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 6%, and that a 10% decrease in mobility at the exporter location led to a 3.3% 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.

*We thank Facebook's Data for Good initiative for sharing Facebook mobility data across the world and Baidu Mobility for sharing mobility data in China. All errors are our own.

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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 of 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. We employ a trade framework featuring firms with short-run decreasing returns to scale, consumers with love of variety over different locations, and a transportation sector with a limited capacity to ship goods across locations to interpret results.

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 Colombian 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 Jan 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 a 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 imports to decrease. In our preferred specification, a 10% reduction in importer mobility lowered imports to that location by 6%; whereas a 10% reduction in exporter mobility decreased imports to that location by 3.3%. We explain this asymmetry by decomposing the impact into quantities and prices: a shock at the importer location lowered quantities but left prices relatively unchanged, whereas a 10% shock at the exporter location decreased quantities by 4.7% but increased prices by 1.4%, reducing the impact on values. This effect is consistent with firms facing stringent production conditions during these shocks and thus charging higher prices.

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 understanding the relationship between local changes in economic activity and trade flows. Autor et al. (2013) were among the first to relate country-level trade changes to local shocks. We study how local, non-trade related labor shocks can affect trade between countries. A usual way to show the importance of local random shocks on trade is by using natural disasters. For instance, different papers have explored the impact of earthquakes on aggregate variables, such as on trade through the localized decimation of internal routes (Volpe Martincus et al., 2014), or on growth through supply chain networks (Carvalho et al., 2021); or the impact of hurricane Sandy on distant supply chain partners. In this sense, we explore local shocks comparable to natural disasters but different in the sense that they summarize local human behavior in response to a pandemic.

Certain points along shipping routes are key for world trade. This suggests that local shocks matter not only within countries but in-between them. Heiland et al. (2020) found that the Panama canal expansion had global welfare gains; Ganapati et al. (2020) showed that improving entrepôts (i.e., trade hubs) increase global welfare ten times more than improving non-entrepôts; and Cosar and Thomas (2021) found substantial regional welfare losses in the event of the closure of key maritime waterways in Southeast Asia. We add to this literature by showing that labor shortages at port locations also affect trade through port congestion.

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, 2019), 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 within countries and narrowly defined products and time, providing further evidence of its endogeneity.

Our paper also relates to the literature understanding 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 US-China trade war reduced imports and exports in the short-run entirely through quantities. In our setting, quantities and prices react differently depending on the location of shocks.

Finally, this paper also relates to recent research studying the impact of the pandemic on trade and economic activity in general. Available evidence shows that lockdowns reduced import demand, and Covid deaths in third countries increased imports from China (Liu et al., 2021); that the impact of the pandemic was heterogeneous across sectors at its onset, and high participation in global value chains propagated the effect (Espitia et al., 2021); that trade in services rose due to the offshorability of remote work (Baldwin and Dingel, 2021); and changes in consumers preferences affected food supply chains (Lu et al., 2021). Other papers used theory to investigate the relationship between trade and the pandemic by merging a gravity model to the SIR models used in epidemiology (Antras et al., 2020); studied whether long supply chains were riskier (Baldwin and Freeman, 2021); quantitatively found that one-quarter of GDP declines due to the pandemic was explained by global supply chains transmissions (Bonadio et al., 2021); and showed that the severity of supply chain losses was associated with the number of countries imposing lengthy lockdowns (Guan et al., 2021. To the best of our knowledge, We are the first to measure the impact of the pandemic through changes in local mobility and interpret results using a simple trade model with endogenous trade costs, and production and shipping congestion.

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 conclude.

2 Data and motivating facts

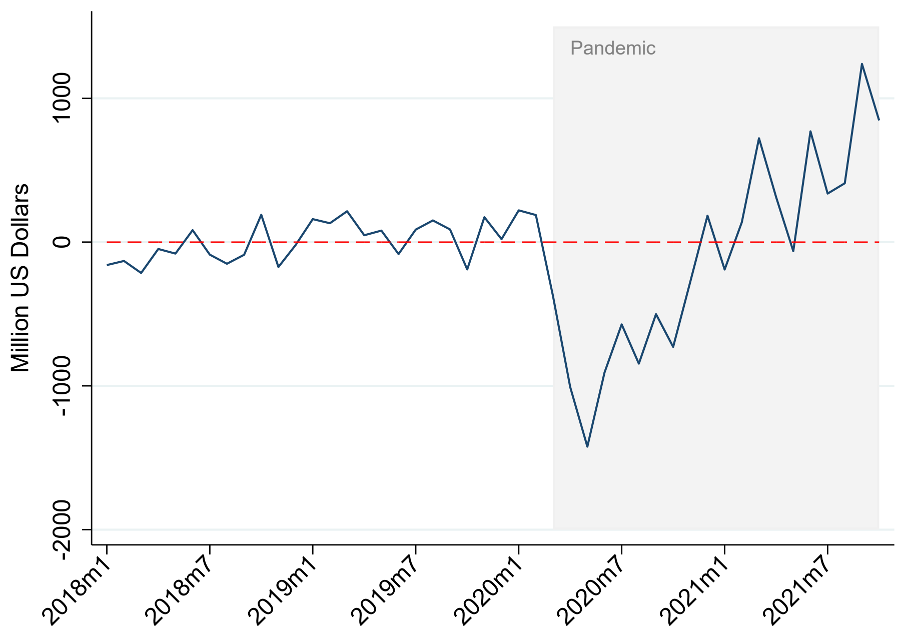
2.1 Trade Data

In this section, we characterize monthly changes in Colombian import trade variables over the years 2020 and 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 data 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 28 major trade partners for the analysis, which account for about 90% of total 2018 imports.[1]

We start by documenting total monthly imports over the 2018-2021 period in Figure 1.

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



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).

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. Immediately after the pandemic struck, aggregate imports to the selected countries declined by almost 40% —

[1] The reason why we do not use all exporting countries is that within country exporter location required extensive cleaning.

1.4 billion US dollars — and during 2021 they increased by as much as 35% — 1.2 billion US dollars.

These values mask the different underlying changes that took place in terms of quantities, export prices, trade costs, and import prices. In order to characterize the change in these variables, we aggregate the data at the exporter location, importer location, product and month level to accurately define quantities and prices and reduce composition biases.

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

$$\hat{m} \equiv \hat{q} + \hat{p}^X + \hat{\tau} \tag{1}$$

where q are quantities, p^F are export (FOB) prices dollars, and τ are the ad-valorem trade costs (defined as freight and insurance costs) in logs. Note that the log change in import prices is defined as $\hat{p}^M \equiv \hat{p}^X + \hat{\tau}$.

In equation 1, all variables have exporter location (i)-importer location (j)-product (k)-time (t) variation. Therefore, we estimate the following equation to characterize changes in each of them over the trade disruption period generated by the pandemic:

$$m_{ijkt} = \sum_{s=01/2020}^{10/2021} \alpha^s \times \mathbb{1}\{t = s\} + \delta^I_{ijkm} + \delta^S_{ijk} \times t + \varepsilon_{ijkt} \tag{2}$$

where m are imports or any of the other of the import variables, δ^I and δ^S capture the month-specific pre-pandemic intercept and the slope with respect to linear trends, and ε_{ijkm} are idiosyncratic deviations. Including these fixed effects allows us to focus on average deviations and avoid compositional effects.[2]

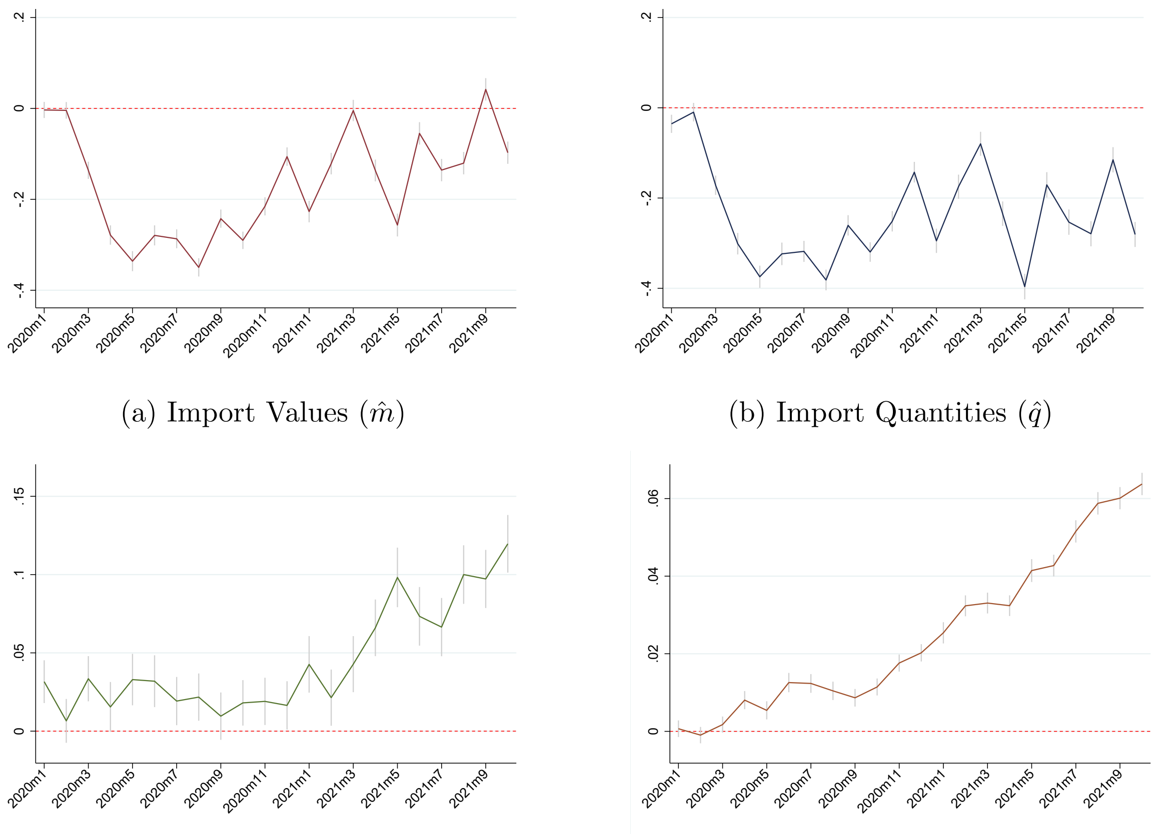
Figure 2a shows that the average impact on import values had a similar dynamic pattern as the aggregate: a sharp decrease at the beginning of the pandemic and a slower and non-monotonic recovery. This pattern is mostly explained by changes in the quantities imported, as seen in Figure 2b.

Export prices had a different dynamic. They remained relatively unchanged during the 2020 and the first quarter of 2021 but started rising in the second quarter. Ad-valorem trade costs increased steadily since the beginning of the pandemic. In summary, quantities led changes in import values, and export prices showed relative upward rigidity up until the second quarter of 2021 but not afterwards. In comparison, trade costs seemed more flexible.

We followed the standard approach of the trade literature in constructing ad-valorem trade costs, but we can actually construct freight and insurance unit values with the Colombian data. In Figure 3 we show the dynamics of both.

[2]Month-specific intercepts to account for seasonality.

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



(a) Import Values ($\hat{m}$)

(b) Import Quantities ($\hat{q}$)

(c) Exporter Prices ($\hat{p}^X$)

(d) Ad-valorem Trade Costs ($\hat{\tau}$)

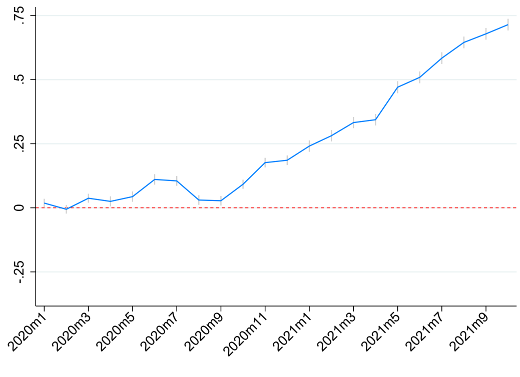
Each point is the estimated coefficient of equation 2 with 95% confidence intervals. Standard errors clustered at exporter-importer-product level.

Figure 3a shows that freight unit values increased more than 10% during the June-July 2020 period —right after some developed countries started relaxing lockdown measures. However, they began a monotonic increase in October 2020 to reach an average increase of almost 75% in the last month available (October 2021).

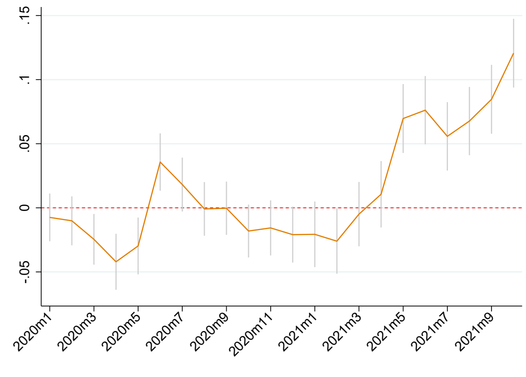
Insurance unit values show a different pattern. As showed in Figure 3b, they remained relatively unchanged up until the beginning of 2020, showing, if something, a downward trend. In March 2021, they started increasing, reaching an increase of about 12% in October 2021. Note that March 2021 saw the Suez Canal Blockage, which reportedly increased losses of global reinsurers.[3]

[3] See https://www.fitchratings.com/research/insurance/suez-canal-blockage-large-loss-event-for-global-reinsurers-29-03-2021

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



(a) Freight Unit Values ($\hat{m}$)

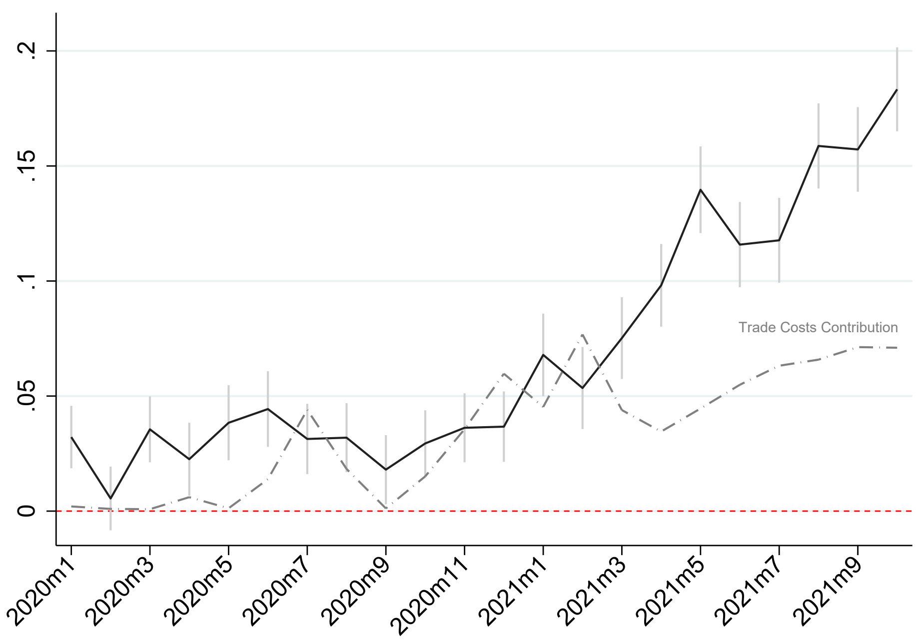


(b) Insurance Unit Values ($\hat{q}$)

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

All the the analysed prices showed an increase over the 2020-2021 period, which means that import prices also necesarilly increased, as shown in Figure 4.

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



Each point is the estimated coefficient of equation 2 with 95% confidence intervals. Standard errors clustered at 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.

What was the contribution of trade costs to such an increase over time? We decompose the import price change as follows:

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

where p^F are freight unit values, p^I are insurance unit values, θ^X, θ^F and θ^I are the average pre-pandemic share of export prices, freight and insurance unit costs respectively.[4] Figure 4 shows that the contribution of freight and insurance cost hikes explain almost half of the increase in import prices towards the end of 2021.[5]

In conclusion, import variables experienced large swings relative to the pre-pandemic years. Import quantities declined and stayed below pre-pandemic trends, whereas import prices and its 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. The platform collects and processes AIS data on ship movements of over 220,000 ships of 100 gross tonnage and above around the world. The 27 countries include 25 countries and regions that are top trade partners with Colombia (excluding Switzerland and Bolivia, which are landlocked), Colombia, and Singapore (as an important intermediate port). We include the most important ports in these countries. The 150 ports 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 A2.

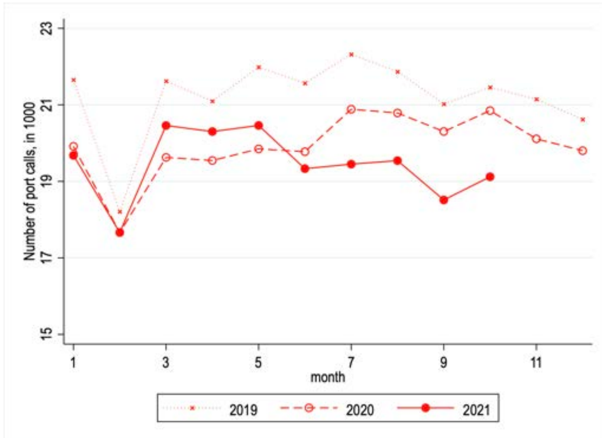
Figure 5 presents the important trends in port performance from 2019 to 2021. Panel (a) shows the total number of port calls. We can see that the container ship trade was at a lower level in 2020 and 2021 than in 2019. The first half of 2020 had an about 10% decline, and the second half of 2020 experienced 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 the total twenty-foot-equivalent units of the ships that made port calls.

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

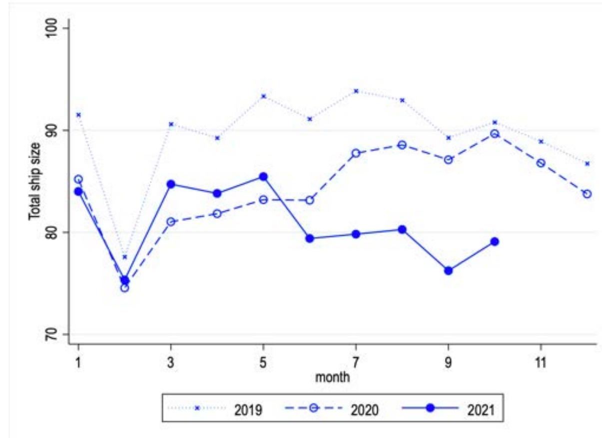
[5] Contribution is calculated as $(\theta^F \hat{p}^F + \theta^I \hat{p}^I)/\hat{p}^M$.

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

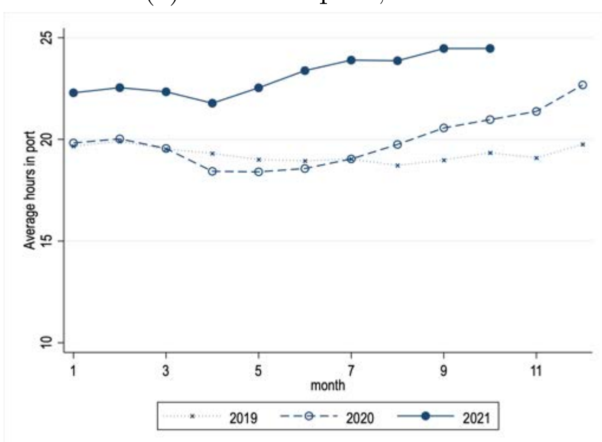
(a) Total number of port calls in 1000



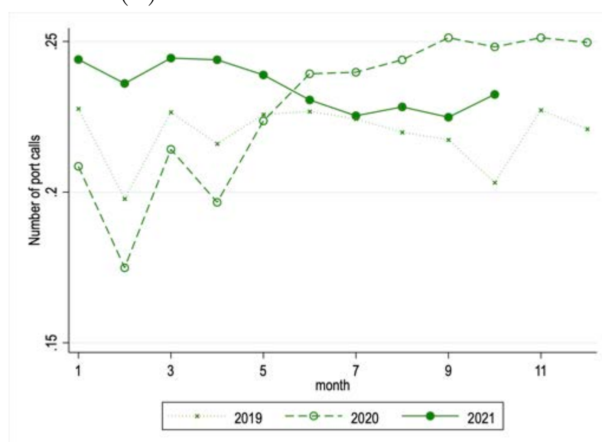
(b) Total ship size in million



(c) Hours in port, mean



(d) Share of call from China



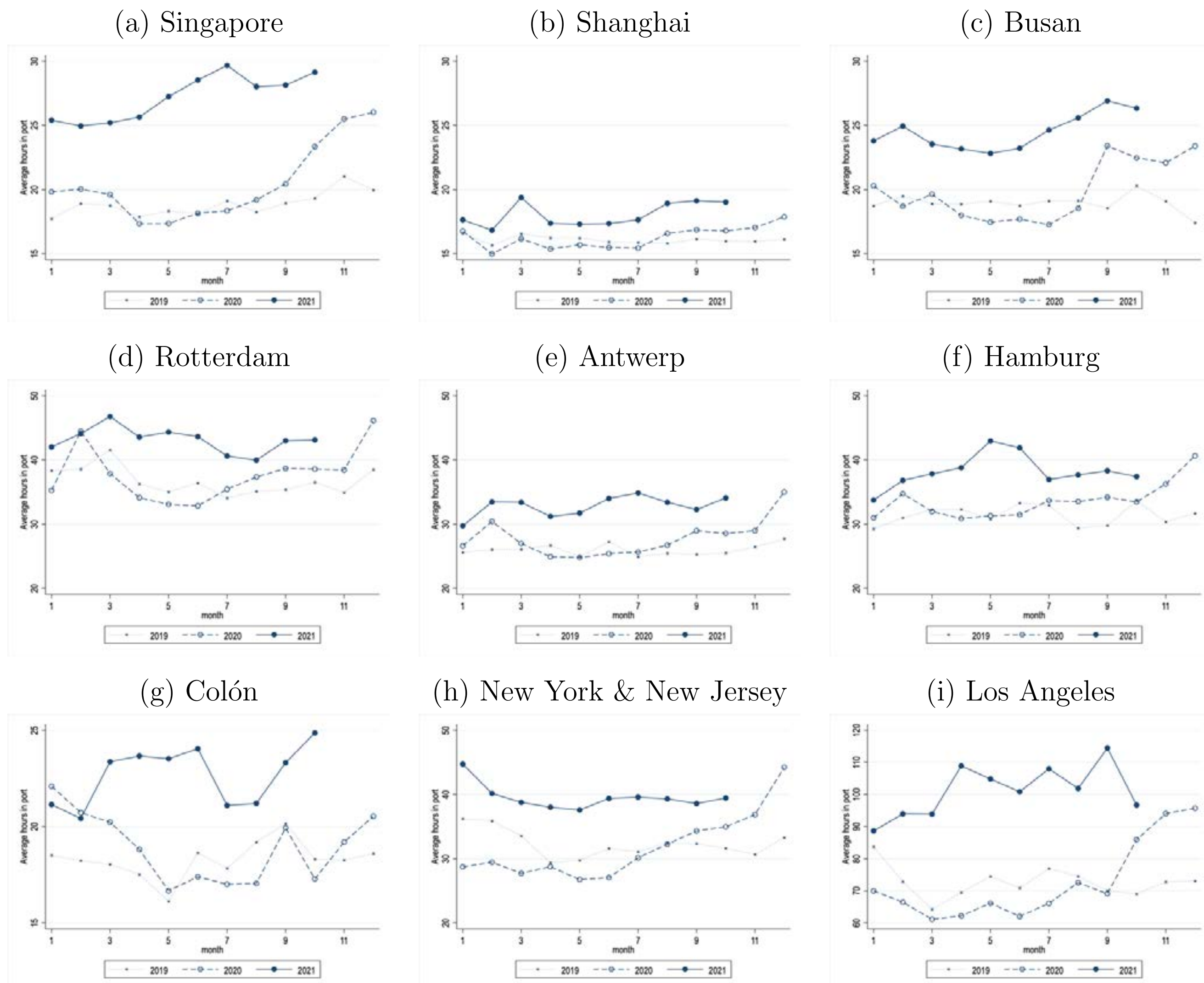
Note: Data is from the IHS Markit Maritime & Trade Platform. The figures use port calls made by container ships at 150 ports in 27 countries. The total number of port calls are in 1000 units, and the total ship size is in millions of twenty-foot equivalent units. The hours in port is measured as the difference between the sailed time and the arrival time at the port. The share of call 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.

Figure 6: Average hours in port, 9 important ports



(a) Singapore (b) Shanghai (c) Busan

(d) Rotterdam (e) Antwerp (f) Hamburg

(g) Colón (h) New York & New Jersey (i) Los Angeles

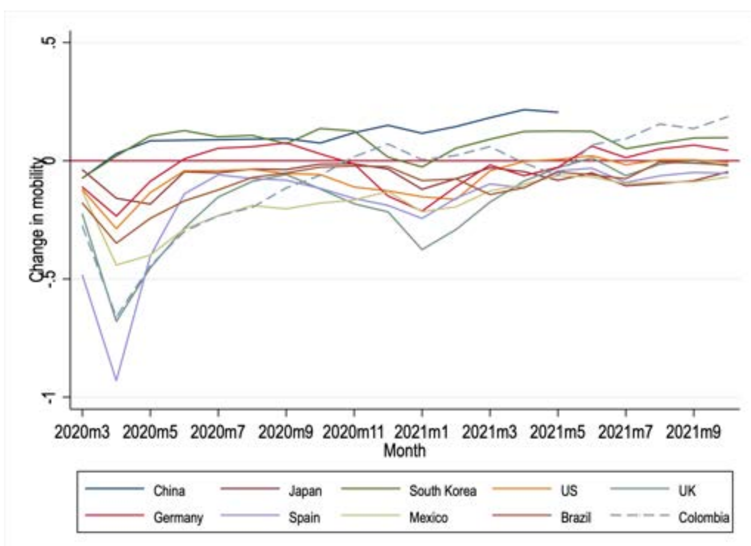
Note: Data is from the IHS Markit Maritime & Trade Platform. The hours in port is measured as the difference between the sailed time and the arrival time at the port.

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 incidence 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.[6]

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.[7] 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 major trade partners, the data is from Facebook, and the baseline period is the February 2020. Venezuela does not have Facebook data.[8] 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, come from Facebook.

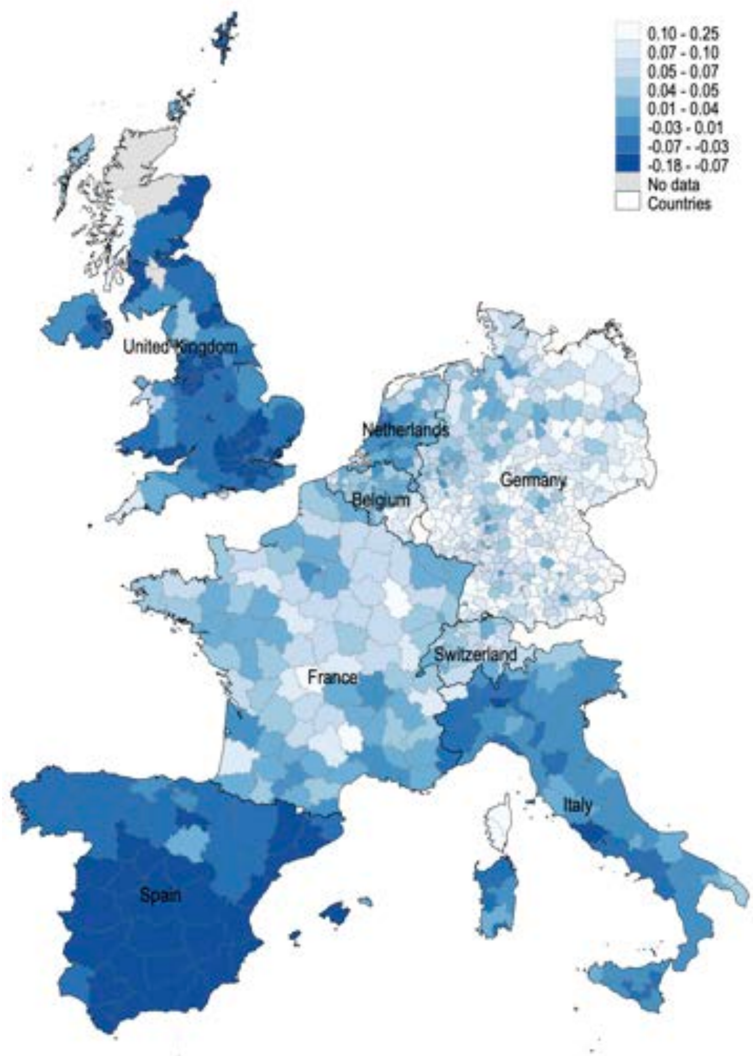
[6]News articles about the Los Angeles port congestion: `www.wsj.com/articles/why-container-ships-cant-sail-around-the-california-ports-bottleneck-11632216603?mod=article_inline`.

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

[8]https://dataforgood.facebook.com/dfg/tools/movement-range-maps

Figure 7 present the change 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.

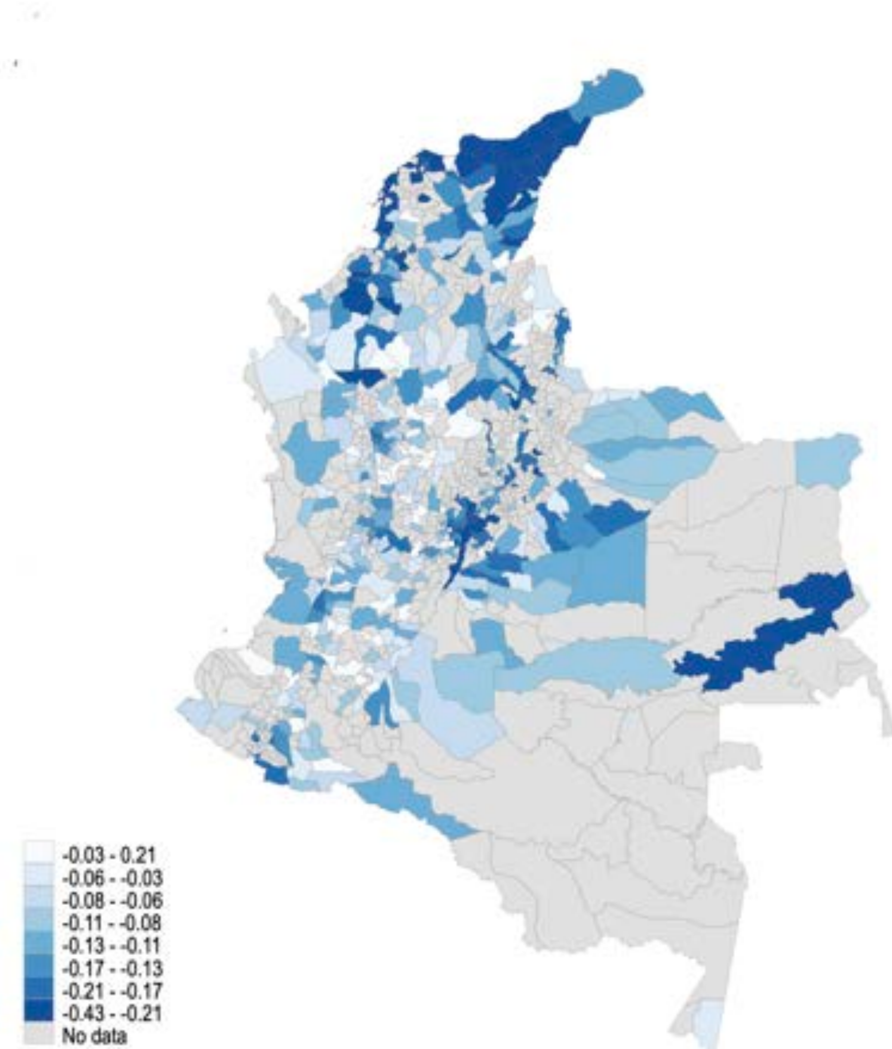
Figure 8: The decline in mobility across NUTS3 units in eight European countries, September 2020



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 US, 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 the Facebook covers only 530 out of 1065 *municipios* in Colombia. In Appendix A.1, 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, with competitive firms producing a variety of a product at each i. At each location there is a representative consumer with love of variety over varieties produced at different locations and an elasticity of substitution $\sigma > 1$. Trade between locations is subject to an ad-valorem transport cost τ_{ijk}, which is defined as $1 + t_{ijk}/p^f_{ijk}$, where i indexes the seller location ("exporter"), j the buyer location ("importer"), and k the product. The variable p^X identifies the exporter price, which we assume is the F.O.B. price at i, and t_{ijk} is the per-unit transport price. Note that the transport price depends on k, capturing that different products may face different transport prices potentially for differences in size or weight.

3.2 Local Demand

Demand at location j is given by the standard CES:

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

where p^M_{ijk} is the import price of the variety produced at i, P_{jk} is the local CES price index, and Z_{ijk} is a demand shifter.

3.3 Local Technology

We assume that production at each location has decreasing returns of scale in the short-run. Specifically, we assume that the cost function is:

$$C_{ik} = A_{ik}\Big[\int_{\Omega^J_{ik}} q(j)_{ik}dj\Big]^{\alpha} \tag{5}$$

where A_{ik} is a cost-shifter, Ω^J_{ik} is the set of locations served by i, and $\alpha > 1$ captures that expanding production can generate congestion. The cost-shifter A_{ik} captures differnt factors such as local changes in labor supply, profits in other destinations, and any other factors shifting the supply curve at j.

3.4 Export Prices

A representative firm maximizes their profits by deciding prices at each location in Ω_{ik}^{J}:

$$\Pi_{ik} = \int_{\Omega_{ik}^{J}} p_{ijk}^{X} q_{ijk} - C_{ik} \tag{6}$$

The firm charges the following optimal export price :[9]

$$p_{ijk}^{X} = \frac{\sigma}{\sigma - 1} \alpha A_{ik} C_{ik}^{\frac{\alpha}{\alpha-1}} + \frac{1}{\sigma - 1} t_{ijk} \tag{7}$$

This expression captures different features of export prices. First, they increase when there is congestion in production. As firm at i faces more demand, the marginal cost $C^{\frac{\alpha}{\alpha-1}}$ increases, raising prices of its variety. Second, cost shocks to location i's also increases prices through A. For instance, labor shortages may increase local wages and thus increase A. Finally, trade costs also raise export prices, given that they reduce the quantity demanded, increasing the marginal utility of its variety.

3.5 Transportation Services

We assume there is a representative global transport firm that charges a price t_{ij} to ship a unit of weight v from i to j. This firm starts with a capacity to move a weight V_{ij} from i to j. Changing the capacity to move weight across locations is subject to adjustment costs (i.e. it is costly to move ships from one location to another). Moreover, we assume there is a fixed short-run capacity $\bar{V}$.

Adjustment costs are assume to be quadratic:

$$S^{T} = \frac{\mu}{2} \left[\int_{\Omega^{I}} \int_{\Omega^{I}} \left[v_{ij} - \delta_{ij} V_{ij} \right] di dj \right]^{2} \tag{8}$$

where μ captures the cost sensibility to re-arranging the weight transportation capacity, and δ are idiosyncratic shocks to the installed capacity.[10] Note that having a fixed capacity to transport weight $\bar{V}$ implies that $\int_{\Omega^{I}} \int_{\Omega^{J}} \left[v_{ij} - \delta_{ij} V_{ij} \right] di dj = 0$.

[9] Derivation in Appendix.

[10] Sets Ω^{I} and Ω^{J} are assume to include all locations and have measure I and J respectively.

3.6 Transport Prices

Transport firm's profits are as follows:

$$\Pi^T = \int_{\Omega^I} \int_{\Omega^J} \Big[t_{ij} - B_{ij}\Big] v_{ij} di dj - S^T \tag{9}$$

were v_{ij}. The transport firm chooses transport prices subject to its total initial capacity, noting that charging a price that changes the volume shipped between location is costly.

The optimal transport price is implicitly given by:

$$t_{ij} = \tilde{p}^M_{ij} + B_{ij} + \mu\Big[v_{ij} - \delta_{ij} V_{ij}\Big] \tag{10}$$

where $\tilde{p}^M_{ij}$ is the weighted harmonic average of import prices.[11]

The optimal transport price captures the following things. First, demand or supply shocks affecting locations j or i respectively will imply a demand shock for transportation between them. This is summarized by the average import price $\tilde{p}^M_{ij}$. For instance, an increase in demand will rise import prices and thus rise transport prices as well. Second, the assumption of having a fixed capacity to move goods in the short run implies that transport prices actually change relative to the overall average, as capture by the term in brackets. Finally, changes in mobility that affect transportation such as at ports are captured by B_{ij}. For instance, a negative mobility shock at location i's closest port may induce a labor shortage and rise the cost of shipping from i.

3.7 Prices, Quantities and Local Disruptive Shocks

Import prices are the sum of export and transport prices —C.I.F. price:[12][13]

$$p^M_{ijk} \equiv p^X_{ijk} + t_{ijk} \tag{11}$$

Given the previous results, we can derive a series of results linking local mobility shocks to changes in export prices, import prices, and import quantities.

3.7.1 Exporter Shocks

We can model the impact of mobility shocks as follows:

$$\hat{A}_{ik} = -\gamma^I \hat{x}^I_i + a_{ik} \tag{12}$$

[11] Derivation in the appendix.

[12] We assume insurance costs are included in transportation services.

[13] Transport prices are indexed by k given that each weight unit is equal to κ_k physical units, i,e, $t_{ijk} = t_{ij}\kappa_k$

where $\hat{x}_i^I$ are changes in mobility at the exporter location and a_{ik} are other unrelated changes. The parameter γ^I summarizes how strong reductions in local mobility translate into higher costs of production at that location. For instance, local increases in covid infection rates may rise the opportunity cost of working, pushing wages upwards.

The elasticity of export prices to local changes in mobility is as follows:

$$\varepsilon(p^X, A)_{ik} = -\theta_{ik}^C \frac{\sigma\alpha}{\sigma - 1}\gamma^I < 0 \tag{13}$$

The effect of a decrease in local mobility is to raise export prices. The impact is stronger the more sensitive to congestion and higher relationship between local mobility and the local cost shifter are. The variable θ_{ik}^C captures the importance of production costs in the price determination. In periods when transportation costs are low, it tends to one.

The impact on import prices is qualitatively the same, but assigns more weight to transport costs. Having the impact on these prices, and given the assumed CES structure, the elasticity of quantities to mobility shocks quantities is positive — i.e. a local shock that reduce mobility decreases quantities imported from that location.

3.7.2 Importer Shocks

We model importer mobility shocks as affecting the demand shifter:

$$\hat{Z}_{ijk} = \gamma^J \hat{x}_j^J + z_{ijk} \tag{14}$$

where $\hat{x}_j^J$ are changes in mobility at the importer location and z_{ijk} are other unrelated changes. The parameter γ^J summarizes how strong reductions in local mobility translate into a decrease in demand. For instance, a local lockdown may change the expected future income of consumers and induce precautionary savings, reducing demand.

Export prices are not affected by changes in local importer mobility, as firms charge a common fixed markup across locations. However, import quantities are directly affected. In this sense, the elasticity of import quantities to local changes in mobility is as follows:

$$\varepsilon(q, Z)_{ijk} = \gamma^J > 0 \tag{15}$$

The effect of a decrease in local mobility is to decrease demand. The impact depends on the strength at which local mobility is related with the demand shifter.[14]

[14] A decrease in mobility may be also associated with an increase in demand through changes in tastes. We assume that $\gamma^J > 0$, but we acknowledge it is a net effect.

3.7.3 Transportation Shocks

We model shocks at the transportation sector during the pandemic period as follows:

$$\hat{B}_{ij} = -\gamma^P \hat{x}^P_{ij(p)} + b_{ij} \tag{16}$$

where $\hat{x}^P_{ij(p)}$ are changes in mobility along the most efficient shipping route between i and j, indexed by p (e.g. ports).

The elasticity of transport prices to mobility shock is then:

$$\varepsilon(t, B)_{ij} = -\gamma^P \theta^P_{ij} < 0 \tag{17}$$

where θ^P_{ij} is the share of the operating costs on the price determination. As expected, shocks that make shipping goods from i to j more costly, increase transport costs.

3.7.4 Production Congestion Shocks

A location j may see an increase in export prices from i due to demand shocks from another location j':

$$\varepsilon(p^X, q_{j'})_{ik} = \theta^C_{ik} \frac{\sigma\alpha^2}{(\sigma-1)(\alpha-1)} > 0 \tag{18}$$

This implies that increases in demand frim a reshuffling due to pandemic shocks across locations may induce an increase in prices from locations that were not experience a direct shock.

3.7.5 Transportation Congestion Shocks

We assume that the capacity of shipping goods is fixed in the short run. Therefore, sudden increases in demand from a specific region may induce the transportation firm to increase shipping prices. This is capture by the last term in equation 10.

$$\varepsilon(t, \tilde{v})_{ik} = \mu > 0 \tag{19}$$

which implies that an increase in $\tilde{v} \equiv v_{ij} - \delta_{ij} V_{ij}$ raises transport prices.

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.

4.1 Bilateral Evidence

In order to study the relationship between trade disruptions and imports, we estimate the following semi-parametric regression:

$$\hat{m}^D_{ijt} \quad = \quad g(\hat{x}^J_{jt}, \hat{x}^I_{it}) + \mathbf{\Theta} + \varepsilon_{ijkt} \tag{20}$$

where $\hat{m}^D_{ijt}$ are detrended imports relative to the base period (February 2020).[15] The term $g(\hat{x}^J_{jt}, \hat{x}^I_{jt})$ is an unknown function of changes in mobility at the importer location ($\hat{x}^J_{jt}$) and exporter location ($\hat{x}^I_{jt}$), which we assume orthogonal to the error ε_{ijkt} after conditioning on a vector of fixed effects $\mathbf{\Theta}$.

Note that this regression is at the exporter, importer and time level. This means that the function $g(\hat{x}^J_{jt}, \hat{x}^I_{it})$ captures both changes in quantities and prices within products, and changes in the product mix traded between locations.

We approximate $g(\hat{x}^J_{jt}, \hat{x}^I_{it})$ by a third-order polynomial of $\hat{x}^J_{jt}$ and $\hat{x}^I_{jt}$, and include exporting country-time fixed effects.

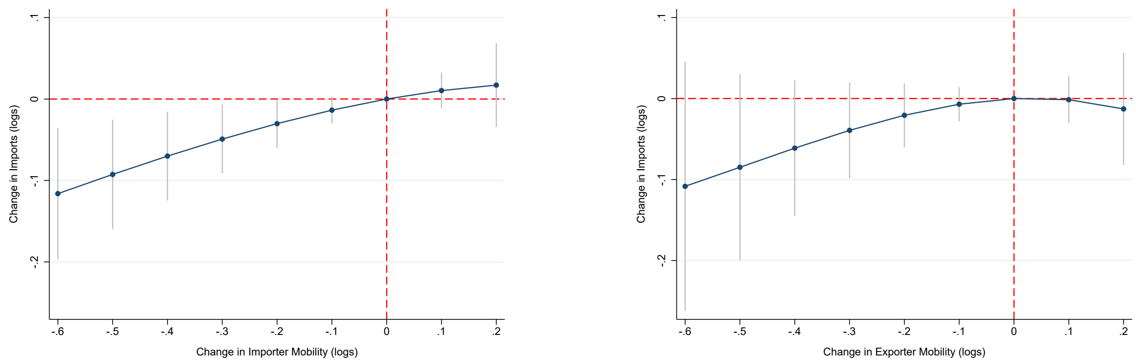
On the left graph in Figure 10, we show that a decrease in mobility at the importer location reduces its imports from an exporter location, conditional on changes in mobility at the latter. At the average of -23 log points, the reduction in imports is of about 4 log points.

On the right graph, we show that a decrease in exporter mobility also tends to reduce imports. However, estimates are noisier and we can not reject the absence of an effect at any mobility change.

These estimations capture different mechanisms that may be in place. For instance, the product mix traded between i and j may have changed depending on mobility. On top of that, prices and quantities within products may have changed differently as well. We investigate this in the next section.

[15] We construct detrended imports by estimating $m_{ijt} = \delta^I_{ijt} + \delta^S_{ijt} \times t + \epsilon_{ijt}$ for the 2018-2019 period, and then using the δ^I_{ijt} and δ^S_{ijt} estimates to detrended 2020-2021 values: $m^D_{ijt} = m_{ijt} - [\hat{\delta}^I_{ijt} + \hat{\delta}^S_{ijt} \times t]$.

Figure 10: Import Values and Exporter and Importer Mobility



(a) Importer Mobility

(b) Exporter Mobility

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4.2 Product Level Evidence

4.2.1 Import Values

In this section, we estimate the impact of local changes in mobility on product-level import variables. Doing so allows us to examine the quantity and price effects of demand and supply shocks.

The basic structure of our estimating equations is as follows:

$$\hat{m}_{ijkt} \quad = \quad \beta^J \hat{x}^J_{jt} + \beta^I \hat{x}^I_{it} + \tilde{\mathbf{\Theta}} + \varepsilon_{ijkt} \tag{21}$$

where $\hat{m}_{ijkt}$ are changes relative to February 2020, and $\tilde{\mathbf{\Theta}}$ is a vector of fixed effects. The coefficients β^J and β^I capture the relationship between local trade variables and mobility.

In Table 1, we estimate the relation between local exporter and importer mobility and import value for different specifications. It is worth noting that the sign of the coefficients can be either negative or positive in the case of imports, given that the impact depends on the different impacts on quantities and prices and the elasticity of substitution across products.

In column 1, we do not include any fixed effects. The correlation between local shocks at the importer location is positive and significant — i.e., a disruptive shock that decreases mobility at the importer location also reduces import values to that location. Mobility shocks at the exporter location is not correlated to exports from that location.

The size of exporters' locations differs across countries based on their geography and extension. Therefore, we include exporting country fixed effects in column 2 to restrict comparisons for regions with similar size. Estimates do not change.

Table 1: Exporter and Importer Mobility Shocks and Import Values. 2020-2021.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Importer mobility	0.4317***	0.4149***	0.5093***	0.5771***	0.6024***	0.9163***		
	(0.0756)	(0.0779)	(0.0646)	(0.0644)	(0.0886)	(0.1106)		
Exporter mobility	-0.0355	-0.0019	-0.0126	0.1050	0.3312**		0.3458**	0.2689*
	(0.0532)	(0.0715)	(0.0807)	(0.0976)	(0.1303)		(0.1442)	(0.1446)
Fixed Effects	No	Exporting Country	Exporting Country -Month	Exporting Country -Time	Exporting Country -Product-Time	Export Location -Product-Time	Import Location -Product-Time	Import Location -Exporting Country -Product-Time
Observations	551,366	551,366	551,366	551,366	423,236	176,271	325,087	245,080
R-squared	0.0037	0.0060	0.0089	0.0115	0.2283	0.4156	0.3239	0.3027

OLS Regressions. Dependent Variable: Log-change in imports relative to February 2020 at the exporter-importer-product-Time level, where product is defined at the 6-digit HS level and time is defined at month-years. Sample period is March 2020 to October 2021. Standard errors clustered at the Exporter location-Time and Importer Location-Time level in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

It is reasonable to assume that mobility has a seasonal component. In this regard, the impact may affect different locations depending on their seasonal cycle. To control for it, we include exporting country-month fixed effects in column 3, and results do not change substantially. The coefficient of the impact of shocks at importer locations increases magnitude.

Country-specific containment measures may be driving results rather than local shocks. To account for it, we include country-time fixed effects in column 4. Results remain the same, with the importer shock increasing a bit further in magnitude.

Previous results do not control for shocks to product composition within months. In column 5, we include exporting country-product-time fixed effects to restrict comparisons within products. Shocks at the exporter location becomes positive and significant —i.e. a disruptive shock that decreases mobility at the exporter location also reduces import values from that location for a given product. Mobility shocks at the importer location remain positive and significant.

Another time-varying exporter-product specific factors may be affecting estimates due to their omission. In column 6, we include exporter-product-time fixed effects, which implies we cannot estimate the exporter mobility shock. The impact of importer mobility further increases its magnitude. Specifically, a reduction in mobility of 10% relative to the base period decreases imports from that location by 9.1% within products.

We control for importer-product-time factors and exporting country-product-time in column 8. The exporter mobility shocks coefficient remains positive. In column 9, we restrict the comparison to locations within exporting countries and products, and although noisier, the impact is still positive.

The size of the impact of an importer shock is larger than of an exporter shock. Using their standard deviations and results in column 5, we calculate that an decrease of one s.d.

Table 2: Exporter and Importer Mobility Shocks and Import Variables. 2020-2021.

	(1)	(2)	(3)	(4)
	Import Values	Import Quantities	Import Prices	Export Prices
	Exporting Country-Product-Time F.E.			
Importer mobility	0.6024***	0.6649***	-0.0626	-0.0529
	(0.0886)	(0.0747)	(0.0498)	(0.0500)
Exporter mobility	0.3312**	0.4686***	-0.1374**	-0.1133*
	(0.1303)	(0.1642)	(0.0546)	(0.0593)
Observations	423,236	423,236	423,236	423,236
R-squared	0.2283	0.2276	0.2049	0.2036
	Exporter-Product-Time F.E.			
Importer mobility	0.9163***	0.8525***	0.0638	0.0533
	(0.1106)	(0.1120)	(0.0806)	(0.0827)
Observations	176,271	176,271	176,271	176,271
R-squared	0.4156	0.4091	0.3770	0.3764
	Importer-Product-Time F.E.			
Exporter mobility	0.3458**	0.4660***	-0.1203*	-0.0931
	(0.1442)	(0.1790)	(0.0647)	(0.0711)
Observations	325,087	325,087	325,087	325,087
R-squared	0.3239	0.3239	0.2977	0.2961

OLS Regressions. Dependent Variable: Log-change of the variable indicated at the column heading relative to February 2020 at the exporter-importer-product-Time level, where product is defined at the 6-digit HS level and time is defined at month-years. Import prices defined as C.I.F. imports over quantities, and export values defined as F.O.B. imports over quantities. Sample period is March 2020 to October 2021. Standard errors clustered at the Exporter location-Time and Importer Location-Time level in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

in importer mobility caused a decline in imports to that location of 16%, whereas a decrease of one s.d. in exporter mobility caused a decline of 6%.

4.2.2 Prices and Quantities

Using highly disaggregated product data allows us to study the relationship between local mobility shocks and import quantities and prices. We construct export price measures by dividing the FOB imports value by the HS6-level quantity.[16]

In Table 2, we estimate the impact of mobility shocks on these variables for the most demanding specifications. In the first panel, we include country-product-time fixed effects, so we compare location pairs relative to the base period for given products. Both Import and

[16]Different products have different units, but note that we can compare across products once we take logs and differences against a base period, provided this units of measurement do not change — which did not.

export mobility shocks are positively related to import values and quantities. This means that reduction in mobility effectively decline the average number of goods getting to a specific location.

Import and export prices are negatively associated to shocks at the exporter location but not at the importer location.

In the middle panel, we fully control for exporter-product-time factors, and confirm that the impact of importer shocks on import values are fully explained by import quantities. In the lower panel, we control for importer-product-time and exporting country-product-time fixed effects, so we compare locations within a country, and also verify that the impact of exporter local shocks affects quantities positively and prices negatively. Therefore, the fact that exporter mobility has a smaller impact on import values masks that it has an opposite effect on prices and quantities

4.2.3 Pre-Trends and Seasonality

What is the right control group? There are a priori two factors that may affect estimates that may not be related with the effect per-se: product seasonality and bilateral pre-trends. To account for them, we employ 2018 and 2019 data to estimate exporter-importer-product specific trends and product-specific seasonal factors. We then transform the 2020 and 2021 data using that information.[17]

In Table 3, we show the results when we include exporting country-product-time fixed effects. There are two differences with respect to the baseline. First, the impact of shocks at exporter mobility is only significant for prices, indicating that quantities did not seem to react relative to pre-trends. This means that prices the ones to mostly react to changes in exporter mobility, probably capturing the fact that producing became more costly.

Second, reductions in importer mobility strongly lowered importer quantities, with some indication of an increase in prices as well.

[17]The transformation is $m^{DS}_{ijkt} = m_{ijkt(m)} - [\hat{S}_{km}] - [\hat{T}^i_{ijk} + \hat{T}^s_{ijk} \times t]$, where $\hat{S}_{km}$, $\hat{T}^i_{ijk}$, and $\hat{T}^s_{ijk}$ are the estimated fixed effects of the following regression: $m_{ijkt} = S_{km} + T^i_{ijk} + T^s_{ijk} \times t + \zeta_{ijkt}$, which is estimated using 2018-2019 data. We then use $m^{DS}_{ijkt} - m^{DS}_{ijk,Feb20}$.

Table 3: Exporter and Importer Mobility Shocks and Detrended and Deseasonalized Import Variables. 2020-2021.

	(1)	(2)	(3)	(4)
	Import Values	Import Quantities	Import Prices	Export Prices
Importer Mobility	0.8686***	0.9890***	-0.1204*	-0.1212*
	(0.1829)	(0.2006)	(0.0632)	(0.0629)
Exporter Mobility	-0.0053	0.2549	-0.2602***	-0.2570***
	(0.2643)	(0.2810)	(0.0650)	(0.0686)
Observations	403,692	403,692	403,692	403,692
R-squared	0.2079	0.2076	0.2046	0.2030

OLS Regressions. Dependent Variable: Log-change of the variable indicated at the column heading relative to February 2020 at the exporter-importer-product-Time level, where product is defined at the 6-digit HS level and time is defined at month-years. Import prices defined as C.I.F. imports over quantities, and export values defined as F.O.B. imports over quantities. Dependent variables detrended using exporter-importer-product specific 2018-2019 monthly trends, and deseasonalized using 2018-2019 product-month specific factors. Sample period is March 2020 to October 2021. Exporting country-Product-Time fixed effects included. Standard errors clustered at the Exporter location-Time and Importer Location-Time level in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

4.2.4 Transport Costs

In the previous results, we showed that prices tended to increase when local mobility decline, especially if it was at the exporter locations. In this section, we estimate the impact of mobility shocks on freight unit values, which constitute the wedge between exporter and importer prices.

If local reduction in mobility decline trade, then the demand for transportation decreased. Therefore, we could expect a decrease in freight unit values too. However, shipping companies have a relatively fixed number of ships in the short run. Given that these firms want to fill up their ships, then a negative mobility shock at a specific location may induce a reduction in the supply of transportation, actually rising prices.

In Table 4, we show the impact of mobility in the entire period, and also in 2020 and 2021 separately. Negative shocks at the exporter location strongly increase shipping prices in both years. Negative shocks at the importer location increases prices only in 2020. Note, however, that given that importer locations are all in Colombia, it is expected that variation across locations may be less affected.

Table 4: Exporter and Importer Mobility Shocks and Shipping Costs. 2020 and 2021.

	(1)	(2)	(3)
	All	2020	2021
Importer Mobility	-0.1268	-0.2589**	0.0718
	(0.0892)	(0.1057)	(0.1483)
Exporter Mobility	-0.2603***	-0.1529**	-0.4620***
	(0.0770)	(0.0771)	(0.1472)
Observations	423,236	213,126	210,110
R-squared	0.2323	0.2168	0.2379

OLS Regressions. Dependent Variable: Log-change of shipping unit values relative to February 2020 at the exporter-importer-product-Time level, where product is defined at the 6-digit HS level and time is defined at month-years. Sample period is March 2020-October 2021 in All column, March 2020-December 2020 in 2020 column, and January 2021-October 2021 in 2021 column. Exporting country-Product-Time fixed effects included. Standard errors clustered at the Exporter location-Time and Importer Location-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:

$$\Delta \log Y_{iym} = \alpha_0 \Delta \log(\text{mobility}_{iym}^{\text{Ports}}) + I_m + I_y + I_i + \epsilon_{iym}, \tag{22}$$

where Y can be the number of hours each container ship spend in ports, or the number of port calls made by container ships in exporter country i, year t, and calendar month m. We control for calendar month fixed effects to take into account seasonality, year fixed effects to allow for different levels in 2020 and 2021, and exporter country fixed effects to allow different countries to have different overall changes.

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

$$\Delta \log(\text{mobility}_{iym}^{\text{Ports}}) = \sum_{p(i)} \frac{\text{TEU}_{p(i)2020}}{\sum_{p'(i)} \text{TEU}_{p'(i)2020}} \Delta \log(\text{mobility}_{p(i)ym}), \tag{23}$$

where $\Delta \log(\text{mobility}_{p(i)ym})$ is the change in mobility in the city where port p in country i is located in, year y, and month m, compared to February 2020, and TEU_{p2020} is the average monthly twenty-foot-equivalent units 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 using the same TEU weights and replacing $\Delta \log(\text{mobility}_{p(i)ym})$ with the $\Delta \log(\text{Call}_{p(i)ym})$ and $\Delta \log(\text{Hour}_{p(i)ym})$, respectively. Again, the differences are taken with respect to the corresponding values in February 2020.

The parameter of interest α_0 captures the impact of port mobility changes on port performances in the exporter country. More productive ports are able to process 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 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.[18]

The cost of shipping can be measure 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:

$$\Delta \log \text{freight cost}_{kiym} = \beta_0 \Delta \log(\text{mobility}^{\text{Ports}}_{iym}) + I_m + I_y + I_i + I_k + \epsilon_{kiym}, \tag{24}$$

where $\Delta \log \text{freight cost}_{kiym}$ is the change in freight cost in product k, exported by country i, and in year y, and month m. We control for month fixed effects to take into account seasonality, year fixed effects to allow for different levels in 2020 and 2021, product fixed effects, and origin country fixed effects.

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.

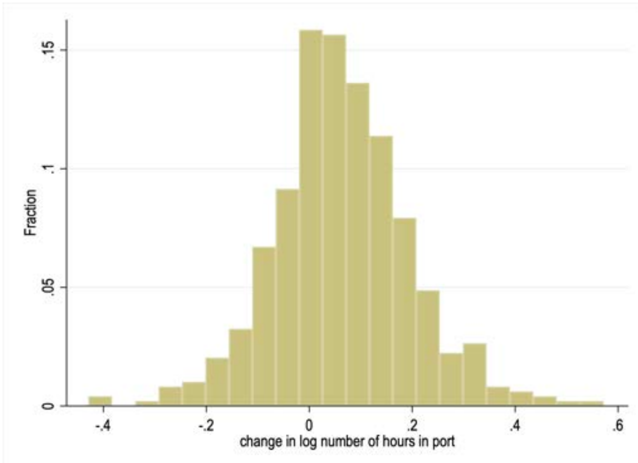
5.2 Variation in the port performance and freight costs

This section presents the variation in the outcome variables of interest. Figure 11 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 positive change than negative changes. This is consistent with the aggregate trend in Figure 5 Panel (c). In addition, as shown in Figure 11 Panel (c), the positive changes are concentrated in 2021.

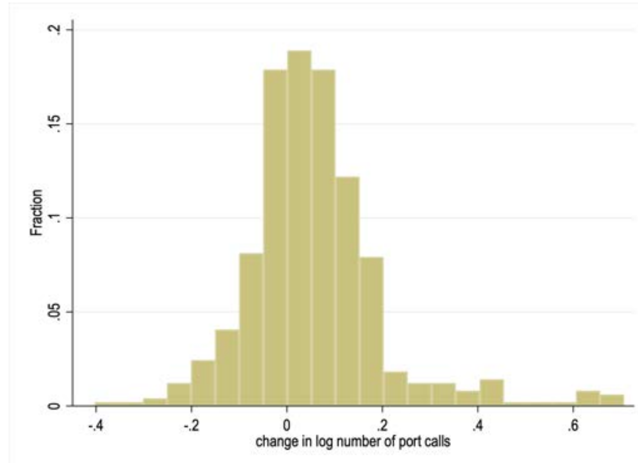
[18] We use the mapping between HS codes and BEC codes as in Staff and Division (2003) and drop goods that have a BEC code of 31, 32, and 322.

Figure 11: The histogram of country-level port performance variation

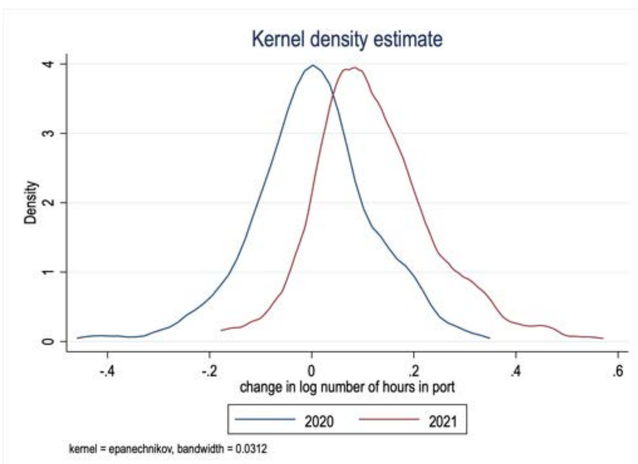
(a) Changes in log number of hours in port
March 2020 to October 20201



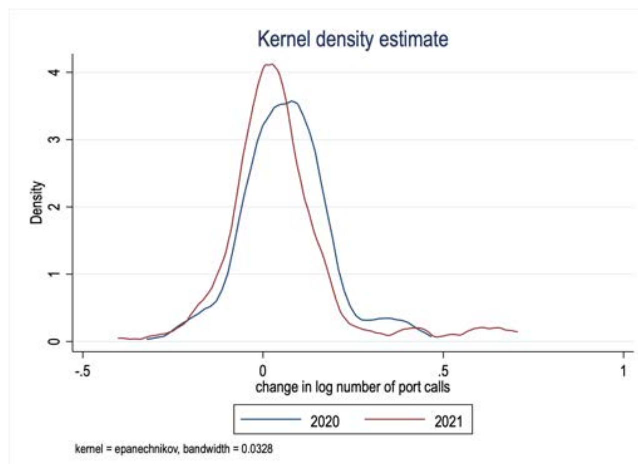
(b) Changes in log number of port calls
March 2020 to October 20201



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



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



Note: Panel (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. Panel (c) and (d) show the variation in 2020 and in 2021 separately, using kernel densities.

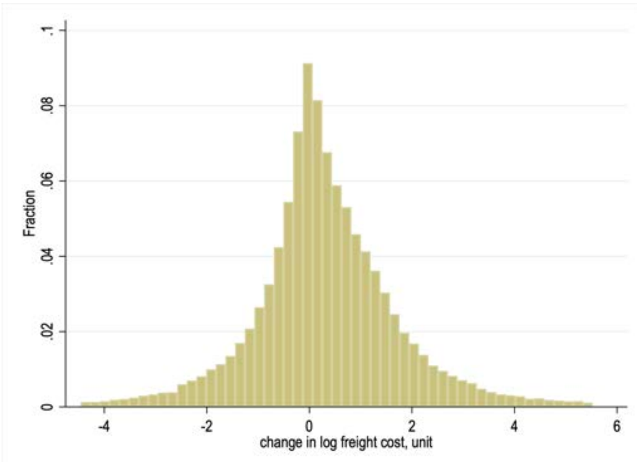
Panels (b) and (d) present the distribution of changes in the log number of port calls in the post-Covid period. Note that the baseline period is February 2020. As noted in Figure 5 Panel (a), the aggregate number of port calls is the lowest in February in all three years (2019, 2020, and 2021). This 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 are small in this period.[19] 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

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

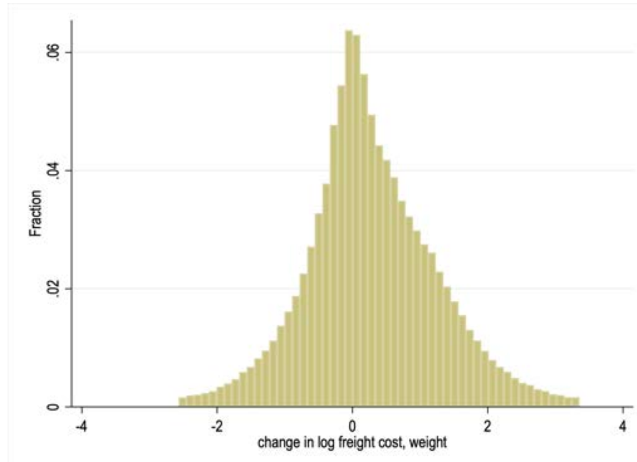
distribution. This is consistent with the overall trend in Figure 5 Panel (a), where we observe a decline in the number of port calls since June 2021.

Figure 12: The histogram of product-level freight cost variation

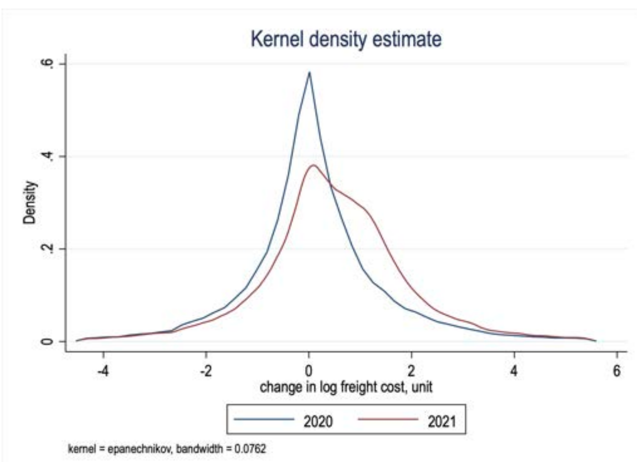
(a) Changes in log freight cost, unit
March 2020 to October 20201



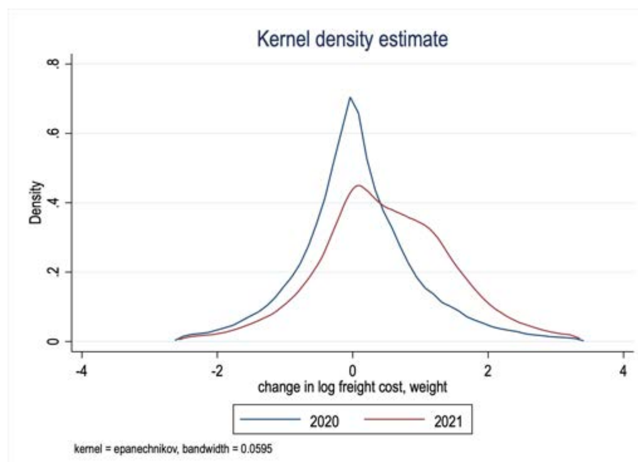
(b) Changes in log freight cost, weight
March 2020 to October 20201



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



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



Note: Panel (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. Panel (c) and (d) show the variation in 2020 and in 2021 separately, using kernel densities. Panel (a) and (c) do not include the changes in log freight costs (unit) in the top 1% and the bottom 1% of the distribution. Panel (b) and (d) do not include the changes in log freight costs (weight) in the top 1% and the bottom 1% of the distribution.

Figure 12 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.[20] In both cases, there are more observations with positive changes, indicating

[20] Our regression results are robust to keeping all observations.

an increase in freight cost. In addition, the positive changes are more prominent in 2021 than in 2020.

5.3 Regression results

Table 5 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 changes 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 spend 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 percentage 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 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.[21]

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 addition 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 allow more more calls being processed. Evaluated at the mean

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

Table 5: 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**	-0.129**	0.108**	0.108**		
	(0.053)	(0.053)	(0.049)	(0.049)		
Δ log number of calls					-0.268***	-0.268***
					(0.090)	(0.090)
I (Year=2021)	0.169***		-0.021		0.149***	
	(0.021)		(0.020)		(0.018)	
Time trend		0.014***		-0.002		0.012***
		(0.002)		(0.002)		(0.002)
Constant	-0.042**	-0.106***	0.084***	0.092***	0.003	-0.052***
	(0.016)	(0.023)	(0.011)	(0.017)	(0.010)	(0.016)
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	0.018	-0.022	-0.022		
	(0.020)	(0.020)	(0.023)	(0.023)		
Δ log number of calls					-0.072	-0.072
					(0.087)	(0.087)
I (Year=2019)	0.025**		0.005		0.028***	
	(0.009)		(0.009)		(0.009)	
Time trend		0.002**		0.000		0.002***
		(0.001)		(0.001)		(0.001)
Constant	0.014**	0.005	-0.157***	-0.159***	-0.001	-0.011
	(0.006)	(0.009)	(0.007)	(0.010)	(0.016)	(0.018)
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).

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) confirms 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 the 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 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 13 shows the residual plots for results in Table 5 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 B1, B2, and B3. Overall, we find that the results are not driven by one particular country or period.

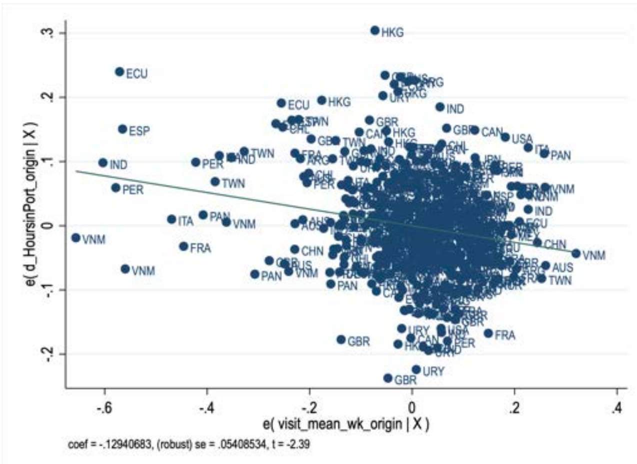
Overall, we find that mobility reductions at the ports indeed have a negative impact on port performance, and that the pandemic has an accumulated effect on port delays.

Then we proceed to investigate the impact of mobility changes on freight costs. Table 6 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.

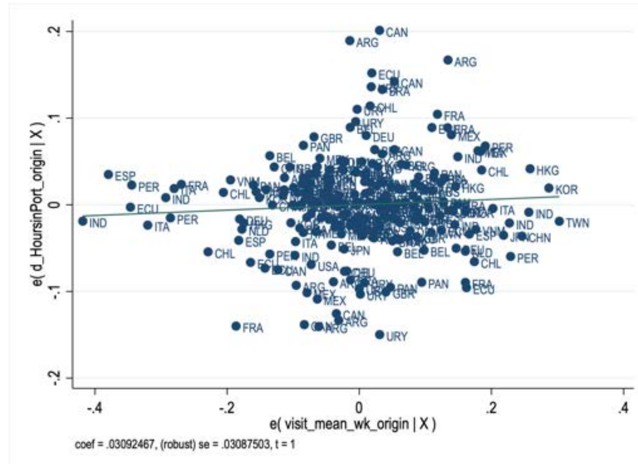
Panel A Columns (1)–(4) use the change in log freight cost per unit as the outcome variable. Column (1) controls for year fixed effects, calendar month fixed effects, product fixed effects, and exporter country fixed effects. The coefficient estimate for the change in log mobility in the exporter country 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 Columns (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 13: The impact of mobility changes on the number of hours in port, residual plot for the post-Covid period and the pre-Covid period

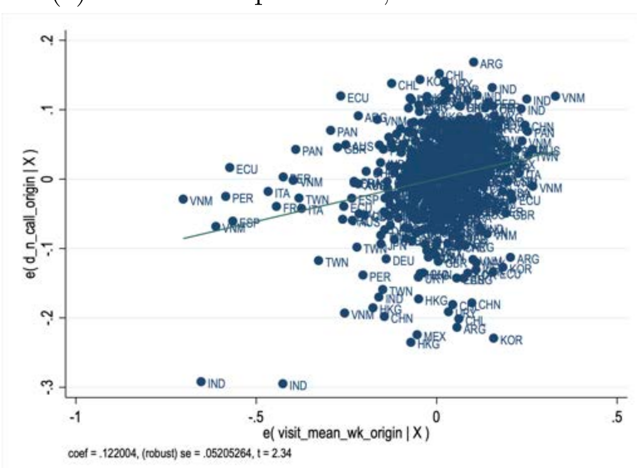
(a) Hours in port, 2020 and 2021



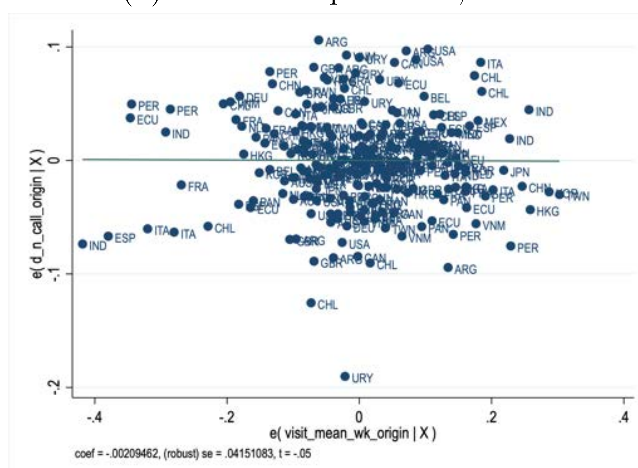
(b) Hours in port, 2018



(c) Number of port calls, 2020 and 2021



(d) Number of port calls, 2018



Note: Panel (a) is the residual plot for the results in Table 5 Panel A Column (1), and Panel (b) is the residual plot for Panel B Column (1). Panel (c) and (d) are the residual plot for the results in Table 5 Column (3) in Panel 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 residual plot. Thus, we take the mean of price changes at the country-period level and run similar regression as in Table 6. The residual plots are shown in Figure 14. Reassuringly, the country-level regression results are similar to the product-level results.

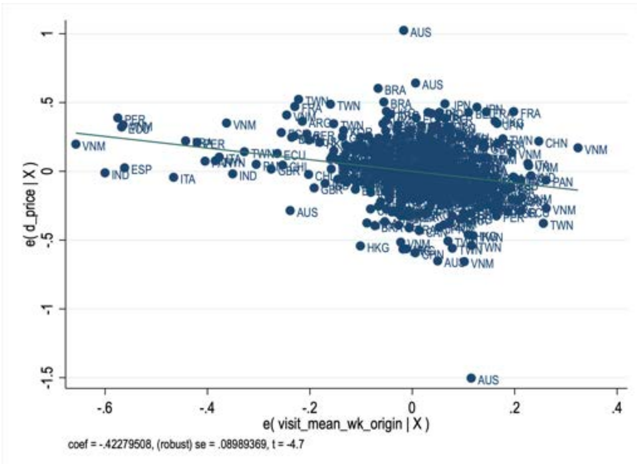
Table 6: The relationship between freight costs and port mobility in the exporter country

Panel A.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome: 2020 and 2021	Δ log freight cost, unit				Δ log freight cost, weight			
Δ log mobility change	-0.25**	-0.25**	-0.29**	-0.53**	-0.30***	-0.30***	-0.34***	-0.57***
	(0.11)	(0.11)	(0.12)	(0.20)	(0.10)	(0.10)	(0.11)	(0.18)
I (year=2021)	0.51***		0.51***	0.54***	0.55***		0.55***	0.58***
	(0.08)		(0.08)	(0.08)	(0.07)		(0.07)	(0.07)
Time trend		0.04***				0.05***		
		(0.01)				(0.01)		
Constant	0.02	-0.17**	0.01	-0.04	-0.04	-0.25***	-0.05	-0.09*
	(0.05)	(0.07)	(0.05)	(0.06)	(0.04)	(0.07)	(0.04)	(0.05)
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	Δ log freight cost, unit				Δ log freight cost, weight			
Δ log mobility change	0.04	0.02	0.03	0.03	-0.01	0.00	-0.02	-0.04
	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)
I (year=2019)	0.02**		0.03**	0.03**	0.03**		0.03**	0.04**
	(0.01)		(0.01)	(0.01)	(0.01)		(0.01)	(0.01)
Time trend		0.00				0.00*		
		(0.00)				(0.00)		
Constant	0.04***	0.03***	0.04***	0.03***	-0.03***	-0.03**	-0.03***	-0.03***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
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

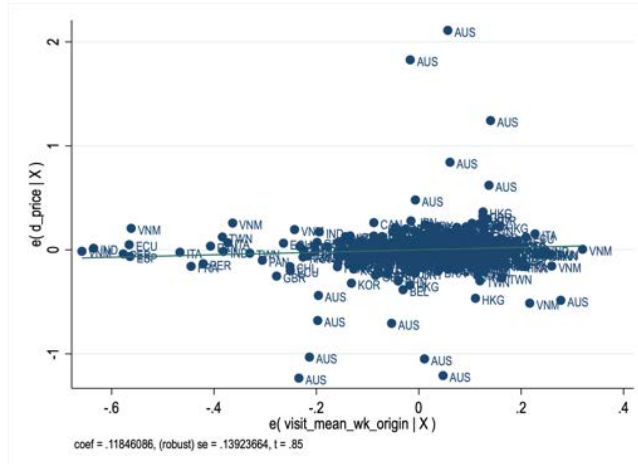
Note: Standard errors are clustered at the product level and at the exporting country level. *** p<0.01, ** p<0.05, * p<0.1. In Panel A, The mean (s.d.) of the change in log freight cost by unit is 0.31 (1.38), and 0.28 (0.96) by weight. The mean (s.d.) of the change in log mobility is -0.14 (0.18) in 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 14: The impact of mobility changes on the freight costs, residual plot for the post-Covid period and the pre-Covid period

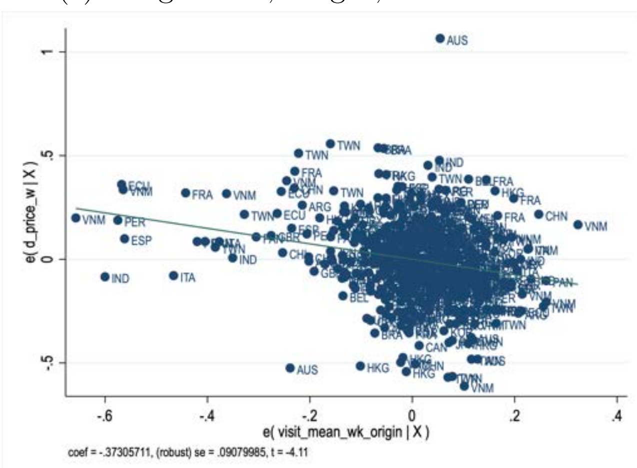
(a) Freight cost, unit, 2020 and 2021



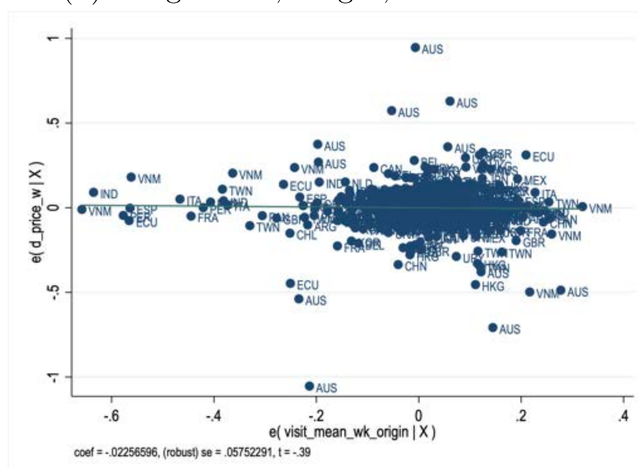
(b) Freight cost, unit, 2018 and 2019



(c) Freight cost, weight, 2020 and 2021



(d) Freight cost, weight, 2018 and 2019



Note: Panel (a) is the residual plot for the results in Table 5 Panel A Column (1), and Panel (b) is the residual plot for Panel B Column (1). Panel (c) and (d) are the residual plot for the results in Table 5 Column (3) in Panel 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, by 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

$$\Delta \log(\text{mobility}^{K}_{iym}) = \sum_{k} \frac{\text{prob}(k(i))}{\sum_{k'} \text{prob}(k'(i))} \Delta \log(\text{mobility}^{\text{Ports}}_{k(i)ym}), \tag{25}$$

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 ($\Delta \log(\text{mobility}^{L}_{iym})$), 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 7: The relationship between freight costs and port mobility in the exporter country and in the intermediate country

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	Δ log freight cost, unit			Δ log freight cost, weight		
Δ log mobility, exporter country	-0.25**			-0.30***		
	(0.11)			(0.10)		
Δ log mobility, first intermediate		-0.53***			-0.59***	
		(0.16)			(0.15)	
Δ log mobility, second intermediate			-0.72***			-0.76***
			(0.20)			(0.20)
I (year=2021)	0.51***	0.57***	0.69***	0.55***	0.62***	0.74***
	(0.08)	(0.08)	(0.11)	(0.07)	(0.08)	(0.11)
Constant	0.02	-0.06	-0.16*	-0.04	-0.12**	-0.23**
	(0.05)	(0.06)	(0.09)	(0.04)	(0.06)	(0.09)
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 7 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 6 Panel A Column (1), Columns (2) and (3) use changes in mobility in the first and the second intermediate country, respectively Interesting, 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 are more costly than in individual export countries.

6 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 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 imports. On the importer shock side, the reduction was fully explained by a decline in import quantities, whereas on the exporter shock side, the reduction in import quantities was partially offset by an increase in export prices and shipping costs. We then documented that country-level average port congestion and mobility shocks at ports increased freight unit values.

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Online Appendices

(Not for publication)

A Additional data descriptives

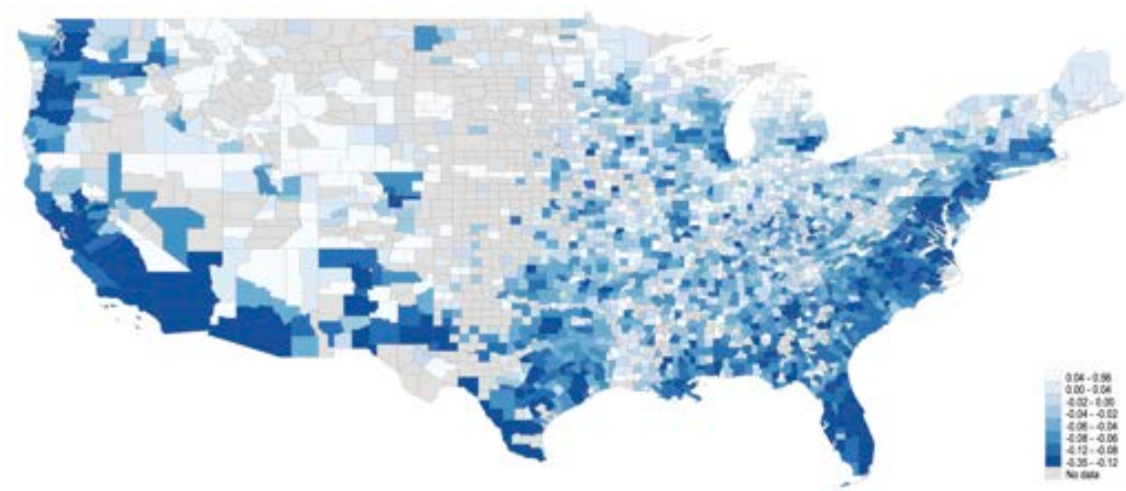
A.1 Levels of aggregation

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

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

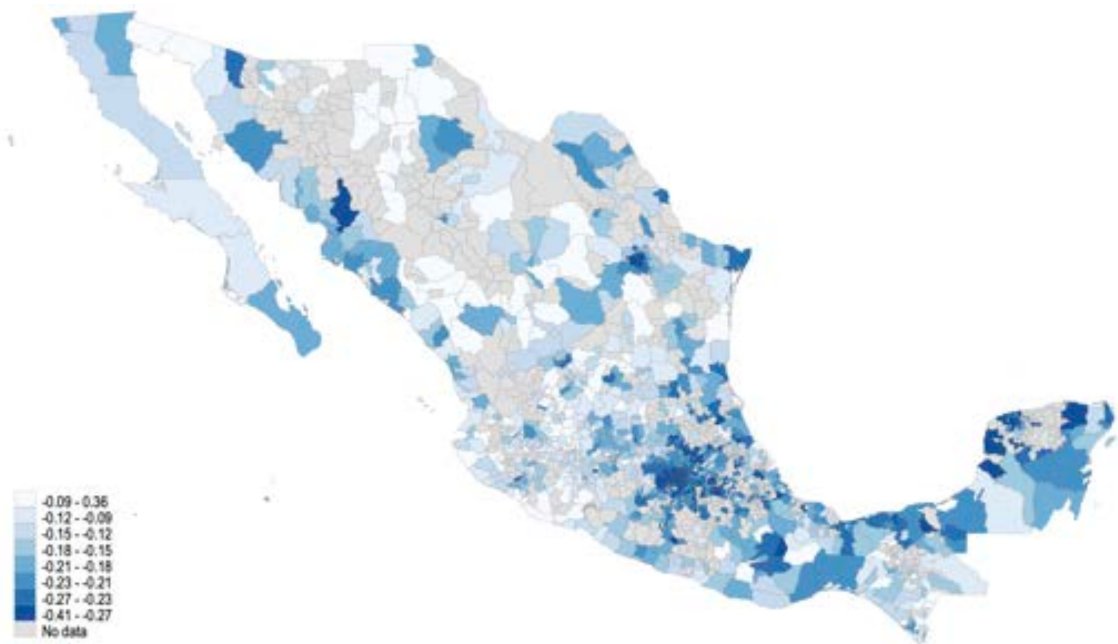
A.2 Mobility change maps

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



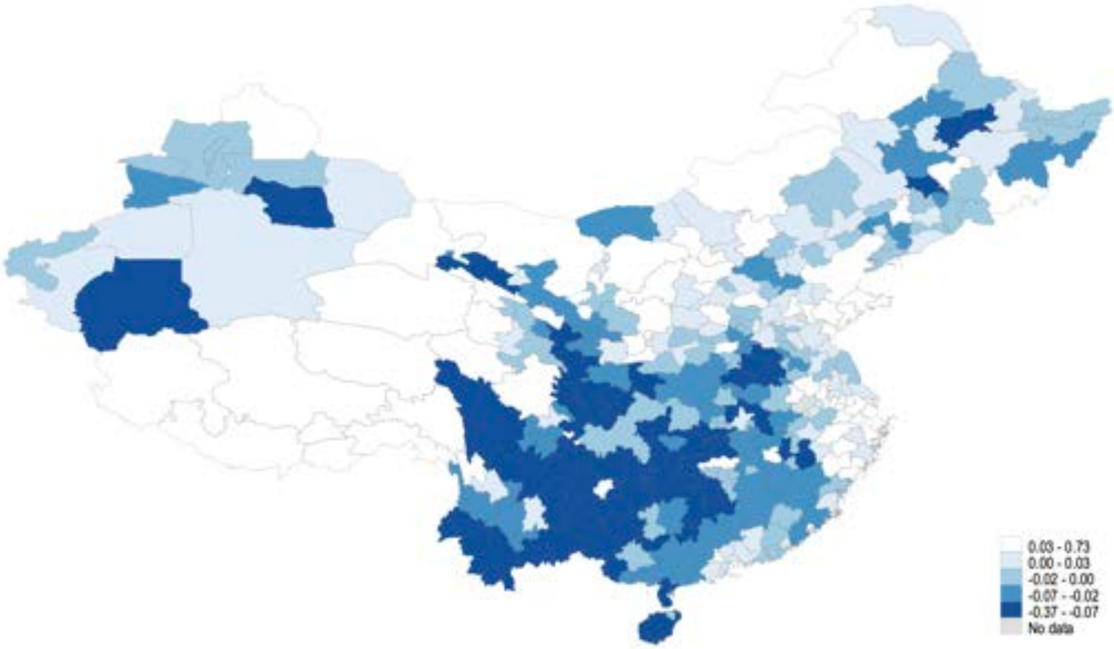
Note: Data is from Facebook.

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 Ports included in the analysis

Table A2: The 150 ports used in the analysis, with TEU in 2019 (millions)

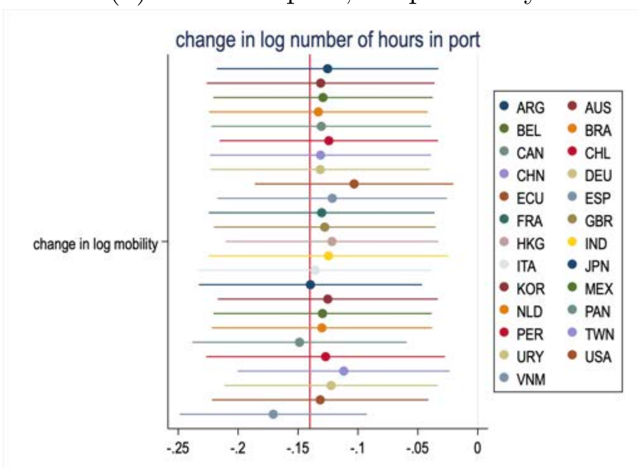
Country	Port	TEU (in millions)	Country	Port	TEU (in millions)	Country	Port	TEU (in millions)
ARG	Buenos Aires	3.93	DEU	Hamburg	17.83	JPN	Nagoya	8.38
AUS	Adelaide	2.27	ECU	Posorja	0.48	JPN	Kobe	8.98
AUS	Fremantle	2.47	ECU	Puerto Bolivar (Ecuador)	0.50	JPN	Tokyo	12.15
AUS	Brisbane	4.45	ECU	Guayaquil	3.50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

B Additional empirical results

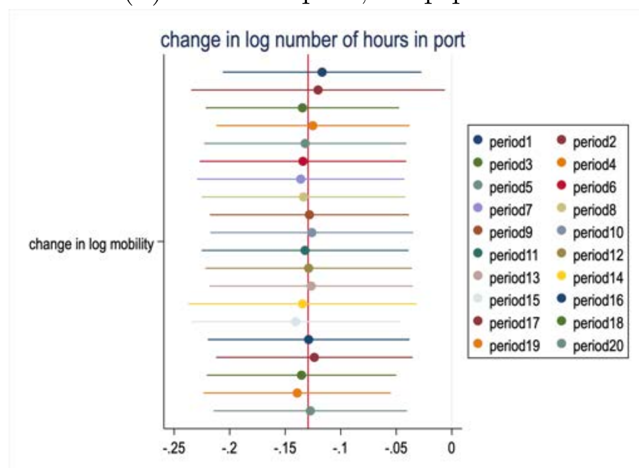
B.1 Country level port performance results

Figure B1: The robustness of country level results in Table 5, the impact of mobility changes on port performance, dropping one country at a time and dropping one period at a time

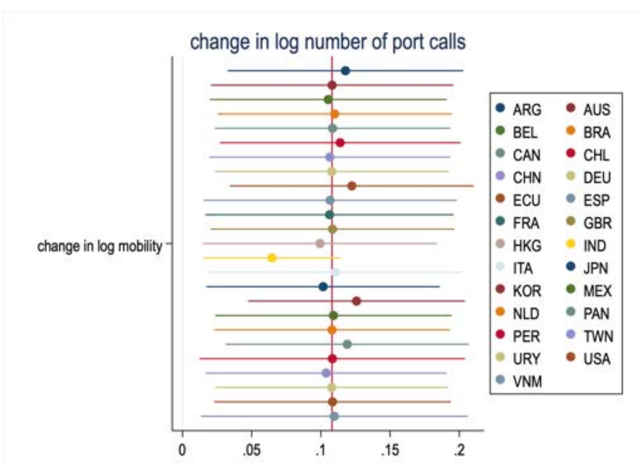
(a) Hours in port, drop country



(b) Hours in port, drop period



(c) Number of calls, drop country



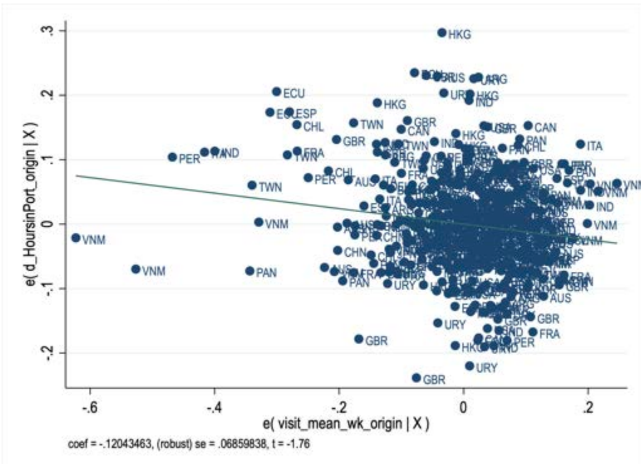
(d) Number of calls, drop period

Figures/origin_ncall_drop_period.png

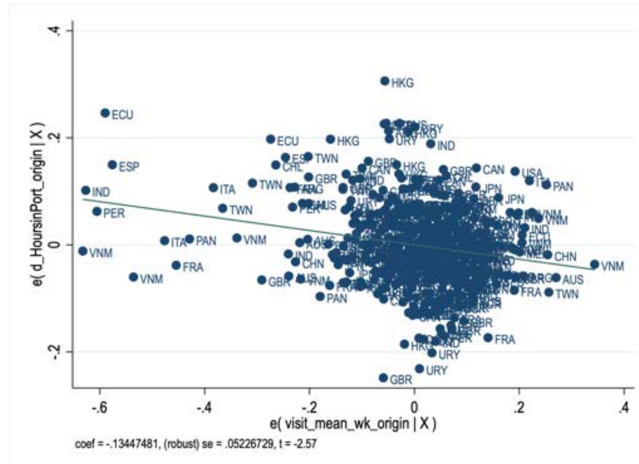
Note: Panel (a) plots the coefficients when replicating results in Table 5 Panel A Column (1) and dropping one country at a time, and Panel (b) plots the coefficients when dropping one period at a time. Panel (c) plots the coefficients when replicating results in Table 5 Panel A Column (3) and dropping one country at a time, and Panel (d) plots the coefficients when dropping one period at a time.

Figure B2: The robustness of country level results, the impact of mobility changes on the number of hours in port, residual plot

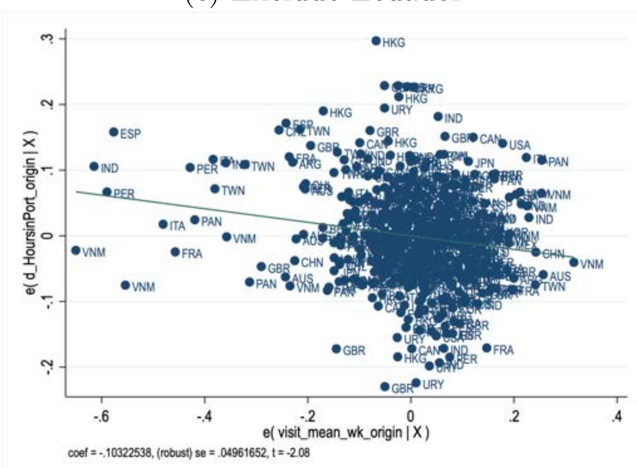
(a) Exclude March 2020



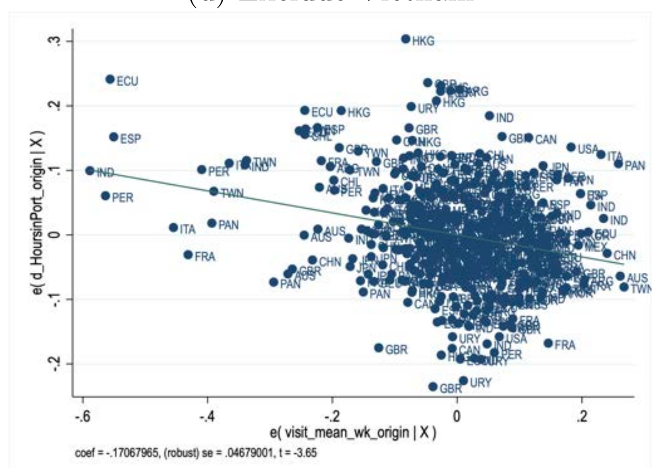
(b) Exclude April 2020



(c) Exclude Ecuador



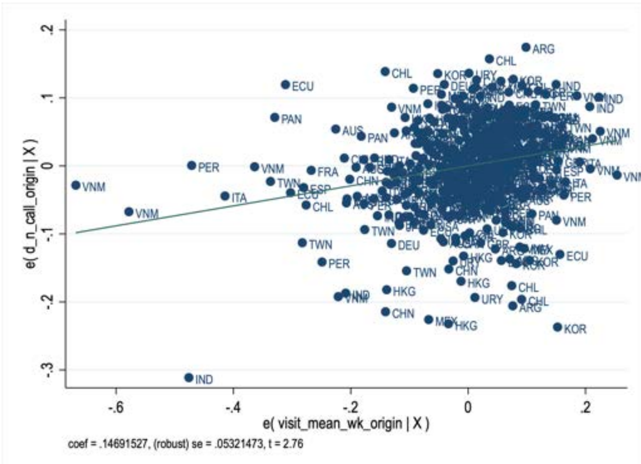
(d) Exclude Vietnam



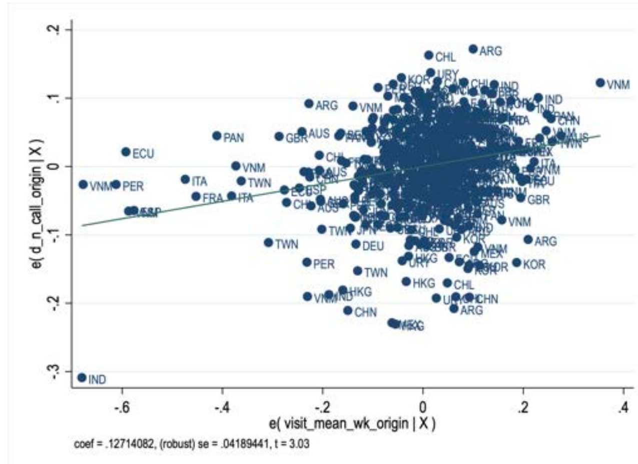
Note: Panel (a) is the residual plot for replicating results in Table 5 Panel A Column (1) and dropping March 2020. Panel (b) drops April 2020, Panel (c) drops Ecuador, and Panel (d) drops Vietnam.

Figure B3: The robustness of country level results, the impact of mobility changes on the number of port calls, residual plot

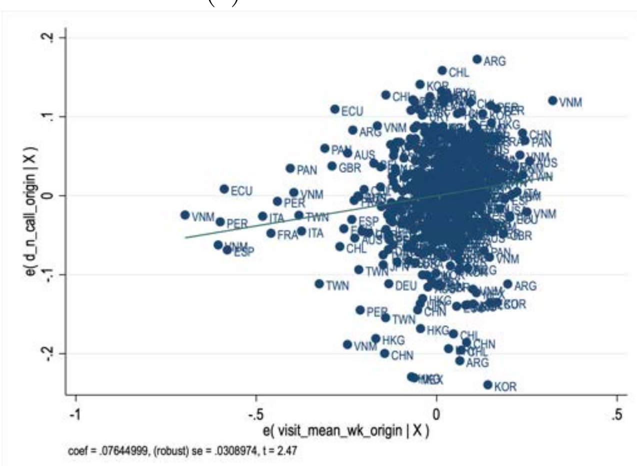
(a) Exclude March 2020



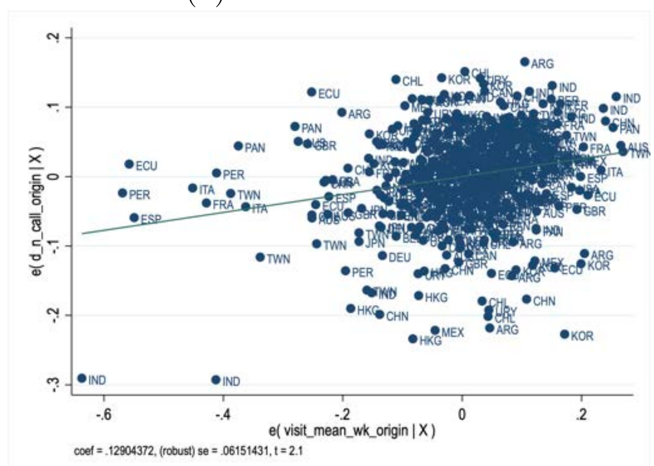
(b) Exclude April 2020



(c) Exclude India



(d) Exclude Vietnam



Note: Panel (a) is the residual plot for replicating results in Table 5 Panel A Column (3) and dropping March 2020. Panel (b) drops April 2020, Panel (c) drops India, and Panel (d) drops Vietnam.

Table B1: 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	Δ log freight cost, unit				Δ log freight cost, weight			
Δ log mobility change	-0.31**	-0.31**	-0.35***	-0.62***	-0.34***	-0.34***	-0.37***	-0.63***
	(0.11)	(0.11)	(0.12)	(0.21)	(0.10)	(0.10)	(0.11)	(0.17)
I (year=2021)	0.57***		0.57***	0.60***	0.60***		0.60***	0.63***
	(0.08)		(0.08)	(0.08)	(0.07)		(0.07)	(0.07)
Time trend		0.05***				0.05***		
		(0.01)				(0.01)		
Constant	-0.02	-0.23***	-0.02	-0.08	-0.07	-0.29***	-0.07	-0.12**
	(0.05)	(0.08)	(0.05)	(0.06)	(0.04)	(0.07)	(0.04)	(0.05)
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	Δ log freight cost, unit				Δ log freight cost, weight			
Δ log mobility change	0.05	0.02	0.04	0.03	-0.02	-0.00	-0.03	-0.04
	(0.04)	(0.05)	(0.04)	(0.05)	(0.03)	(0.04)	(0.03)	(0.05)
I (year=2019)	0.02*		0.03*	0.03**	0.03**		0.03**	0.03**
	(0.01)		(0.01)	(0.01)	(0.01)		(0.01)	(0.02)
Time trend		0.00				0.00		
		(0.00)				(0.00)		
Constant	0.05***	0.04**	0.05***	0.04***	-0.02***	-0.03*	-0.02***	-0.03**
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
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.

C Theory

C.1 Producer Problem

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

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

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

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

C.2 Transport Firm Problem

The transport firm solves the following problem:

$$\max_{\{t(i,j)\}\in\Omega} \int_{\Omega^I}\int_{\Omega^J} \Big[t(i,j) - B(i,j)\Big]v(i,j)didj - \frac{\mu}{2}\Big[\int_{\Omega^I}\int_{\Omega^J}\Big[v(i,j) - V(i,j)\Big]didj\Big]^2$$

subject to $\int_{\Omega^J}\Big[v(i,j) - V(i,j)\Big] = 0$, $v(i,j) = \int_{\Omega^{IJ}} v(i,j,k)dk$. Weight demanded by product k is $v(i,j,k) = (\kappa_k)^{-1}(p^M(i,j,k))^{-\sigma}(P^M(j,k))^{\sigma-1}Z(i,j,k)$.

The first order condition for transport price between i and j is (i and j subscripts omitted):

$$\begin{aligned}
v + \Big[t - B\Big]\frac{\partial v}{\partial t} - \mu\Big[v - V\Big]\frac{\partial v}{\partial t} &= 0 \\
\Big[t - B\Big] - \mu\Big[v - V\Big] &= \Big[\frac{\partial v}{\partial t}\frac{1}{v}\Big]^{-1} \\
t &= \Big[\frac{\partial v}{\partial t}\frac{1}{v}\Big]^{-1} + B + \mu\Big[v - V\Big]
\end{aligned}$$

We need to derive the first term, that captures the relative change in total weight demanded to ship goods from i to j when transport prices change.

$$
\begin{aligned}
\frac{\partial v}{\partial t}\frac{1}{v} &= \frac{\partial\Big[\int_\Omega v(k)dk\Big]}{\partial t}\frac{1}{v} \\
&= \int_\Omega \frac{\partial v(k)}{\partial t}dk\frac{1}{v} \\
&= \int_\Omega -\sigma\frac{v(k)}{p^M}dk\frac{1}{v} \\
&= -\sigma\int_\Omega \nu(k)\frac{1}{p^M}dk \\
&= -\sigma[\tilde{p}^M]^{-1}
\end{aligned}
$$

where $\nu(k) \equiv \frac{v(k)}{v}$ is the weight share of product k, and $\tilde{p}^M$ is the weighted harmonic average across products of import prices. It summarizes the per-unit of weight return of changing transport prices between i and j.

The expression for the optimal transport price is then:

$$
t = \frac{\tilde{p}^M}{\sigma} + B + \mu\Big[v - V\Big]
$$

There are $I \times J$ transportation prices chosen by the transport firm, but the capacity constrain still needs to be considered.

We can take the integral over all possible routes:

$$
\begin{aligned}
(IJ)^{-1}\int_{\Omega^J}\int_{\Omega^I} t(i,j)didj &= (IJ)^{-1}\int_{\Omega^J}\int_{\Omega^I}\frac{\tilde{p}^M(i,j)}{\sigma}didj + (IJ)^{-1}\int_{\Omega^J}\int_{\Omega^I} B(i,j)didj + \\
&+ (IJ)^{-1}\int_{\Omega^J}\int_{\Omega^I}\mu\Big[v(i,j) - V(i,j)\Big]didj \\
\bar{t} &= \bar{\tilde{p}}^M + \bar{B}
\end{aligned}
$$

where the constrain implies that the average deviation from the starting capacity is zero.

Using this equation, we can see that the transport price can be defined around the average:

$$
t - \bar{t} = \frac{\tilde{p}^M - \bar{\tilde{p}}^M}{\sigma} + (B - \bar{B}) + \mu\Big[v - V\Big]
$$