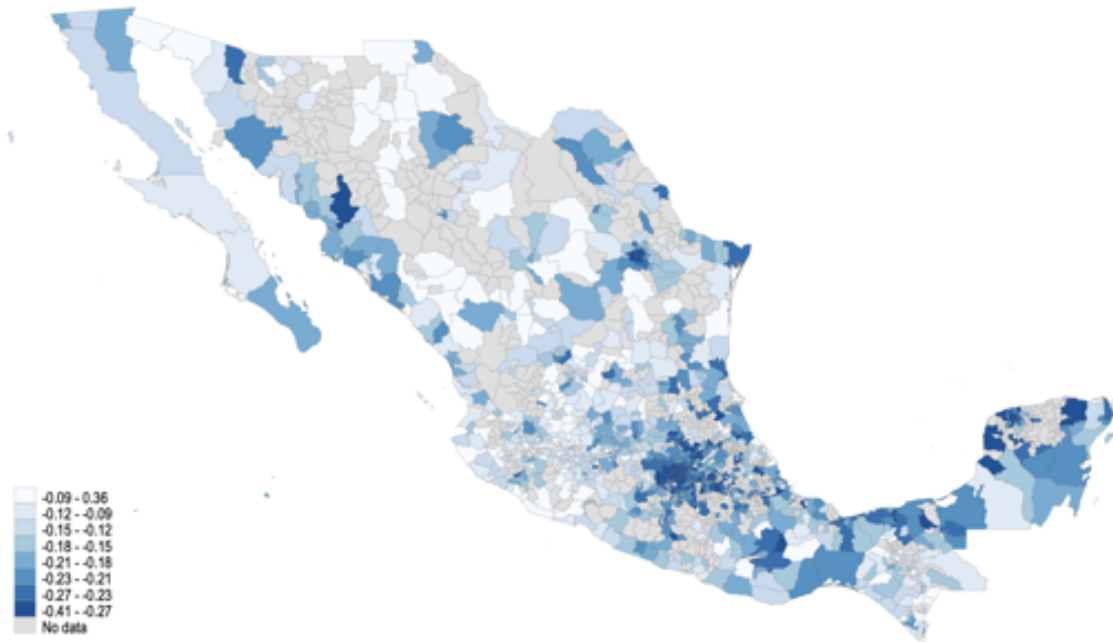
A.2 Mobility Change Maps

Figure A1: The decline in mobility across NUTS3 units in the US, September 2020



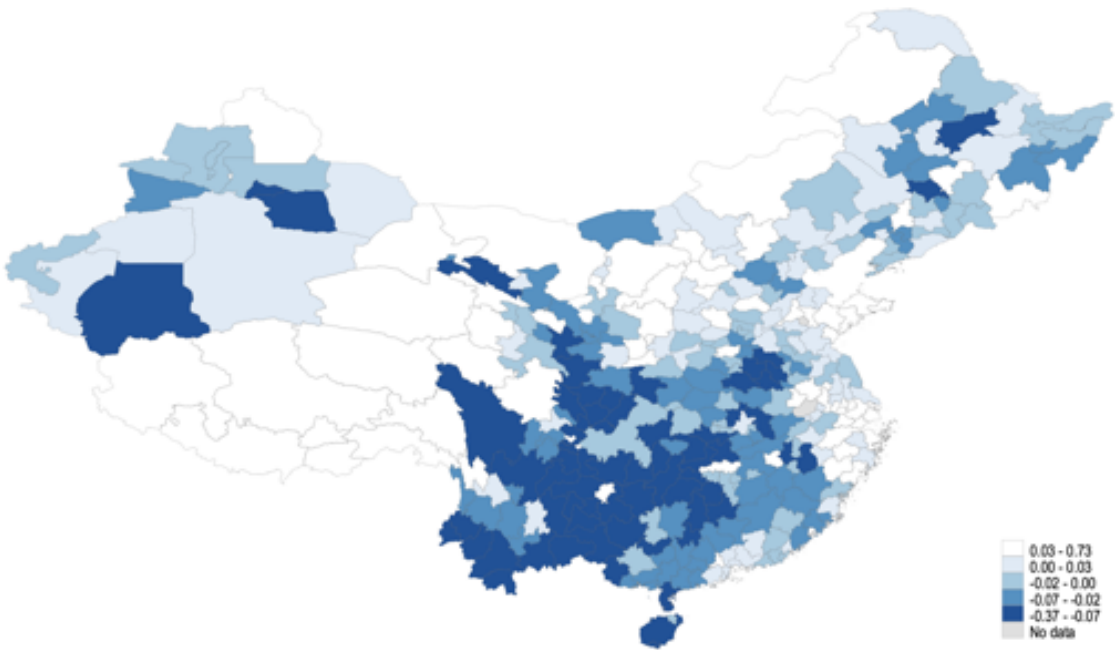
Note: Data is from Facebook.

Figure A2: The decline in mobility across *municipios* in Mexico, September 2020



Note: Data is from Facebook.

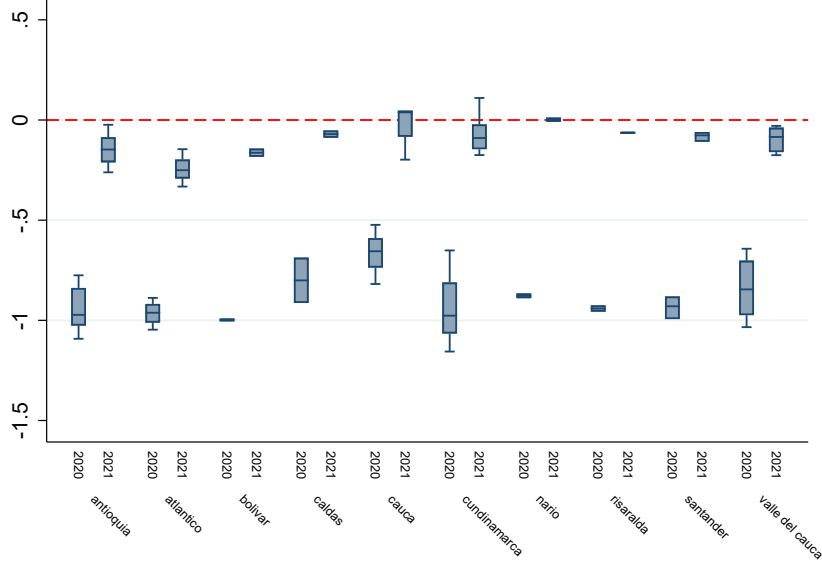
Figure A3: The decline in mobility across prefectures in China, September 2020



Note: Data is from Baidu.

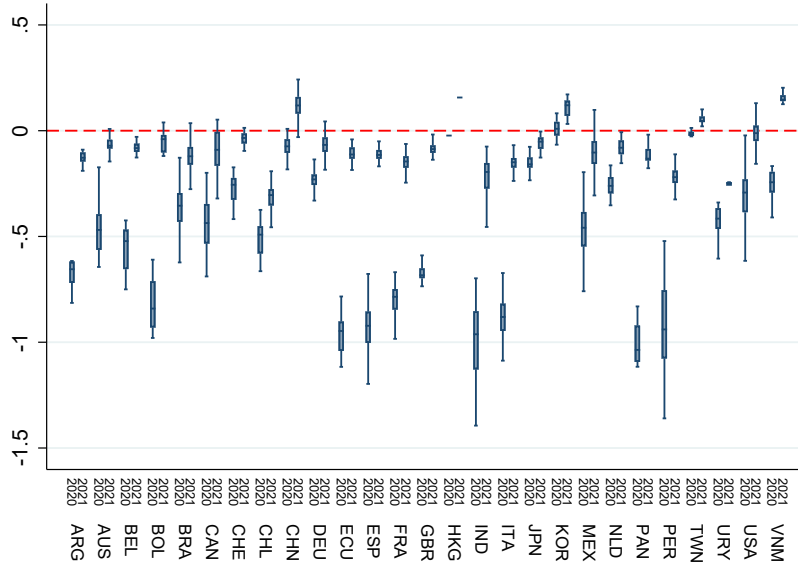
A.3 Mobility Variation at Colombia and Exporting Countries

Figure A4: Change in Average Importer Mobility by Colombian Department. April 2020 and April 2021



Note: Each observation is a municipality-month log change in importer mobility with respect to February 2020. Only departments of the top 60 municipalities in terms of 2018-2019 imports included.

Figure A5: Change in Average Exporter Mobility by Country. April 2020 and April 2021



Note: Each observation is a exporter city-month log change in exporter mobility with respect to February 2020.

A.4 Descriptive Statistics of Variables Used in Baseline Product Regressions

Table A2: Descriptive Statistics of Variables Used in Baseline Product Regressions

	Mean	sd	Q1	Median	Q3	N
<i>Dependent Variables</i>						
$\Delta \log$ Import Values	-.069	1.802	-.992	-.027	.862	458858
$\Delta \log$ Import Prices	.035	1.332	-.348	.023	.422	458858
$\Delta \log$ Import Quantities	-.104	2.004	-1.081	-.016	.858	458858
<i>Mobility Variables</i>						
$\Delta \log$ Importer Mobility	-.202	.191	-.303	-.152	-.062	458858
$\Delta \log$ Exporter Mobility	-.123	.131	-.2	-.119	-.032	458858
<i>Controls</i>						
$\Delta \log$ Congestion ($\hat{S}$)	-.194	.156	-.304	-.165	-.067	458858
$\Delta \log$ Congestion ($\hat{D}$)	-.229	.15	-.327	-.214	-.102	458858

A.5 Ports Included in the Analysis

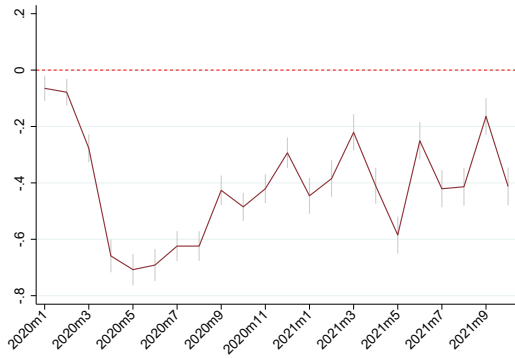
Table A3: The 150 ports used in the analysis, with TEU in 2019 (millions)

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

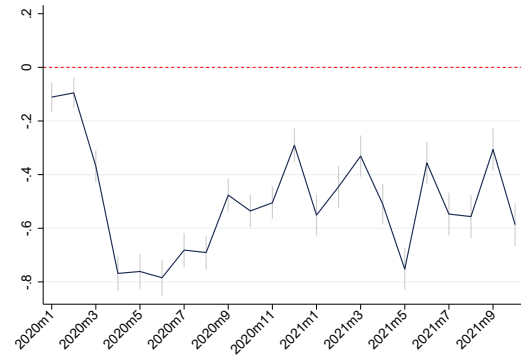
B Additional Empirical Results

B.1 Trade Trends for the Balanced Sample

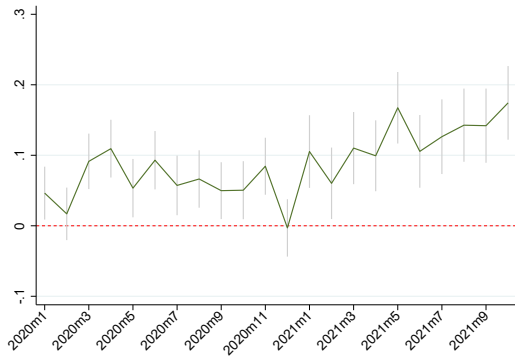
Figure B1: Average Change in Import Variables Relative to Pre-Pandemic Trends, Balanced Sample



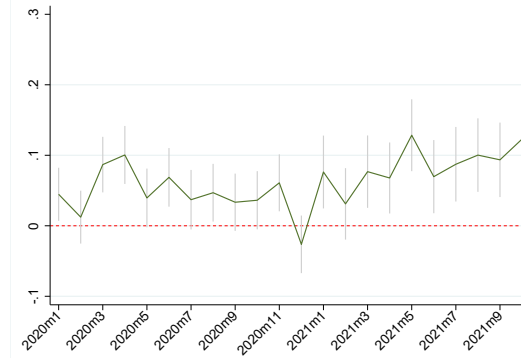
(a) Import Values (m)



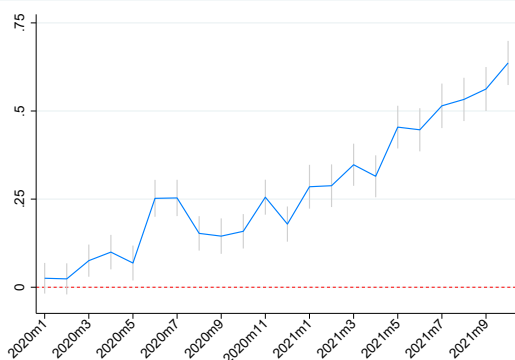
(b) Import Quantities (q)



(c) Importer Prices (p^X)



(d) Exporter prices



(e) Freight cost

Note: Each point is the estimated coefficient of Equation 2 with 95% confidence intervals, using the balanced sample only. Standard errors clustered at the exporter-importer-product level.

B.2 Validation of the Mobility Measure

In this section, we provide evidence on the relationship between mobility changes, local covid outbreak, and policies.

In this paper, we use the observed mobility changes as an aggregate measure which captures the reduction in economic activity. The mobility reduction can be the result of the increased risks of infection and the 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 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 in regions with larger reductions in mobility, they also have larger numbers of cases and more stringent policy.

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 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., period-city, where a period 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 a period.

Table B1: The Relationship between the mobility change and the number of new cases.

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

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 a 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-period 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 period 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-period level, we only include region fixed effects and period 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 a 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 stringency index, which are 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: $\Delta \log$ mobility				
StringencyIndex	-0.007*** (0.000)	-0.007*** (0.000)			
GovernmentResponseIndex			-0.008*** (0.000)		
ContainmentHealthIndex				-0.009*** (0.000)	
EconomicSupportIndex					0.003*** (0.000)
Average daily new cases (per 1000 persons)		-0.034*** (0.004)	-0.022*** (0.004)	-0.028*** (0.004)	-0.013*** (0.004)
Constant	0.361*** (0.006)	0.369*** (0.006)	0.395*** (0.009)	0.452*** (0.009)	-0.262*** (0.008)
Observations	16,445	16,443	16,443	16,443	16,443
R-squared	0.855	0.856	0.822	0.839	0.803

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

B.3 Robustness Exercises to Exporter-Importer-Product Level Local Shocks Results

Table B3: Local Importer and Exporter Mobility and Import Variables. Pre-Trends Controls.

	(1)	(2)	(3)	(4)	(5)	(6)
\textit{Dependent Variable:}	Import Value	Import Quantity	Import Price	Import Value	Import Quantity	Import Price
Importer Mobility	0.391** (0.171)	0.537*** (0.181)	-0.148* (0.081)	0.497*** (0.099)	0.512*** (0.100)	-0.013 (0.061)
Exporter Mobility	1.427*** (0.260)	1.754*** (0.395)	-0.311* (0.161)	0.201 (0.129)	0.342** (0.172)	-0.140** (0.067)
Sample	Balanced	Balanced	Balanced	Full	Full	Full
Pre-period control	Yes	Yes	Yes	Yes	Yes	Yes
N	64,579	64,579	64,579	257,049	257,049	257,049
R ²	0.236	0.230	0.162	0.147	0.147	0.107

Note: OLS regressions at exporter, importer, product (6-digit HS) and time level, where time is at the monthly frequency. Dependent variable indicated at the top in each column. Exporting country-main port of entry-time, and product-time fixed effects included. Pre-period control included is the dependent variable for the corresponding 2018-2019 period (i.e. lagged 24 months). Robust standard errors clustered at the exporter-time and importer-time level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table B4: Local Importer and Exporter Mobility and Import Variables. Alternative Fixed Effect Specifications.

	(1)	(2)	(3)	(4)	(5)	(6)
\textit{Dependent Variable:}	Import Value	Import Quantity	Import Price	Import Value	Import Quantity	Import Price
Importer Mobility	0.309** (0.147)	0.465*** (0.167)	-0.157*** (0.055)	0.014 (0.210)	0.077 (0.232)	-0.063 (0.062)
Exporter Mobility	1.199*** (0.214)	1.447*** (0.311)	-0.248** (0.110)	1.232*** (0.234)	1.498*** (0.331)	-0.267** (0.127)
Fixed Effects	Exporting country-Main entry port-Time			Exporting country-Main entry port-Department Time Product-Time		
N	86,180	86,180	86,180	76,281	76,281	76,281
R ²	0.086	0.079	0.029	0.248	0.244	0.164

Note: OLS regressions at exporter, importer, product (6-digit HS) and time level, where time is at the monthly frequency. Dependent variable indicated at the top in each column. Robust standard errors clustered at the exporter-time and importer-time level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table B5: Local Importer and Exporter Mobility and Import Variables. Alternative Standard Errors Clustering.

	(1)	(2)	(3)	(4)	(5)	(6)
\textit{Dependent Variable:}	Import Value	Import Quantity	Import Price	Import Value	Import Quantity	Import Price
Importer Mobility	0.357** (0.174)	0.400** (0.197)	-0.043 (0.049)	0.357* (0.185)	0.400* (0.218)	-0.043 (0.069)
Exporter Mobility	1.372*** (0.245)	1.632*** (0.365)	-0.260* (0.142)	1.372*** (0.234)	1.632*** (0.328)	-0.260* (0.137)
Clustering	Exporting country-time and Importer location-time			Exporting country-time and Importer department-time		
N	77,351	77,351	77,351	77,351	77,351	77,351
R ²	0.219	0.216	0.152	0.219	0.216	0.152

Note: OLS regressions at exporter, importer, product (6-digit HS) and time level, where time is at the monthly frequency. Dependent variable indicated at the top in each column. Exporting country-main port of entry-time, and product-time fixed effects included. Robust standard errors clustered as indicated on the clustering row. *** p<0.01, ** p<0.05, * p<0.1

Table B6: Local Importer and Exporter Mobility and Import Variables. Congestion Controls.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Goods			Intermediate Goods			Capital Goods		
\textit{Dependent Variable:}	Import Value	Import Quantity	Import Price	Import Value	Import Quantity	Import Price	Import Value	Import Quantity	Import Price
Importer Mobility	-0.557* (0.307)	-0.601* (0.353)	0.043 (0.250)	0.696*** (0.186)	0.771*** (0.202)	-0.076 (0.077)	-0.223 (0.237)	-0.010 (0.248)	-0.213* (0.125)
Exporter Mobility	0.383 (0.334)	1.315*** (0.387)	-0.932*** (0.190)	1.721*** (0.323)	2.213*** (0.404)	-0.492*** (0.138)	2.180*** (0.227)	1.467*** (0.340)	0.713*** (0.229)
Congestion, demand side	-0.970 (2.866)	-5.022** (2.359)	4.052*** (1.266)	-2.459** (1.139)	-2.790*** (0.994)	0.332 (0.508)	-2.322 (2.394)	0.249 (1.687)	-2.572 (1.638)
Congestion, supply side	3.611** (1.835)	6.267*** (1.409)	-2.656 (1.861)	0.418 (0.798)	-0.045 (0.747)	0.464 (0.512)	2.944** (1.490)	0.157 (1.696)	2.787** (1.366)
N	9,720	9,720	9,720	48,078	48,078	48,078	14,752	14,752	14,752
R ²	0.393	0.337	0.206	0.222	0.219	0.165	0.229	0.234	0.195

Note: OLS regressions at exporter, importer, product (6-digit HS) and time level, where time is at the monthly frequency. Dependent variable indicated at the top in each column. Exporting country-main port of entry-time, and product-time fixed effects included. Robust standard errors at the exporter-time and importer-time level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table B7: Local Importer and Exporter Mobility and Import Variables. Interaction Term.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Goods			Intermediate Goods			Capital Goods		
\textit{Dependent Variable:}	Import Value	Import Quantity	Import Price	Import Value	Import Quantity	Import Price	Import Value	Import Quantity	Import Price
Importer Mobility	-0.539* (0.306)	-0.648* (0.353)	0.110 (0.216)	0.615*** (0.235)	0.574** (0.266)	0.041 (0.087)	-0.255 (0.259)	-0.323 (0.303)	0.068 (0.164)
Exporter Mobility	-0.298 (0.390)	0.778 (0.537)	-1.076*** (0.333)	1.232*** (0.311)	1.369*** (0.353)	-0.137 (0.153)	2.133*** (0.332)	0.954*** (0.322)	1.179*** (0.226)
Interaction	-1.032 (0.686)	-0.330 (1.005)	-0.702 (0.521)	-0.643 (0.633)	-1.404** (0.683)	0.760*** (0.202)	0.200 (0.781)	-1.116 (0.761)	1.316*** (0.320)
N	10,723	10,723	10,723	50,044	50,044	50,044	15,511	15,511	15,511
R ²	0.400	0.351	0.218	0.224	0.221	0.163	0.228	0.232	0.189

Note: OLS regressions at exporter, importer, product (6-digit HS) and time level, where time is at the monthly frequency. Dependent variable indicated at the top in each column. Exporting country-main port of entry-time, and product-time fixed effects included. Robust standard errors at the exporter-time and importer-time level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table B8: Local Importer and Exporter Mobility and the Extensive Margin.

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	Congestion	Interaction	Consumer Goods	Intermediate Goods	Capital Goods
Importer Mobility	0.039*** (0.005)	0.036*** (0.006)	0.038*** (0.005)	0.045*** (0.010)	0.040*** (0.006)	0.030*** (0.006)
Exporter Mobility	0.021*** (0.007)	0.034*** (0.007)	0.019** (0.008)	0.007 (0.014)	0.035*** (0.007)	-0.001 (0.008)
Congestion, demand side		-0.082*** (0.017)				
Congestion, supply side		0.017* (0.010)				
Interaction Exp x Imp Mobility			-0.003 (0.017)			
N	10,888,687	9,576,408	10,888,687	1,879,724	6,578,096	2,367,405
R ²	0.012	0.013	0.012	0.020	0.011	0.008

Note: OLS regressions at exporter, importer, product (6-digit HS) and time level, where time is at the monthly frequency. Dependent variable is a dummy variable that takes the value of one if exports are positive and zero otherwise. Exporting country-time, and product-time fixed effects included. Robust standard errors at the exporter-time and importer-time level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

B.4 Covid-Related Medical Goods

A list by World Customs Organization and World Health Organization specifies the list of Covid-related medical goods at HS6 level. 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 sterilisation products; (4) oxygen therapy equipment and pulse oximeters; (5) other medical devices and equipment; (6) other medical consumables; (7) vehicles. Overall, these goods comprises about 7.7% of the total trade value.

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

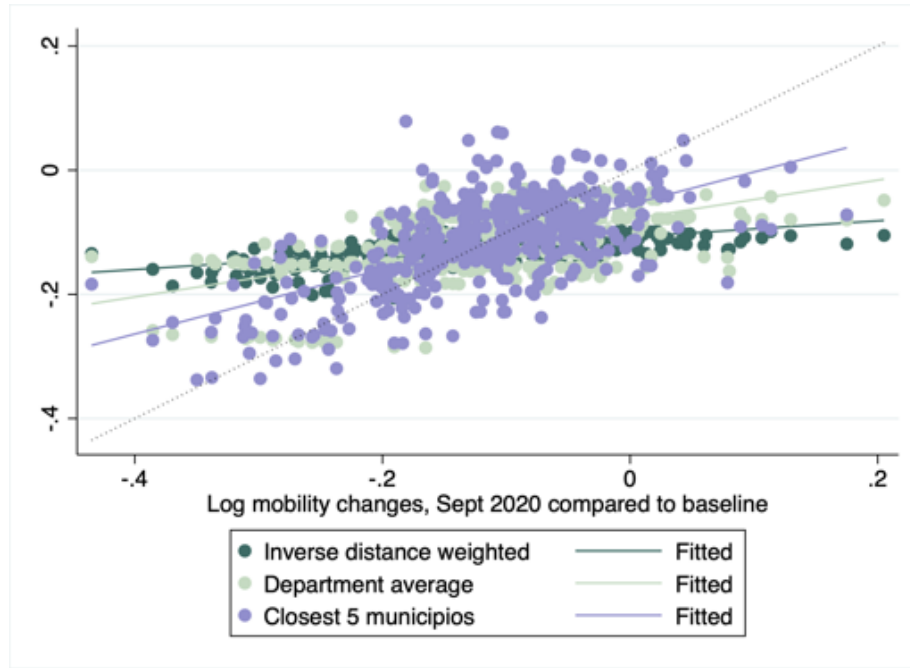
We investigate the impact of importer shock and exporter shock on Covid-related medical supplies in Table B9. We find very intuitive results: lower importer mobility is associated with higher demand.

Table B9: The impact of importer and exporter mobility changes on the price and quantity of medical goods

	(1) Value	(2) Quantity	(3) Price
Importer mobility, non-medical	0.570*** (0.177)	0.617*** (0.197)	-0.047 (0.060)
Importer mobility, medical	-1.653*** (0.278)	-1.559*** (0.306)	-0.094 (0.276)
Exporter mobility, non-medical	1.418*** (0.231)	1.608*** (0.334)	-0.190 (0.128)
Exporter mobility, medical	0.994*** (0.226)	1.807*** (0.295)	-0.812*** (0.132)
Observations	77,351	77,351	77,351
R-squared	0.220	0.216	0.152

B.5 Importer Region vs Importer City

Figure B2: Regional mobility changes are highly correlated with city-level mobility changes in Colombia



B.6 Fixed Effect Averages for Baseline Regression

B.6.1 Quantity Equation

Figure B3: Sum of Country-Port-Time and Product-Time FE

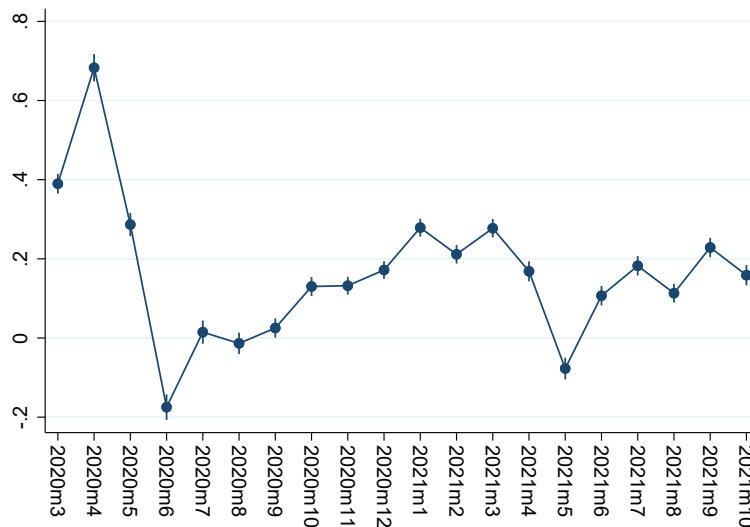


Figure B4: Country-Port-Time FE

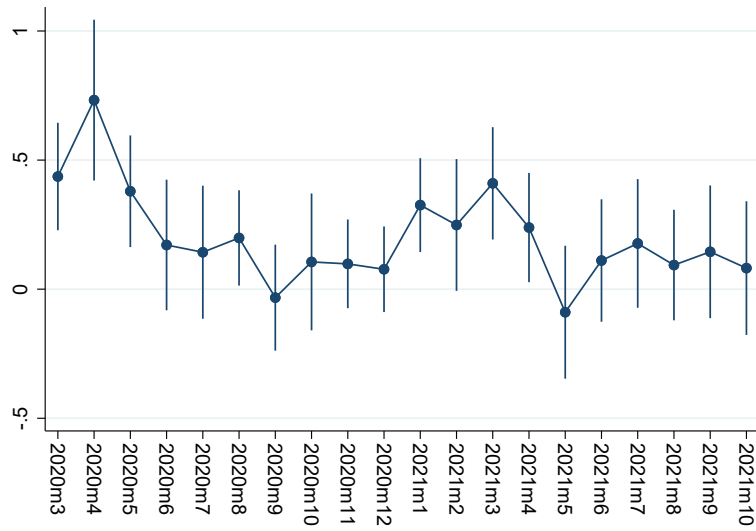
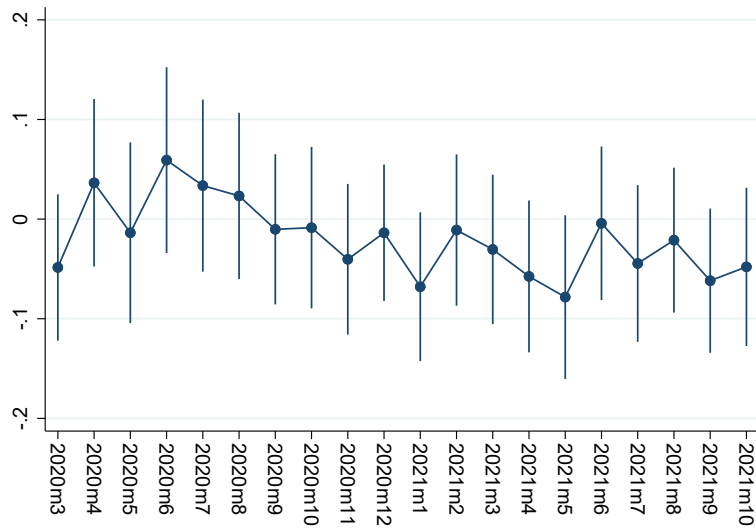


Figure B5: Product-Time FE



B.6.2 Price Equation

Figure B6: Sum of Country-Port-Time and Product-Time FE

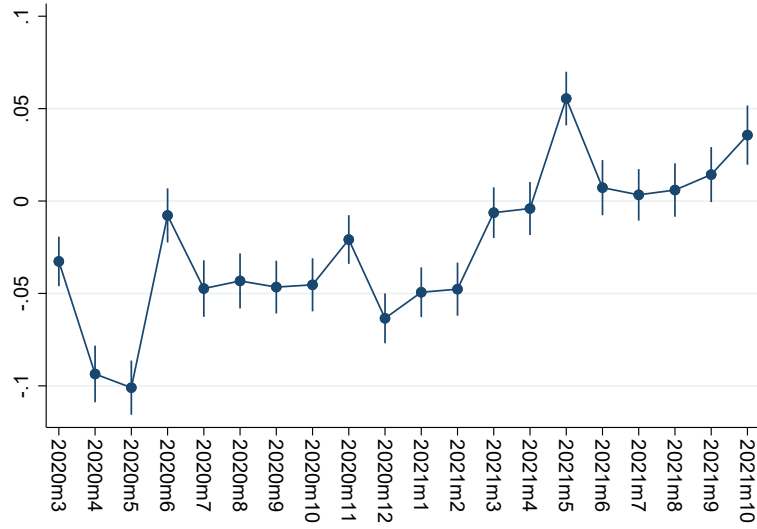


Figure B7: Country-Port-Time FE

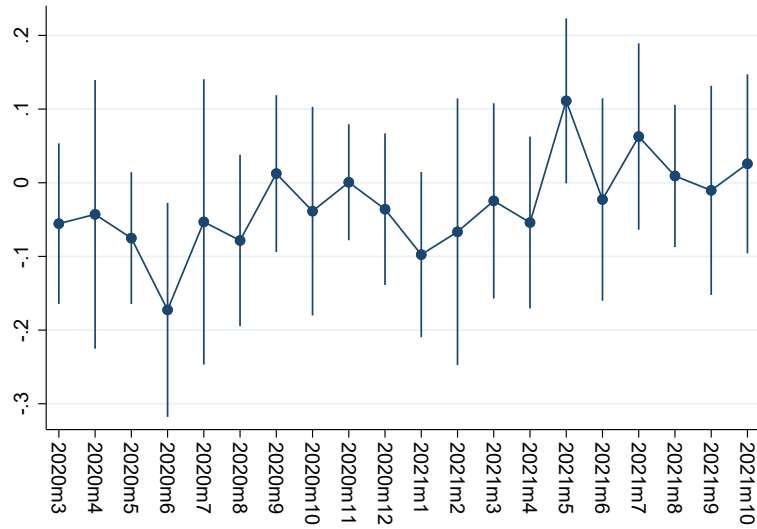
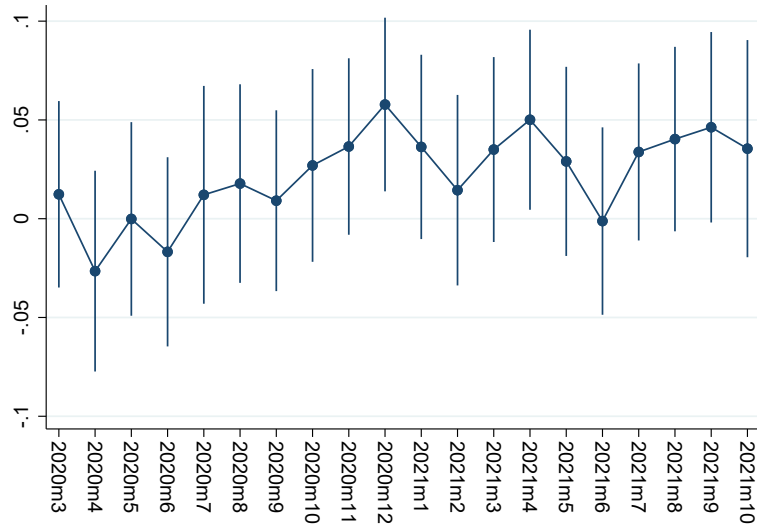


Figure B8: Product-Time FE



B.6.3 Correlation Between Country-Port-Time Fixed Effect (δ^{Tr}) and Country-Port-Time Observed Freight Unit Values Averages

Figure B9: Quantity Regression

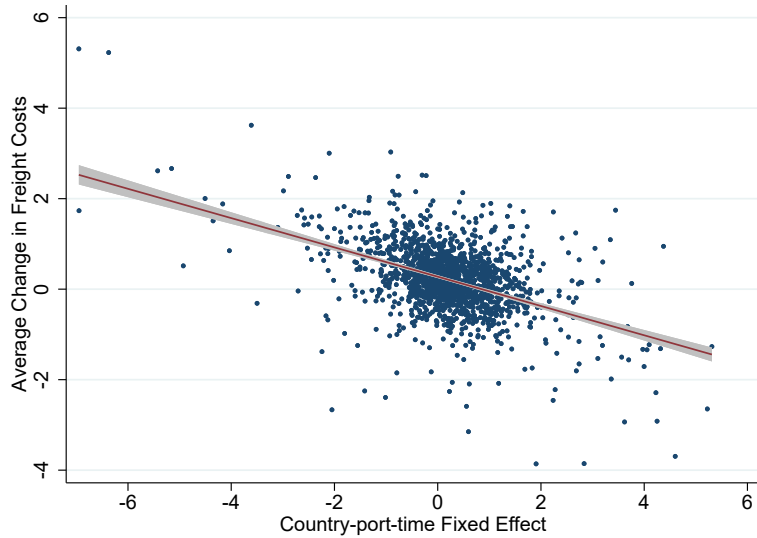
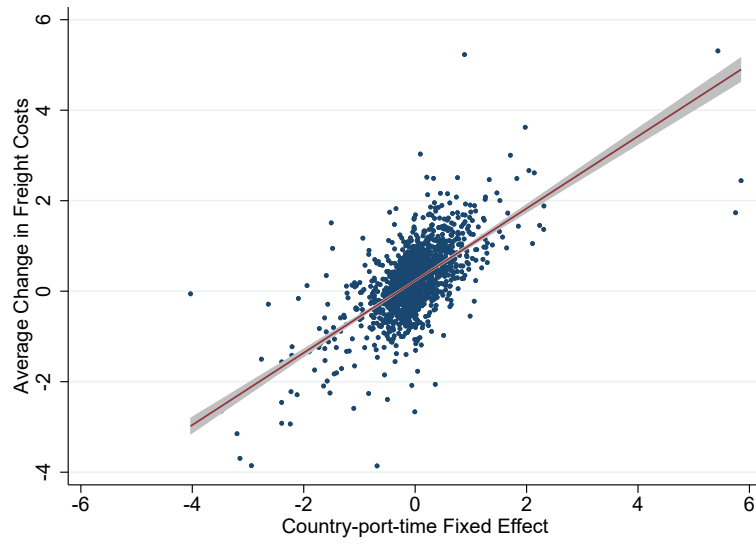
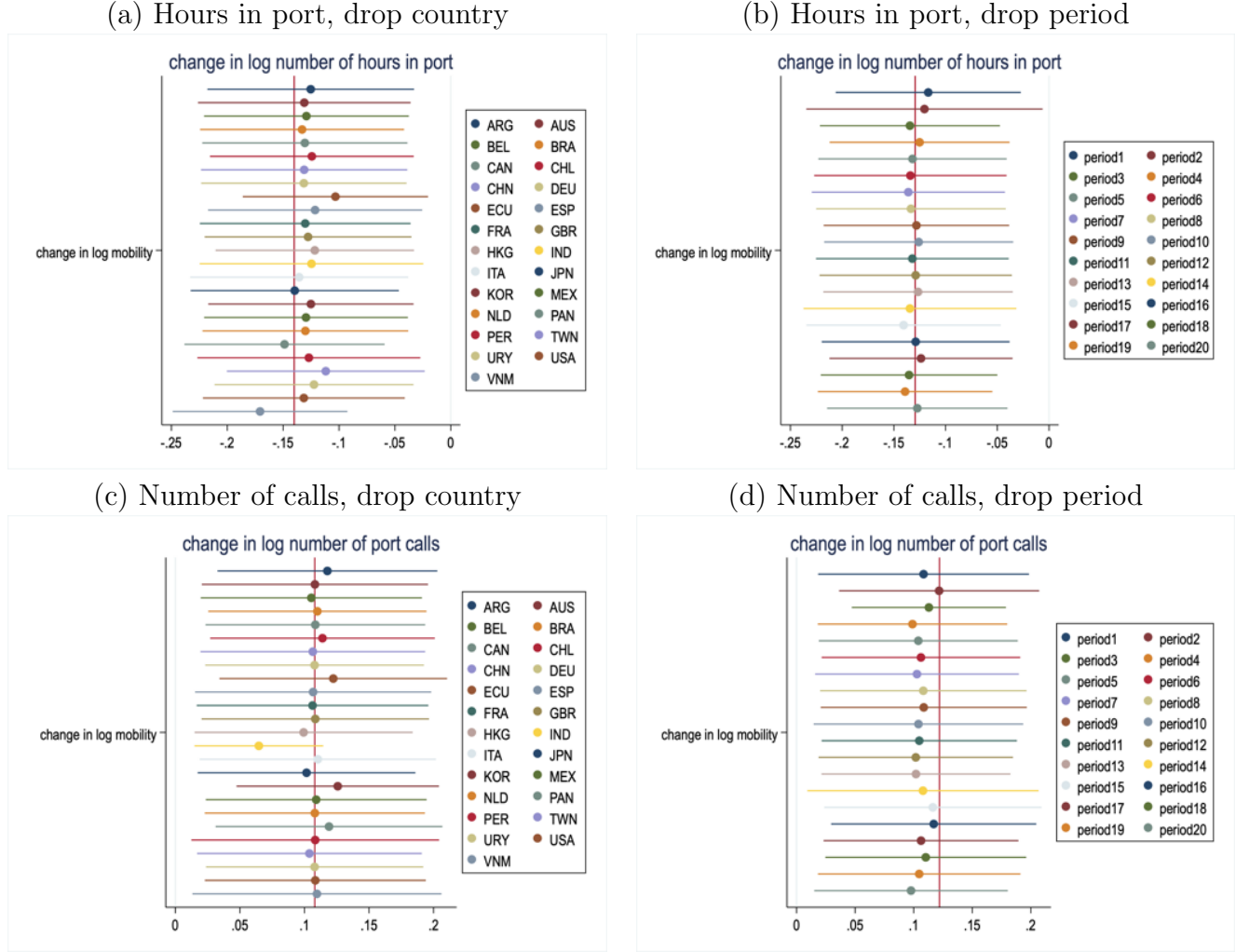


Figure B10: Price Regression



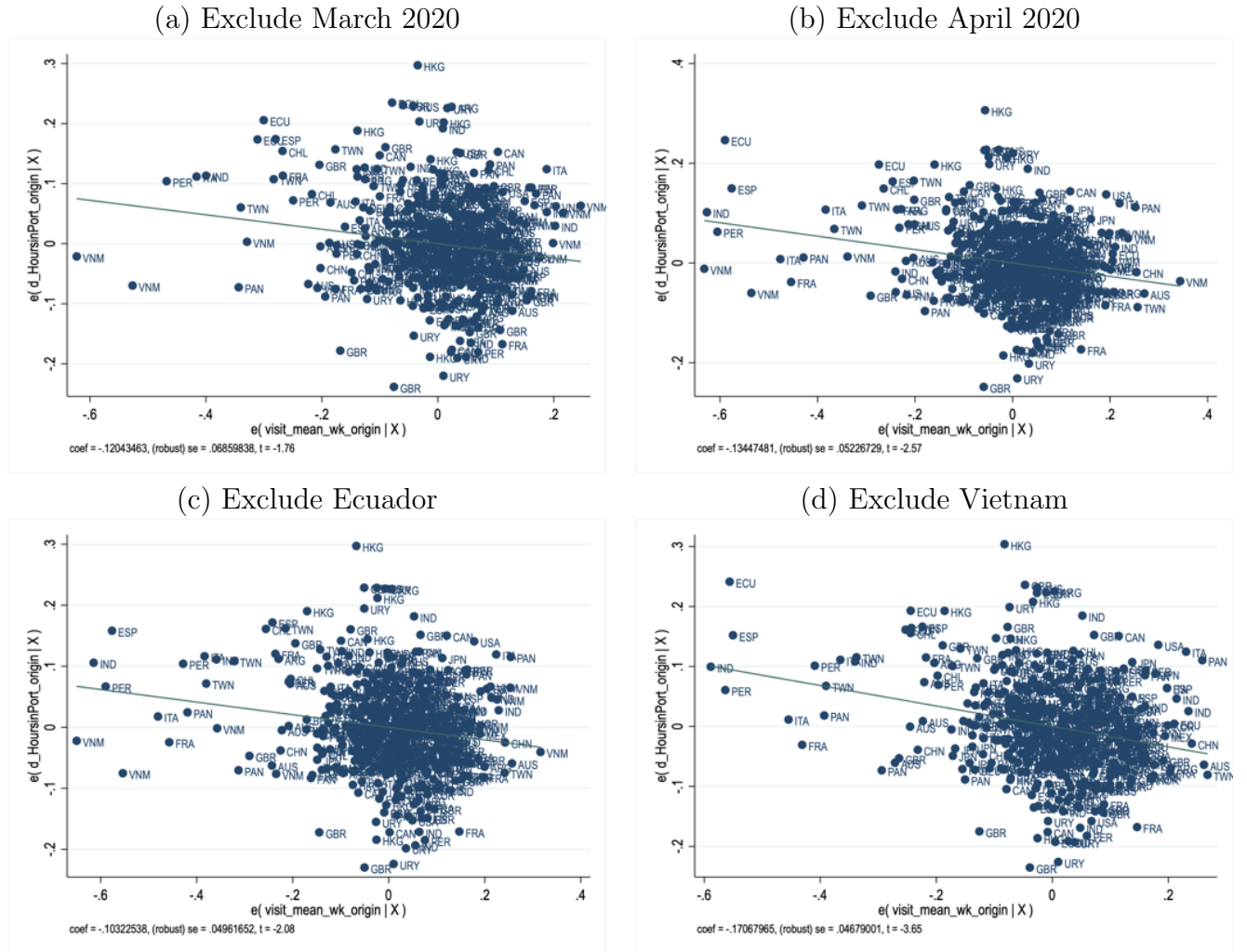
B.7 Country-Level Port Performance Results

Figure B11: The robustness of country level results in Table 6, the impact of mobility changes on port performance, dropping one country at a time and dropping one period at a time



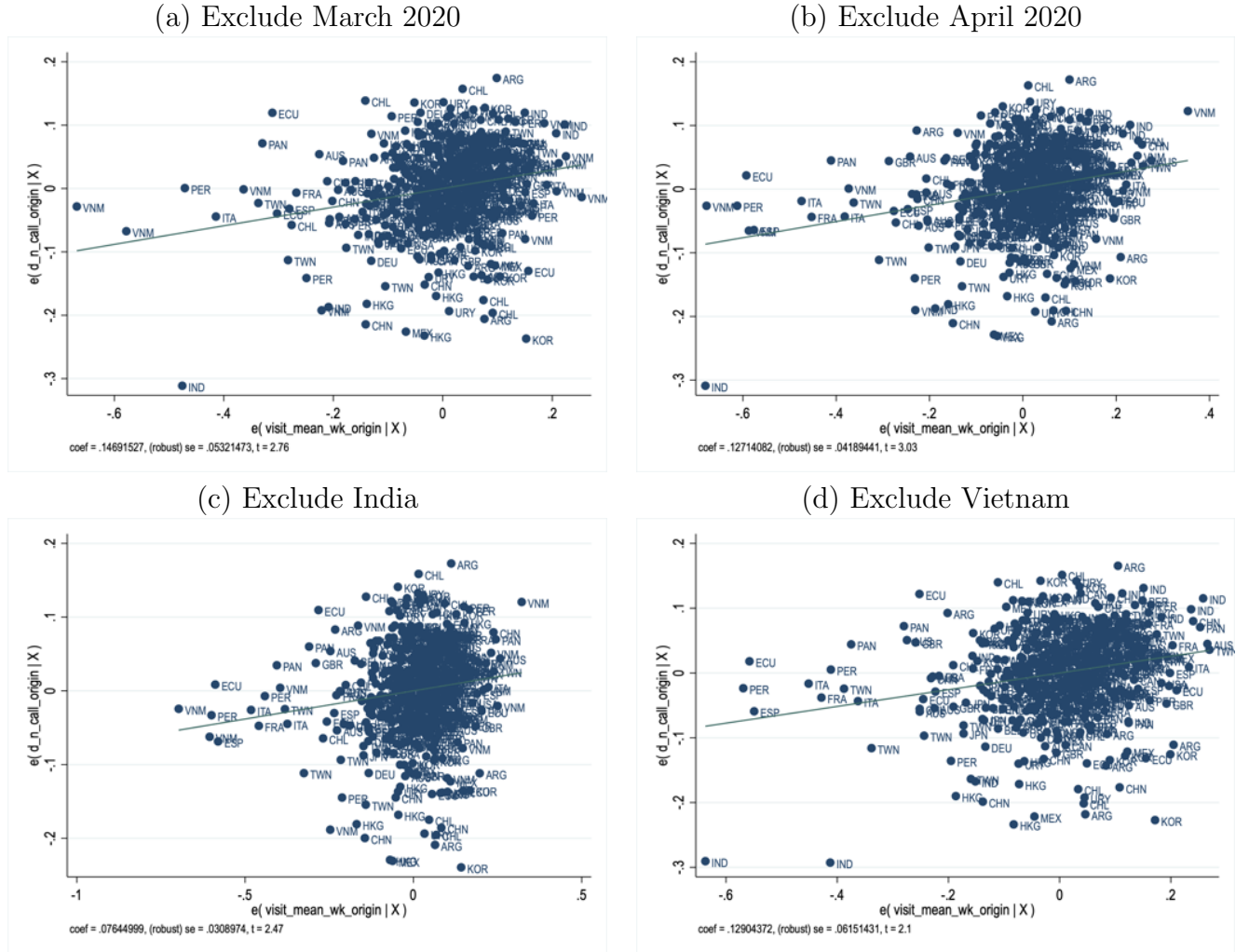
Note: Panel (a) plots the coefficients when replicating results in Table 6 Panel A Column (1) and dropping one country at a time, and Panel (b) plots the coefficients when dropping one period at a time. Panel (c) plots the coefficients when replicating results in Table 6 Panel A Column (3) and dropping one country at a time, and Panel (d) plots the coefficients when dropping one period at a time.

Figure B12: The robustness of country level results, the impact of mobility changes on the number of hours in port, residual plot



Note: Panel (a) is the residual plot for replicating results in Table 6 Panel A Column (1) and dropping March 2020. Panel (b) drops April 2020, Panel (c) drops Ecuador, and Panel (d) drops Vietnam.

Figure B13: The robustness of country level results, the impact of mobility changes on the number of port calls, residual plot



Note: Panel (a) is the residual plot for replicating results in Table 6 Panel A Column (3) and dropping March 2020. Panel (b) drops April 2020, Panel (c) drops India, and Panel (d) drops Vietnam.

Table B10: The relationship between freight costs and mobility, without dropping the top 1% and the bottom 1%

Panel A.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome: 2020 and 2021	$\Delta \log \text{ freight cost, unit}$				$\Delta \log \text{ freight cost, weight}$			
$\Delta \log \text{ mobility change}$	-0.31** (0.11)	-0.31** (0.11)	-0.35*** (0.12)	-0.62*** (0.21)	-0.34*** (0.10)	-0.34*** (0.10)	-0.37*** (0.11)	-0.63*** (0.17)
I (year=2021)	0.57*** (0.08)		0.57*** (0.08)	0.60*** (0.08)	0.60*** (0.07)		0.60*** (0.07)	0.63*** (0.07)
Time trend		0.05*** (0.01)				0.05*** (0.01)		
Constant	-0.02 (0.05)	-0.23*** (0.08)	-0.02 (0.05)	-0.08 (0.06)	-0.07 (0.04)	-0.29*** (0.07)	-0.07 (0.04)	-0.12** (0.05)
Observations	255,346	255,346	248,813	255,342	255,346	255,346	248,813	255,342
R-squared	0.12	0.12	0.16	0.12	0.15	0.15	0.19	0.16
Panel B.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome: 2018 and 2019	$\Delta \log \text{ freight cost, unit}$				$\Delta \log \text{ freight cost, weight}$			
$\Delta \log \text{ mobility change}$	0.05 (0.04)	0.02 (0.05)	0.04 (0.04)	0.03 (0.05)	-0.02 (0.03)	-0.00 (0.04)	-0.03 (0.03)	-0.04 (0.05)
I (year=2019)	0.02* (0.01)		0.03* (0.01)	0.03** (0.01)	0.03*** (0.01)		0.03** (0.01)	0.03** (0.02)
Time trend		0.00 (0.00)				0.00 (0.00)		
Constant	0.05*** (0.00)	0.04** (0.01)	0.05*** (0.01)	0.04*** (0.01)	-0.02*** (0.01)	-0.03* (0.01)	-0.02*** (0.01)	-0.03** (0.01)
Observations	271,942	271,942	265,877	271,942	271,942	271,942	265,877	271,942
R-squared	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: Standard errors are clustered at the product level and at the exporting country level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 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.8 Decomposition for consumer goods

Figure B14: Decomposition: Import Quantities and Prices of Consumer Goods



C Theory

C.1 Producer Problem

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

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

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:

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