One Way or Another: Modes of Transport and International Trade

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Abstract

The transport sector is the backbone of international trade and has faced multiple disruptions in recent years. I study the substitutability between different transport modes and how mode-specific trade cost shocks affect international trade flows. I use the closure of Russian airspace in 2022 as an exogenous change in transport costs to provide novel estimates of the elasticity of substitution between transport modes. To quantify the importance of this margin of adjustment in equilibrium, I develop a Ricardian model of international trade with multiple transport modes. Modes are substitutable but endogenous congestion forces limit substitutability. I apply this framework to quantify the effects of recent trade cost shocks such as the closure of Russian airspace and the Suez Canal blockage. Transport mode substitution reduces welfare losses by 4% relative to a non-substitution scenario. However, substitution has potentially negative consequences for the carbon footprint of international trade. Higher sea transport costs can lead to increased carbon emissions due to substitution toward more carbon-intensive air transport.

Keywords: Transport, Substitution, Ukraine, Suez, Trade costs, Carbon emissions

JEL Classification: F10, F12, F14, F18, R4, Q56

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1 Introduction

Transport plays a pivotal role in international trade, facilitating the global movement of goods and sustaining both consumption and production across nations. Recent years have witnessed unprecedented challenges to the transport sector, stemming from both geopolitical events and natural phenomena. For example, the Russian invasion of Ukraine in 2022 led to airspace restrictions over the conflict zone, disrupting air traffic between Europe and Asia, which accounts for more than 20% of global cargo volume.[1] The years 2023 and 2024 also saw significant disruptions to maritime traffic in the Panama and Suez canals—two critical waterways for global trade.[2] At the same time, discussions surrounding policies to reduce the carbon footprint of international transport have gained traction, potentially impacting the industry through increased costs.

These events mostly affect one transport mode at a time. The Ukrainian-Russian airspace closure only disrupted air routes. The Suez incident only disrupted water routes. This makes unaffected modes relatively cheaper, potentially prompting a switch between modes, rather than a reduction in international trade. However, in the international trade literature, it is conventionally assumed that agents have access to a single transport mode. Not only does this assumption fail to make the distinction between different transport modes, it also fails to capture shifts from one transport mode to another in response to trade cost shocks.

Given the crucial importance of transport for global trade, this paper addresses two key questions: How do mode-specific transport cost shocks change international trade flows? Does substitution between transport modes mitigate the welfare effects of shocks?

I answer these questions both empirically and theoretically. First, I document the use of multiple modes of transport along the same origin-destination-sector route. Second, I use an exogenous trade cost shock to provide novel estimates of the elasticity of substitution between transport modes. Third, I develop a quantitative Ricardian model of trade that incorporates multiple modes of transport and endogenous transport costs due to congestion. The model features two new adjustment channels, substitution and congestion, which affect how mode-specific transport shocks are transmitted to aggregate trade flows as welfare. Finally, I study several counterfactual scenarios in which a transport mode is shocked to show quantitatively the importance of the new channels for welfare. Additionally, I show that substitution between modes can affect the effectiveness of environmental policies targeting the transportation sector.

While sea transport continues to dominate by volume, air transport is increasing in value (Hummels, 2007; Feyrer, 2019). Using Eurostat, I find that air transport accounts for about 40% of extra-European trade value, and over 50% of origin-destination-sector triplets use both air and sea transport. Since this evidence indicates that agents have the option of selecting various transport modes, I then look at how changes in the relative price of each mode change the relative trade flows by transport mode.

[1] Source International Air Transport Association (IATA) and International Civil Aviation Organization (ICAO).

[2] Around 30,000 ships per year pass through these two channels accounting for more than 20% of total sea trade. Source: Unctad (2024).

I estimate the elasticity of substitution between transport modes within country pairs, using the Ukraine-Russia conflict as an exogenous shock to transport costs. The sanctions between the European Union and Russia led to the closure of Russian airspace, which in turn increased air transport costs.[3] I employ a difference-in-differences (DiD) strategy to quantify the impact of these sanctions by comparing the changes in flight times and trade shares by mode between affected and non-affected country pairs before and after the onset of the war. To do so, I collect flight time data from 1.8 million flights from OpenSky and combine them with Eurostat data on trade flows. First, I show that the war significantly increased flight times between Europe and East Asia. I then demonstrate that this led to a notable shift toward sea transport in affected origin-destination pairs. I obtain the elasticity of substitution between transport modes by dividing the marginal effect estimated in the second step by that of the first. This methodology, known as the Wald-DiD estimator, allows me to recover an elasticity estimate using a binary dummy (Wald, 1940; Angrist and Pischke, 2009; De Chaisemartin and d'Haultfoeuille, 2023).

As an alternative strategy, I exploit the 2021 congestion event that hit U.S. West Coast ports (Hu et al., 2021). An advantage of this approach is that I directly observe the transport charges paid to import the goods. I use a similar DiD estimator, defining treated countries as U.S. trade partners in Asia with European countries serving as the control group. I first show that sea transport costs in the treated group are relatively higher in 2021 compared to air transport costs. Secondly, I show that the air share of trade with affected countries has grown more relative to non-affected partners.

This approach allows me to separately study substitution from air to sea (using the airspace closure) and from sea to air (using the congestion event). Both quasi-natural experiments yield statistically similar estimates for the elasticity of substitution between transport modes within country pairs. The point estimate for air-to-sea substitution is 1.58 while the sea-to-air elasticity is 2.33. Given the extended duration of these events, I interpret these as long-term effects as they force agents to change their behavior for a significant period.[4]

Motivated by the new evidence, I extend the seminal work of Eaton and Kortum (2002) and Dekle et al. (2008) by incorporating multiple transport modes for trading goods. The transport mode choice is modeled as a discrete decision made after the determination of import quantities from a given origin. Importers select modes based on transport prices and individual preferences for a given shipment between two points. This step yields two key equilibrium outcomes: the share of each mode and a transport cost price index. The latter can be interpreted as the standard iceberg cost that, together with each country's price distribution, determines aggregate trade flows between countries. A new parameter, the elasticity of substitution between transport modes, determines the substitutability between modes, which I show to correspond to the elasticity estimated empirically in the previous section. A key strength of this approach is that it is nested within the "universal gravity" framework (Allen et al., 2020), allowing for the extension of any model of this type to include multiple transport modes.

[3] Russian airspace continues to be used by some non-EU airlines, see Section 3.1. Ukrainian airspace is closed due to security reasons.

[4] In the appendix, I also estimate short-term elasticities.

The ability of agents to switch transport modes introduces an additional adjustment margin in response to changes in transportation costs. This aspect is novel compared to the standard trade literature, which typically assumes the use of a single mode of transport. The implications of this additional margin of adjustment are twofold. First, welfare losses due to an increase in transport costs are partially offset by agents switching to alternative transport modes. Second, the change in the transport price index can vary between country pairs due to their different exposure to a mode-specific cost shock. This can lead to an asymmetric effect across country pairs that again cannot be reproduced by standard trade models with a single iceberg cost. By solving the model in terms of changes, I demonstrate that the only additional data requirement compared to a standard Ricardian model is the initial share of trade by mode between country pairs.

I extend the model to make transport costs endogenous due to congestion costs. In the baseline model, I assume that switching between modes is frictionless and does not affect the price of each mode. However, it is reasonable to argue that as demand for a transport mode increases, its price should rise. In this extension, the usage of each mode determines bilateral transport costs, and therefore changes in bilateral costs now trigger an additional adjustment channel. As agents shift from one mode to another, there is a change in relative prices which limits the scope for substitution. At the same time, since the increase in transport costs causes lower bilateral trade flows, bilateral costs between affected countries go down due to lower congestion, counteracting the initial increase in costs. Again, by solving the model in changes, I show that this extension comes with no additional data requirements if we assume that infrastructure is constant between country pairs.

The substitution and the congestion channels are two novel mechanisms through which changes in transport costs affect international trade flows and welfare. To quantify their importance, I use the model to evaluate the impact of two shocks to transport costs: the closure of Russian airspace and the closure of the Suez Canal. I calibrate the model using data on trade flows by transport mode that I collect from various sources such as Eurostat, US Census Bureau, Japan Ministry of Finance, ASEAN data portal, Inter-American Development Bank (IDB), and the United Nations Comtrade database. This allows me to build a dataset of trade flows by mode with 33 countries and two transport modes, air and sea. I then use the calibrated model to simulate the effects of these shocks on trade flows and welfare.

These experiments highlight the importance of the two new margins of adjustment introduced to understanding welfare changes in response to mode-specific transport cost increases. Allowing for modal substitution increases trade resilience by shifting a part of bilateral trade flows to relatively cheaper modes, thereby diminishing the negative welfare effect. In the case of the Russian sanctions, substitution decreased average welfare losses by 3.77% compared to a scenario with no substitution. I also find that the sanctions affect disproportionately countries that before the shock relied more on air trade such as the European Union and Japan.

Welfare is not the only metric that changes once we take into account multiple modes. As a final exercise, I show that substitution between modes of transport can also affect the effectiveness of trade policies that target the transport sector. This is due to the fact that different modes of transport have different carbon intensities. Therefore, shifting trade from one mode to another may affect the overall carbon emissions coming from international transport.

To study this additional dimension, I examine the effects of IMO23, a policy introduced by the International Maritime Organization (IMO) to reduce carbon emissions from sea trade. Effective from 2023, it aims to cut shipping emissions by 40% by 2030 and 70% by 2050, compared to 2008 levels. The most immediate impact is vessel speed reduction, which, as Lugovskyy et al. (2023) note, decreases the total capacity of sea shipping and therefore increases sea transport costs.

I find that, in the case of the IMO23 policy, compared to a scenario in which there is no substitution, transport mode substitution decreases welfare losses by 1.4% but reduces the policy's effectiveness in terms of emissions reduction by 29% due to a shift towards more carbon-intensive air transport. Therefore, substitution plays a crucial role not only for welfare considerations but also for other topics related to trade and transport such as the carbon footprint of international trade.

Related Literature. This paper contributes to the literature studying the relationship between international trade and transport modes. Typically, this relationship is analyzed as a trade-off between speed and cost, emphasizing the advantages of timely delivery in hedging against or responding to uncertainty. The choice of transport mode is influenced by factors such as the quality of shipped goods (Hummels and Skiba, 2004; Hummels, 2007; Hummels and Schaur, 2013), delivery timing (Evans and Harrigan, 2005; Hummels and Schaur, 2010), and relative prices between modes (Micco and Serebrisky, 2006; Harrigan, 2010). Technological advancements have significantly contributed to the long-term increase in air transport (Campante and Yanagizawa-Drott, 2018; Feyrer, 2019). The key difference of this paper is to look at the aggregate implications of substitution between transport modes. From the empirical perspective, the contribution of this paper is to provide new estimates of the elasticity of substitution between transport modes between country pairs. From the theoretical perspective, it augments the standard multicountry models of trade (Eaton and Kortum, 2002; Allen et al., 2020) to include multiple modes of transport, allowing the study of the effect of mode-specific shocks on aggregate trade and welfare.

This paper contributes also to the growing literature on endogenous transportation costs in international trade and spatial economics (Allen and Arkolakis, 2014; Allen et al., 2020; Asturias, 2020; Brancaccio et al., 2020; Fajgelbaum and Schaal, 2020; Wong, 2022; Jaworski et al., 2023; Fuchs and Wong, 2024). This is the first work that introduces substitution between transport modes and endogenous transportation costs, driven by the demand for each mode, in a multicountry international trade framework. In this context, the most closely related paper is Fuchs and Wong (2024), which examines multimodality and substitution along the same route within the United States. The authors focus on substitution between rail, trucking, and sea transport in the US context and consider within-country transport. My paper instead focuses on air and sea transport in the context of international trade and can therefore be seen as complementary to their analysis.[5]

By introducing substitution between modes of transport in international trade, this paper also contributes to the growing literature on the environmental impact of international trade (Cristea et al., 2013; Shapiro, 2016, 2021; Mundaca et al., 2021; Copeland et al., 2022; Lugovskyy et al., 2023; Hansen-Lewis and Marcus, 2022; Felbermayr et al., 2023; Sogalla et al., 2024). While previous studies assumed fixed trade shares between countries by mode, this paper incorporates an additional adjustment channel, allowing for substitutability between transport modes which can impact the effectiveness of policies that target the transport sector.

Finally, this paper contributes to the literature that studies the effects of transport shocks for international trade (Carballo et al., 2014; Söderlund, 2020; Coşar and Thomas, 2021; Feyrer, 2021; Sandkamp et al., 2022; Al-Malk et al., 2024; Besedeš et al., 2024). Empirically, my contribution is to study the effect of transport-related sanctions caused by the Russian-Ukrainian conflict on trade. Theoretically, I provide a framework to study the general equilibrium effects of this class of shocks, showing that substitution between transport modes partially offsets their negative effect.

The paper is structured as follows. Section 2 describes the data used and key statistics on the composition of trade by mode of transport. Section 3 presents the estimation of the elasticity of substitution between modes of transport. Section 4 introduces the baseline Ricardian model. Section 5 extends the model to include congestion and endogenous transport costs. Section 6 presents the calibration of the model, and Section 7 contains the results of the counterfactual analysis. Section 8 concludes.

2 Trade Patterns by Transport Mode

In this section, I introduce the main dataset used for my empirical analysis and then present some key statistics on trade by transport mode that will motivate the structure of the model.

2.1 Eurostat Data

I collect monthly data from Eurostat on European imports and exports by transport mode between countries. Flows are reported both in terms of value (in euros) and weight (kg).[6] There are four main modes of transport: air, rail, road, and sea, which collectively account for approximately 95% of total trade in the sample.[7] The data are provided at the 6-digit product code

[5]A previous, unpublished working paper by Lux (2011) also looks at substitution between modes in an international trade setting. However, this study differs substantially in several respects. Empirically, I estimate the elasticity of substitution between modes using quasi-exogenous variations, while Lux (2011) only examines descriptive patterns in the data. Theoretically, I introduce a two-step mode decision that preserves tractability and gives a structural interpretation to the empirical elasticities.

[6]All transactions with a weight below 100 kg are reported as zero in Eurostat.

[7]I discard the remaining modes, including unknown, post, fixed mechanisms, inland waterways, and self-propulsion, either because they are seldom used or because I cannot categorize them, such as post or non-categorized.

level following the Harmonised System (HS) classification, which allows for a detailed study of how goods are transported. The data cover the period from January 2010 to December 2022.

I focus on trade flows reported as air and sea only to avoid measurement errors in land transport.[8] A limitation of this dataset is that, for a few country pairs, some modes are reported as being used even if it is geographically impossible. For instance, flows from the US to Germany via road or rail are reported as greater than zero for some sectors. This discrepancy arises because some imports are processed when they enter the Eurozone.[9]

Finally, to minimize the number of zeros, I exclude small countries, restricting my sample to the 80 largest nations in terms of GDP (World Bank data, 2019), which account for approximately 93% of total trade. I also exclude the United Kingdom from the sample due to its exit from the European Union, and Eurostat, after December 2020, and Russia and Ukraine due to the ongoing conflict.

A drawback of this dataset is that it contains data on trade flows only with extra-European countries.[10] Although intra-EU flows are available from 2010 onwards on Eurostat, they are reported at a higher level of aggregation using the Standard Goods Classification for Transport Statistics (NST), which is divided into 20 sectors, and are collected via survey rather than custom declarations. Additionally, most intra-EU trade is conducted via road (Santamaría et al., 2023). The predominant use of road transport is due to the relatively short distances within Europe compared to international routes. As a result, air transport is seldom used, and the geography of the continent does not favor trade via large ships.

2.2 Average Flight Time Data

I complement the Eurostat data with information on monthly average flight times between countries. I use information on daily flights from January 2019 to December 2022 between airports within and across countries, with more than 1.8 million flights recorded from Strohmeier et al. (2021). These data are collected using ADS-B calls from the OpenSky platform.[11] The main variables of interest for this project are the flights' origin and destination and the total flight time. I retain only international flights, excluding all observations where take-off and landing occur within the same country. Consequently, I observe only direct flights. An underlying assumption is that commercial and cargo flights follow the same routes and have similar travel times.[12] I then calculate the monthly average flight time between country pairs, which serves as a proxy for air transport costs.

[8]Trade via air and sea accounts for more than 80% of total trade in value in the sample.

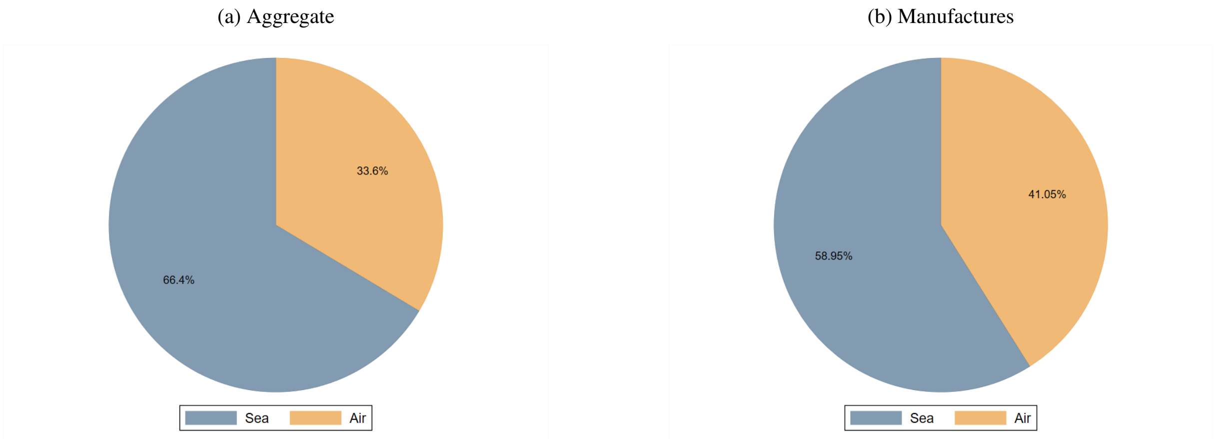
[9]For example, if a shipment by plane from the US lands in Switzerland and is then transported to Austria by truck without passing through Swiss customs, it will be reported as an Austrian import from the US via truck. Currently, I am not aware of a better dataset containing more refined information. Reporting problems are common in international trade datasets (Cotterlaz and Vicard, 2023).

[10]For example, Germany-China is included but Germany-France is not.

[11]All aircraft are required to have this sensor while in flight.

[12]I validate this assumption by using an online platform Flightradar24 that reports real-time flight paths. See Figure H.5 for an example using flights connecting Beijing to Frankfurt.

Figure 1: Transport Mode Share of Trade



Notes: Panel (a) reports the aggregate share of trade in euros by mode of transport. Panel (b) reports the same statistics for the manufacturing sector. The sample consists of imports and exports of European Union members in 2019, collected from Eurostat.

2.3 US Census Bureau Data

As an alternative data source for the second part of my empirical analysis, I also collect data from the US Census Bureau. This allows me to obtain data on US trade by mode of transport at monthly frequency via their API. Similar to the Eurostat data, trade flows are reported at the 6-digit HS level. The data are available from January 2013 to December 2022. In this case, only US import flows by air and sea are reported. In addition to trade volumes in value and weight, the data also contains the total freight costs incurred in the transport of the goods.

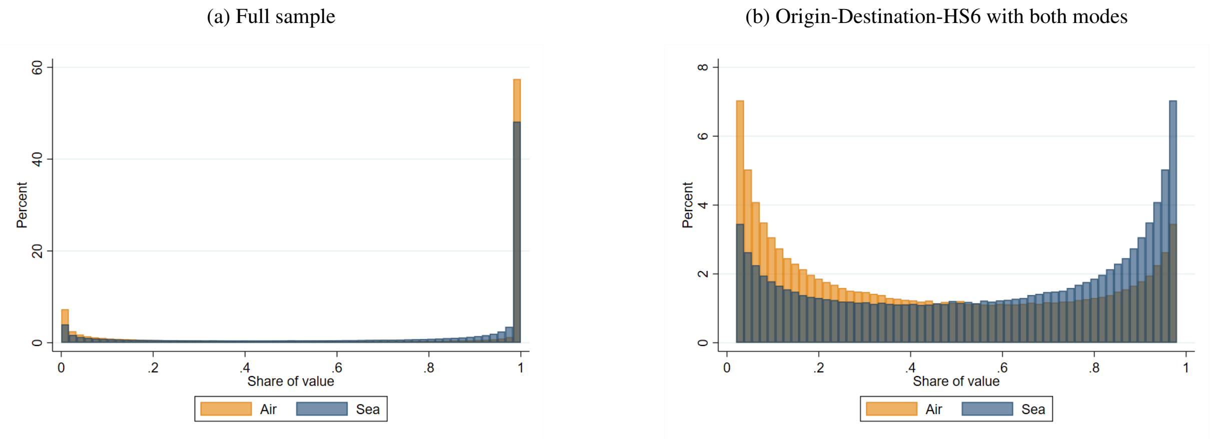
2.4 Composition of European Imports and Exports by Transport Mode

Figure 1a reports the composition of aggregate European trade with non-European countries by air and sea in 2019, measured in euros. The total value of trade transported via air is approximately 760 billion euros, accounting for 33.6% of the total trade value. This means that a significant portion of trade is conducted via air transport, despite its higher cost. Figure 1b shows that the use of air transport is even higher when we focus on the manufacturing sector,[13] which accounts for 42% of the total trade value. This is because air transport is predominantly used for high-value, low-weight goods such as electronics, pharmaceuticals, and precision machinery, which exhibit high value-to-weight ratios. In contrast, sea transport is the preferred mode for heavy, lower-value goods, including raw materials and petroleum products (Hummels, 2007). If we look at trade flows by weight, the proportion shifts significantly in favor of sea trade, as expected, since bulkier items tend to be shipped by sea (Figure H.3 in the Appendix).

Figure 2 shows the trade shares' distribution by mode of transport across origin-destination-HS6 sectors for the year 2019. The left panel displays the distribution for the full sample, while the right panel shows the distribution for triplets that use both air and sea transport. Once we

[13]Defined as *Chemicals* (23-24-25), *Food* (15-16), *Machines* (29-30-31-32-33), *Metals* (27-28), *Minerals* (26), *Other* (36), *Textiles* (17-18-19), *Vehicles* (34-35), and *Wood-Paper* (20-21-22). The corresponding sections from the ISIC revision 3 are listed in parentheses. I use the UN WITS database to map between HS codes and ISIC3.

Figure 2: Transport Mode Share distribution



Notes: Panel (a) shows the distribution of trade value shares by transport mode. Panel (b) shows the distribution of trade value shares across origin-destination-HS6 sectors that use both air and ocean transport. The sample consists of imports and exports of European Union members in 2019, collected from Eurostat.

exclude observations with a single mode, we can see that there is a high degree of heterogeneity in the share of trade across different modes of transport. This suggests that while certain sectors are constrained to a single transport mode due to the nature of their goods or logistics, a significant portion of the sample exhibits variability in mode choice, indicating potential for modal substitution.

Figure 3 reveals that approximately 50% of the origin-destination-HS6 sectors in the dataset utilize both air and sea modes of transport.[14] This percentage is even higher when focusing on the manufacturing sector (see the right panel). European countries frequently use multiple transport modes simultaneously to trade with partners outside the EU for a wide variety of 6-digit products. Data from the US Census Bureau show very similar patterns in terms of value and weight traded by transport mode. Appendix A.1 provides more information on the US data and a comparison with the European data. This is in line with other studies that have shown similar patterns, using even more detailed data, for the US (Hummels and Schaur, 2013).

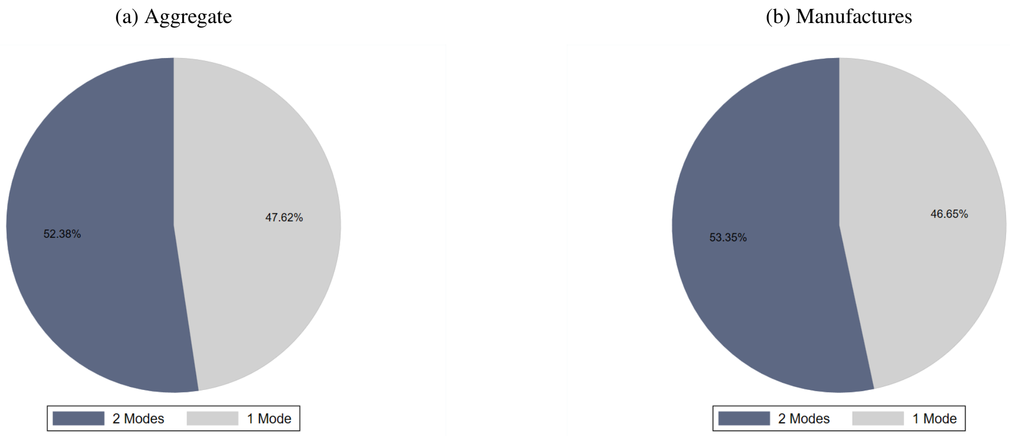
Two key facts emerge from the data. First, air transport plays an important role in European trade with partners outside the EU. Second, multiple modes are often used at the same time to import/export goods from Europe. On the contrary, by assuming a single mode of transport in our models, we do not take these patterns into account. In the next section, I will show how the share of trade transported with each transport is sensitive to changes in the relative price of each mode.

3 Estimating the Substitution Between Transport Modes

In this section, I estimate the elasticity of substitution between air and sea transport. To isolate the causal effect of an increase in mode-specific trade costs, I exploit two shocks to transport costs that significantly affected international trade: (i) the closure of Russian and Ukrainian

[14]This pattern holds true for both value shares and weight shares, as shown in Figure H.2 in the appendix.

Figure 3: Number of Modes Used per Origin-Destination-HS6



Notes: Panel (a) shows the percentage of origin-destination-HS6 sectors that use both air and ocean transport. Panel (b) shows the same distribution in manufacturing sectors only. The sample consists of imports and exports of European Union members in 2019, collected from Eurostat.

airspace, and (ii) the congestion at US West Coast ports in 2021. The Russian airspace is a vital route for trade, as 36% of European trade is with Asian countries.[15] At the same time, the US imported more than 300 billion dollars from ASEAN countries in 2022, making the West Coast a crucial trade hub.[16]

The nature of these shocks is such that they only affected one mode of transport at a time, allowing me to estimate the elasticity of substitution from air to sea using the airspace closure, and from sea to air using port congestion. In addition, given the duration of both disruptions, I argue that the estimated elasticity reflects a long-run elasticity rather than a short-run one. This elasticity is a new parameter in the international trade literature that is not present in standard gravity models of trade between multiple countries and identifies an additional margin of adjustment of trade flows in response to mode-specific transport shocks.

3.1 The Russian and Ukrainian Conflict and Airspace Closure

The Russian invasion of Ukraine in 2022 has been a major geopolitical event with far-reaching consequences, affecting millions of people both directly and indirectly. For European countries, one of the primary effects has been a rapid deterioration of diplomatic and economic relations with Russia. The European Union has implemented a series of trade sanctions, promptly met with retaliatory measures by the Russian state. A significant outcome of this conflict has been the mutual closure of airspace to aircraft from the opposing bloc. Additionally, Ukrainian airspace has been closed to all unauthorized civilian flights due to security concerns. Consequently, European carriers[17] now face significantly longer flight times to Asian destinations,[18]

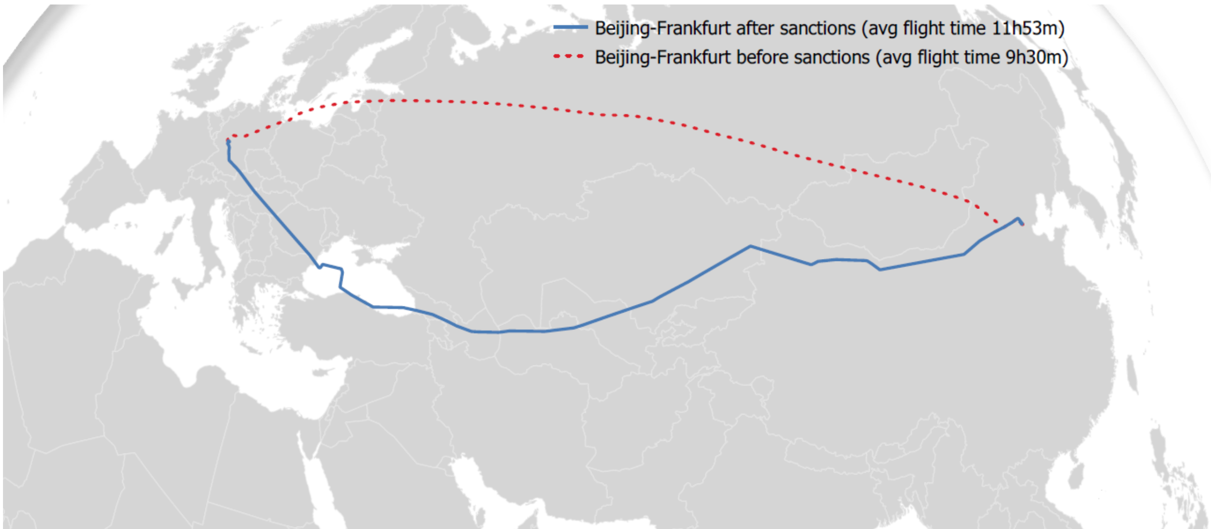
[15]Source: Eurostat.

[16]Source: Office of the United States Trade Representative.

[17]The airspace restrictions also apply to other countries that have sanctioned Russia, such as Japan and South Korea. Chinese carriers, however, continue to fly over Russia.

[18]Affected routes include those to Japan, South Korea, China, and various destinations in Southeast Asia. Flights now typically travel south, crossing through Turkey, Central Asia, China, and Mongolia (source: Flightradar24).

Figure 4: Sanctions and Change in Flight Time



Notes: Change in the flight route between Frankfurt and Beijing after the start of the Ukraine war in February 2022. The flight time increases by 25 percent from 9h30mins to 11h53mins. Author's own calculation based on Flightradar24 data.

as they must modify their routes to accommodate this new geopolitical reality. This has resulted in an increase in travel time per flight,which can serve as a proxy for the increase in transport costs for air-freighted goods.

The roots of the conflict can be traced back to 2014 with Russia's annexation of Crimea, and tensions had been escalating since November 2021 with reports of Russian troop movements along the Ukrainian border. However, for the purposes of this study, the 2022 Russian invasion of Ukraine can be treated as a quasi-natural experiment.

This approach is justified for several reasons. First, the exact timing of the invasion was largely unanticipated, preventing firms from implementing pre-emptive responses. Second, the conflict has lasted much longer than initially forecast (Zabrodskyi et al., 2022), meaning firms eventually had to resume procurement under the new conditions, even if they initially relied on existing inventories. As this study focuses on trade routes connecting Europe to Asia, there is no direct damage to transport infrastructure on these routes that could confound the analysis of trade flows by mode. Finally, any change in trade flows due to sanctions, other than the closure of airspace, should not affect the relative share of each transport mode, as it should increase or decrease overall trade without changing the relative price of each mode of transportation.

3.1.1 Empirical Strategy

In this section, I calculate the elasticity of substitution between transport modes with respect to transport costs within the same origin and destination. Specifically, I want to quantify if changes in the relative costs of each means of transport generate any changes in the relative share of trade by transport mode between two country pairs.

I argue that when multiple modes are available and transport costs for a single mode increase, part of the trade shifts to relatively cheaper modes. Specifically, the mode that experienced the increase in costs will now be used less intensively, and part of the trade flows will be moved by a different means. On the contrary, in the trade literature, the classic margin of adjustment to increases in transport costs is trade diversion, meaning that when costs between two destinations increase, part of the trade flow is diverted towards relatively cheaper partners.

My identification strategy is a difference-in-differences research design, comparing the total flow transported via air and sea along routes that were affected by the war and those that were not, before and after the outbreak of the war in February 2022. This approach exploits the exogenous variation caused by the unexpected closure of Russian and Ukrainian airspace. I argue that affected routes face higher costs due to the need to take longer paths to reach their destinations, which results in increased air transport costs.[19] Figure 4 provides an example of how the war affected air routes. A flight from Frankfurt to Beijing operated by a European carrier, which could previously fly over Russia, now must take a longer detour, increasing the average flight time by more than two hours.

I define a route as an origin-destination pair and define it as affected if the aircraft's trajectory that connects the two countries passed over either Russia or Ukraine before the invasion. The set of treated routes is composed of pairs of a European country and any nation in eastern or southern Asia. To determine which routes are affected, I use reports from the International Civil Aviation Organisation (ICAO) supplemented by manual checks of pre-war routes using Flightradar24.[20] As a control group, I use all countries in North and South America that trade with Europe.[21] I restrict my sample to HS6 sectors that have at least 5% of value traded via both air and ocean transports in 2019. This exclusion of sectors predominantly traded via a single mode of transport allows me to focus on the intensive margin of adjustment rather than the extensive margin. In particular, I only exploit variation between origin-destination-sectors that already use both modes and not the variation that comes from passing from a single mode to multiple. In Appendix D, I estimate a simple linear probability model to check if the shock affected significantly the extensive margin of adjustment by shutting down the use of air on some origin-destination-sectors.

To calculate the elasticity of substitution between air and sea due to the increase in transport costs that followed the closure of Russian and Ukrainian airspace, I employ a two-step procedure. First, I estimate the effect of the sanctions on average flight times between European countries and Asian destinations

$$\ln \text{FlightTime}_{niht} = \beta_1 \text{Post}_t \times \text{Treated}_{niht} + \mu_{nih} + \mu_{ht} + \epsilon_{niht}, \tag{1}$$

where FlightTime_{niht} is the average flight time between country n and i at time t, Treated_{ni} is a

[19]For example, a report from the Federal Aviation Administration indicates an average cost per hour-block, for a wide-body airplane with more than 300 seats, of around 10,000 USD of which more than 90% comes from variable costs such as personnel and fuel. The latter costs account for almost 20% of total expenditure in a flight (FAA, 2022).

[20]The list of affected countries is China and Hong Kong, Indonesia, Japan, South Korea, Malaysia, Myanmar, Philippines, Singapore, Thailand, and Vietnam.

[21]Given that the routes affected by the war are distant, I limit my analysis to air and sea transport only, as the potential for substitution to land transport is limited. An additional reason to drop trade via land is that this transport method cannot be used to trade with the control group.

dummy variable that takes the value of 1 if the route is affected by the airspace closure, Post_t is a dummy that takes value 1 from February 2022 onward, and μ_{nih} and μ_{ht} are pair-sector and time-sector fixed effects. The coefficient of interest is β_1, which captures the change in average flight time due to the war.[22]

Second, I want to estimate the impact of the sanctions on the relative trade flows between transport modes. To isolate this substitution effect, I control for the overall trade volume within each origin-destination-sector triplet by taking the ratio of the flows by air over the flows by sea within each sector. The ratio allows me to control for the overall level of trade between the two countries and part of the variation that could be due to an overall decline in trade between the countries driven by common factors. With this strategy, I am not interested in capturing the overall effect of the war on trade, but only the effect on the relative share of trade between the two modes. In Appendix C, I look at the sanction's effect on trade flows between country pairs by transport mode separately.

I estimate the following equation:

$$\ln\left(\frac{X_{niht}^{Sea}}{X_{niht}^{Air}}\right) = \beta_2 \text{Post}_t \times \text{Treated}_{ni} + \mu_{nih} + \mu_{ht} + \epsilon_{niht}, \tag{2}$$

where $\ln\left(X_{niht}^{sea} \,/\, X_{niht}^{air}\right)$ is the relative share of sea trade with respect to air trade between countries n and i in sector h at time t, Treated_{ni}, Post_t, μ_{nih}, and μ_{ht} are defined as above. The coefficient of interest is β_2, which captures the change in sea trade flows with respect to air trade due to the increase in transport costs that followed the closure of the Russian airspace.

Finally, I calculate the ratio of these two coefficients to recover the elasticity of substitution between air and sea transport. This approach is referred to as the Wald-DiD estimator (Wald, 1940; Angrist and Pischke, 2009; De Chaisemartin and d'Haultfoeuille, 2023)

$$\beta_{DiD} = \frac{E[\ln X_{niht}|\text{Post}_t \times \text{Treated}_{ni} = 1] - E[\ln X_{niht}|\text{Post}_t \times \text{Treated}_{ni} = 0]}{E[\ln \text{FlightTime}_{niht}|\text{Post}_t \times \text{Treated}_{ni} = 1] - E[\ln \text{FlightTime}_{nit}|\text{Post}_t \times \text{Treated}_{ni} = 0]}. \tag{3}$$

The main intuition behind this method is that, conditional on a series of controls, the change in average flight time between two countries serves as a good proxy for the change in air transport costs. This change in average flight time is then used as an instrument for the change in air transport costs. The underlying assumption is that the shock affects the share of trade between affected countries only through the change in flight time, once other factors are controlled for.

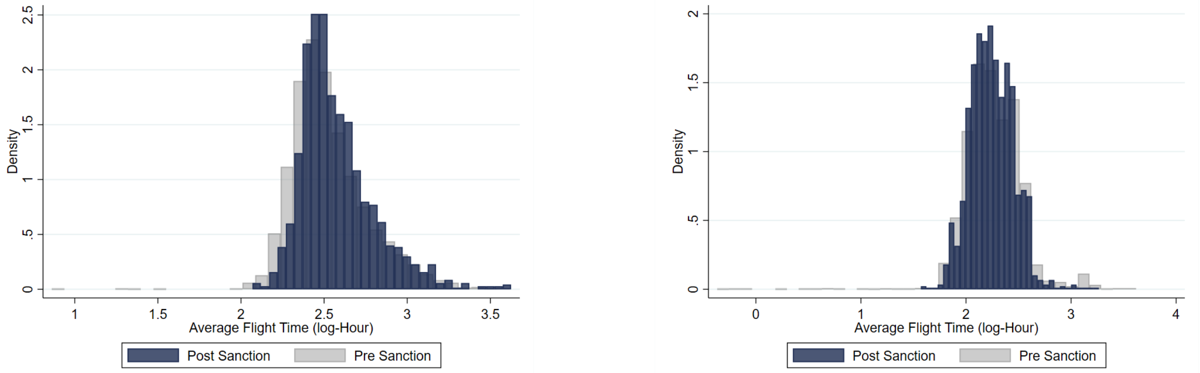
This approach is equivalent to a two-stage least squares (2SLS) regression of the outcome, $\ln\left(X_{niht}^{sea} \,/\, X_{niht}^{air}\right)$, on the treatment, $\ln \text{FlightTime}_{nit}$. Where the instruments used are time (Post_t) and group (Treated_{ni}), with their interaction as the excluded instrument (De Chaisemartin and d'Haultfoeuille, 2018).

Since this is a "sharp" difference-in-differences setting, where the treatment is only applied to the treated group, the key assumption that needs to be addressed is the common trend assump-

[22] Since the sanctions do not affect travel time by sea this coefficient is also the relative change in travel time of air transport with respect to sea transport.

Figure 5: Change in the Average Flight Time

(a) Treated Countries (b) Non-Treated Countries



Notes: Panel (a) shows the average flight time before and after the sanctions that caused the closure of Russian airspace for treated country pairs. A country pair is considered treated if it connects a European country to a nation in eastern or southern Asia. Panel (b) shows the same statistics for the control group, which consists of country pairs connecting European countries to North and South American nations. The sample includes monthly average flight time data based on 1.8 million flight paths from January 2019 to December 2022, derived from AIS calls on the OpenSky platform.

tion. This sharp design is justified by the fact that the group affected by the airspace closure is determined exogenously by the geographical position of the countries.

3.1.2 Identification Assumptions

In this section, I check that the results are not driven by ex-ante heterogeneity between the treated and control routes or by pre-existing trends in the data.

The composition of trade flows by sector and flight time between affected and non-affected routes is similar before the war, as shown in Table I.2. The unit of observation is the air trade flow/share between an origin i and destination n at time t in sector h, where time is a month-year, and sectors are 6-digit products. The moments are similar across the two groups, suggesting no ex-ante heterogeneity (Table I.2).

Figure 5 compares average flight times before and after the war for treated and control countries. The treated group, in the left panel, exhibits a notable increase in average flight time, indicating disruptions to air travel routes, potentially due to airspace restrictions or the need for alternative paths. The control group, however, shows remarkably stable average flight times.

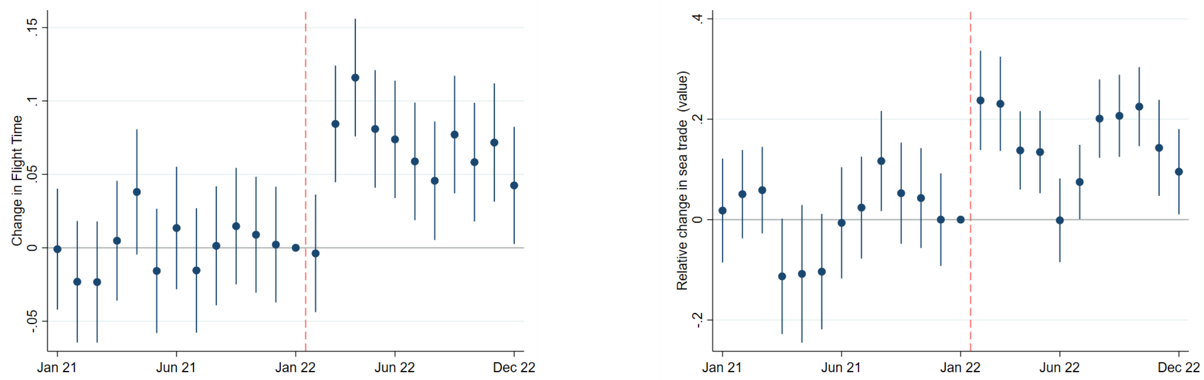
Figure 6a shows that there are no pre-treatment differences in trends in flight time, with a divergence occurring only after the war's outbreak. Specifically, we observe a significant increase in average flight time for the treated countries following this date, while the control group maintains its pre-war trajectory. This pattern supports the causal interpretation that the observed increase in flight time is attributable to the war rather than confounding factors.

Figure 6b shows that treated countries experienced an increase in sea trade relative to air trade following the conflict again with no pre-treatment differences in trends.[23] Interestingly, an anticipatory effect is observed, with air trade beginning to decline as early as February 2022, before the formal onset of hostilities. This suggests that economic agents may have adjusted

[23]The same pattern holds true for trade in kilograms, see Figure H.4 in the appendix.

Figure 6: Event Studies

(a) Flight Time (b) sea Trade relative to Air Trade



Notes: Panel (a) reports the results of the event study based on equation (1) and shows that there is no significant pre-trend in flight time before the closure of the Russian and Ukrainian airspaces between treated and non-treated country pairs. Panel (b) reports the event study based on equation (2) and shows that there is a significant increase in sea trade relative to air trade after the closure of the Russian and Ukrainian airspaces between treated and non-treated country pairs.

their trade strategies in response to escalating tensions. In the robustness checks, I show that the results are robust to including February 2022 in the pre-treatment period.

3.1.3 Results

Table 1 presents the estimates of equations (1) and (2). Column (1) reveals a significant shift in average flight time between treated and non-treated countries following the onset of the war. The estimated β_1 is approximately 0.073, indicating that average flight time increased by nearly 7.3% after the war's commencement.[24] Column (2) shows that the increase in flight time led to significant growth in sea trade. The coefficient of interest is 0.116, suggesting that sea trade, measured in euros, increased by approximately 12% relative to air trade following the war's outbreak.

The Wald estimator can be derived using equation (3) by taking the ratio of the coefficient in column (1) to the coefficient in column (2). The estimation is implemented via the IV-2SLS strategy previously described, and the results are reported in column (3) of Table 1, indicating an elasticity of substitution between air and sea transport of approximately 1.58 in value terms. This implies that a 1% increase in air transport costs leads to a 1.58% increase in the share of trade transported by sea. In Table I.4, I show that the results are robust when using trade flows measured in kilograms rather than euros.

In Appendix E, I show how the elasticity varies once we take into account different products' characteristics. As expected, goods with very high/low unit values tend to have lower substitutability since they are often transported entirely with a mode.

The "naive" OLS regressions are reported in Table I.8 in the appendix; in this case, the effect is not significant. The identification for this experiment comes from short-term variations

[24] Given that the pre-war average flight time in the treated group was approximately 12.5 hours, this corresponds to an average increase in flight time of about 1 hour.

in flight time between country pairs, which are not enough to incentivize firms to adjust their transport mode.

Table 1: Increase in air transport: aggregate effect

	(1)	(2)	(3)
	ln FlightTime	Ln Trade	Ln Trade
Post × Treated	0.073***	0.116**	
	(0.017)	(0.049)	
ln FlightTime			1.580*
			(0.809)
Observations	2,335,503	2,335,503	2,335,503
R-squared	0.844	0.631	
F-stat			18.709
Origin-destination-HS6	Y	Y	Y
Year-Month-HS6	Y	Y	Y

Notes: Column (1) reports the estimates for regression (1). The dependent variable is the log average flight time between two country pairs. Column (2) reports the estimates for regression (2) where the dependent variable is the ratio, in euros, between sea and air trade between a country n and a country i in sector h in month t. Treated is a dummy that takes values 1 if the origin/destination country is in Asia and 0 otherwise. Post is a dummy that takes value 1 after the start of the war (February 2022) and 0 otherwise. The Wald-DiD estimator, equation (3), is calculated via 2SLS and is equivalent to the ratio of the coefficients in columns (1) and columns (2). The coefficient of column (3) can be interpreted as the elasticity of substitution between transport modes. Standard errors are clustered at the origin-destination level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

To the best of my knowledge, this study represents one of the first attempts to estimate this parameter for international trade. A comparable elasticity can be found in Fuchs and Wong (2024) for U.S. domestic trade, where the authors examine substitution between rail and truck transport. Their estimates appear smaller than those presented here, which can be attributed to the different modes of transport studied. Appendix F further explores the short-run effects of changes in transport costs on flows by mode, yielding results more closely aligned with those of Fuchs and Wong (2024).

3.1.4 Robustness Checks

I conduct several robustness checks to ensure that the results are not driven by the choice of sample, timing, or unobservable characteristics of the trade flows.

A potential concern regarding the methodology is the decision to retain only sectors with a 5% share of each mode in 2019. To address this, I conduct a series of robustness checks to demonstrate that the results are not driven by this choice. Table I.5 presents the results of these alternative specifications. The analysis is repeated using a 1% threshold and then using the full sample. Another concern could be the timing of the sample. Again, in Table I.5, the estimations are performed by setting the sanctions to start in March 2022 rather than February 2022. I also restrict the sample to manufacturing sectors only. Furthermore, given that Figure 5 indicates the presence of outliers in average flight time, the baseline results are recalculated after excluding country pairs with average flight times in the top and bottom 1% of the sample.

The results from these robustness checks remain quantitatively and qualitatively consistent with the main findings. This consistency can be attributed to the set of fixed effects employed, which effectively eliminates all origin-destination-sector triplets that exhibit no variation in the mode of transport used.

I perform separate regressions on different subsamples based on the similarity in unit values transported between origin-destination-sector-modes. The rationale is to ensure that, within HS6 product codes, the products transported by each mode are similar in composition. For example, very expensive bottles of wine could be flown, while cheaper wine is transported by sea. I therefore estimate the elasticity of substitution within subsamples created by calculating the ratio of unit values in each origin-destination-sector-mode and then grouping them into four quartiles. The results are reported in Table I.7 in the Appendix. The groups in which the difference in unit values by mode is small, shown in column (1), exhibit the highest degree of substitutability, as one would expect. Conversely, for origin-destination-sectors where the ratio is very far from one, shown in column (4), the elasticity is positive but not significant. This is likely because the products transported by each mode in these categories differ substantially from one another.

In order to check that the shock did not affect within-sectoral changes in the composition of goods transported, I re-estimate my baseline specification using as the dependent variable the ratio between the unit value at origin-destination-sector-mode. I also estimate the impact of the war separately for each mode. The results of this exercise are reported in Table **??**. We can see that neither the unit value ratio nor the unit values by mode are significantly affected by the increase in flight time. Therefore, I exclude that the results are driven by changes in the composition of the trade flows by quality.

Finally, in Appendix D I show that the number of modes used is only marginally affected by the sanctions introduced after February 2022, which motivates me to focus on the change in the relative share, intensive margin, rather than the number of modes used, extensive margin, in the model.

3.2 US West Coast Port Congestion

This section examines the 2021 US West Coast port congestion as an alternative shock to transport modes, using it to estimate the elasticity of substitution between air and sea transport. The congestion, caused by pandemic-related demand surges, labor shortages, and disruptions in shipping networks, led to significant delays, container shortages, and increased transport costs (Hu et al., 2021). This event severely impacted global supply chains and trade flows, forcing companies to seek alternative transport methods.

Some US trade routes were also affected by bilateral sanctions with Russia, particularly flights connecting the US with Asian destinations such as Japan, China, and South Korea. However, since the war in Ukraine occurred while port congestion was still ongoing, I exclude the year 2022 from my sample, as both air and sea transport were affected simultaneously. While the exogeneity assumption of this experiment is less clear than in the previous one, the fact that

I can directly observe transport costs by mode-product-origin allows me to estimate the direct effect on costs without relying on a proxy.

3.2.1 Empirical Strategy

I employ the same empirical strategy used for the Russian-Ukrainian conflict, comparing total air and sea transport flows along affected and unaffected routes before and after the US West Coast port congestion. This approach exploits the exogenous variation provided by the unexpected congestion resulting from the post-Covid recovery. I argue that the affected routes face higher costs due to the congestion, which leads to an increase in sea costs. To illustrate this, I use US Census data that reports total transport costs for each observation. I calculate the average cost per kilogram for each origin-sector pair by dividing the total transport costs by the weight of the shipment. I then compare the relative increase in transport costs via sea versus air for affected and unaffected countries.

As the treated group, I use Asian countries that trade with the US West Coast ports.[25] The control group is formed by European countries since they trade mostly with Eastern Coast ports that were less affected by the congestion (Hu et al., 2021). Again, I restrict my sample to HS6 sectors that have at least 5% of value traded via air and sea in 2019.[26]

First, I estimate the effect of the congestion on the relative cost of sea transport with respect to air transport in affected vs non-affected countries:

$$\ln\left(\frac{\text{Cost}_{iht}^{sea}}{\text{Cost}_{iht}^{air}}\right) = \beta_1 \text{Congestion}_t \times \text{Treated}_i + \mu_{ih} + \mu_{th} + \epsilon_{iht}, \tag{4}$$

where $\ln\left(\text{Cost}_{iht}^{sea} \,/\, \text{Cost}_{iht}^{air}\right)$ is the relative average cost per kilogram between an origin country i and the US in sector h at time t, Treated_i is a dummy variable that takes the value of 1 if the route is affected by the congestion, and μ_{iht} and μ_{mt} are country-sector and mode-time fixed effects, respectively.[27] Congestion_t is a dummy that takes a value of 1 after the congestion started to mount up on the US West Coast; I pick January 2021 as the starting point following the report by Hu et al. (2021). The coefficient of interest is the interaction term between the dummy for congestion and the dummy for sea transport.

The second equation to be estimated is the effect of the congestion on trade flows by mode of transport:

$$\ln\left(\frac{X_{iht}^{sea}}{X_{iht}^{air}}\right) = \beta_2 \text{Congestion}_t \times \text{Treated}_i + \mu_{ih} + \mu_{th} + \epsilon_{iht}, \tag{5}$$

where $\ln\left(X_{iht}^{sea} \,/\, X_{iht}^{air}\right)$ is the relative value of trade between country i and the US in sector h at time t, Treated_i and Congestion_t dummies and the fixed effects are defined as above. The coefficient of interest is β_2, which captures the change in sea trade flows with respect to air trade due to the congestion. As before, the two coefficients are used to calculate the elasticity

[25] In my baseline Specification the countries affected are China and Hong Kong, Japan, South Korea, Taiwan, and Vietnam.

[26] As the Census Bureau data reports only air and sea trade I do not consider land transport.

[27] Since the US Census data reports only imports, the destination country is always the US.

of substitution between air and sea transport using a 2SLS approach which corresponds to the Wald-DiD estimator.

3.2.2 Results

The checks of the identification assumptions are reported in Appendix B. In summary, we can see that trade and trade costs were quite similar before 2021 between the affected and non-affected countries (Table I.3). Moreover, in 2021 there is a significant rightward shift in the distribution of sea trade costs relative to air trade costs in the affected countries (Figure B.1), while this shift is less prominent in the control group. Finally, Figure B.2 shows that there was no significant pre-trend in transport costs; however, the event study for relative trade flows is less clear, as some of the coefficients are not statistically significant.

The results of the estimation of equations (4) and (5) are reported in Table 2. In column (1), we can see that there has been a significant shift in the average cost per kilogram between affected and non-affected countries after the start of the congestion. The coefficient of interest is 0.145, which implies that the average cost per kilogram increased by almost 15% after the start of the congestion. If we look at sea trade with respect to air trade in column (2), we can see that the share of sea trade was significantly affected. The elasticity of substitution between sea and air trade flows is calculated using the IV strategy, column (3), and corresponds to equation (3) by taking the ratio of the coefficients in column (1) to those in column (2). We can interpret this ratio as the effect of a 1% increase in transport costs, proxied by the average cost per kilogram, on the share of trade moved by sea. The results reported in the table show that the elasticity of substitution between air and sea transport is around 2.31. This means that a 1% increase in sea transport costs leads to a 2.3% increase in the share of trade moved by air.

The naive OLS estimates are reported in Table I.9. In this case, the effect is negative and significant as expected, but of lower magnitude. Again, this can be interpreted as a short-run elasticity since the naive OLS exploits short-term variation in bilateral transport costs.

3.3 Discussion on the Empirical Results

In this section, I demonstrate that the relative share of trade between transport modes within country pairs is affected by changes in relative prices. I use the Ukrainian-Russian conflict and the subsequent closure of their airspace as a quasi-natural experiment, serving as a proxy for increased air transport costs. I employ a difference-in-differences strategy, comparing affected and non-affected routes. I find that the elasticity of substitution between air and sea transport is approximately 1.58.

In the second part of the analysis, I use the US West Coast port congestion as an alternative shock to transport modes. Here, I find that the elasticity of substitution between air and sea transport is around 2.3. These two results suggest the presence of substitution patterns between air and sea transport in both directions. While the point estimates for the elasticities differ between the two strategies, they are not statistically different from each other. Therefore, I

Table 2: Increase in air transport: Aggregate effect

	(1)	(2)	(3)
	ln Cost	Ln Trade	Ln Trade
Congestion × Treated	0.115*	-0.266***	
	(0.062)	(0.034)	
ln Cost			-2.313***
			(0.338)
Observations	1,195,534	1,195,534	1,195,534
R-squared	0.365	0.707	-5.111
F-stat			52.854
Origin-HS6	Y	Y	Y
Year-Month-HS6	Y	Y	Y

Notes: Column (1) reports the estimates for regression (4). The dependent variable is the log costs for an origin-HS6 sector to the US. Column (2) reports the estimates for regression (5). The dependent variable is the relative log value of trade imported from an origin-HS6 sector pair. Treated is a dummy that takes a value of 1 if the trade partner is in Asia and 0 otherwise. Congestion is a dummy that takes a value of 1 after January 2021. The Wald estimator, equation (3), is calculated as the ratio of the coefficient of interest in column (1) to that in column (2) and can be interpreted as the elasticity of substitution between transport modes. Column (3) reports the estimate for the equivalent 2SLS-IV estimator. Standard errors clustered at the origin-HS6 level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

argue that the elasticity of substitution between air and sea transport falls within the interval [1.58, 2.3].

As noted at the start of this section, the estimated elasticity can be interpreted as a long-run measure, as it is based on shocks with prolonged effects on transport costs. In Appendix F, I examine short-run substitution between transport modes by exploiting time variation in US Census Bureau transport costs. I find that monthly price variations affect the share of trade by mode for origin-sectors, though the substitution effect is smaller, with an average elasticity of 0.2. This aligns with the findings of Fuchs and Wong (2024), who report a similar elasticity for US internal trade, specifically between road and rail transport. The lower elasticity in the short run is likely because firms expect such shocks to be temporary and therefore adjust less.

To the best of my knowledge, standard trade models cannot account for these patterns. In classic gravity models, a single iceberg cost typically summarizes all bilateral costs between two countries. However, in this section, I show that multiple modes of transport can be used simultaneously along the same origin-destination route (Figure 3). Furthermore, I show that the share of each mode responds to changes in relative transport costs. These two observations offer new insights into what determines trade costs between country pairs and what happens when these costs change.

Typically, a change in trade costs is assumed to result in a proportional reduction in trade flows. However, when multiple transport modes are available, trade diversion effects [28] can be partially offset by substitution between transport modes.[29]

In Appendix C, I examine the effect of sanctions on trade flows by mode and in aggregate

[28] Higher costs generate lower bilateral trade.

[29] E.g., shifting to relatively cheaper modes.

terms. I find that air trade flows suffered an average negative drop in the affected group of origin-destination pairs, which was not offset by an increase in sea trade flows. Therefore, aggregate trade flows also experienced a negative impact. The effect on bilateral sea trade flows was negative but not statistically significant. Thus, substitution between modes is not sufficient to fully compensate for the increase in bilateral costs and uncertainty between countries.

To fully understand the implications of this additional margin of adjustment for trade flows and welfare, it is not enough to focus solely on the elasticity of substitution between transport modes.[30] Therefore, in the next section, I will incorporate multiple transport modes into a static Ricardian model of trade, allowing me to study the effects of changes in transport costs on trade flows and welfare.

4 Ricardian Model with Multiple Modes of Transport

To understand the general equilibrium effect of transport mode substitution, I combine a discrete choice model with a Ricardian trade model. I build on a standard multi-country trade model, based on Eaton and Kortum (2002), which governs global trade flows, wages, and prices. The discrete choice model of transport modes determines the equilibrium share of each mode in bilateral trade and produces a transport price index. This index is then used as an iceberg cost in the trade model.

In this section, I introduce a model in which substitution is freely allowed and does not affect prices, to build the intuition behind the new mechanism. In Section 5, I will introduce congestion costs, which cause transport costs by mode to respond to changes in transport mode.

4.1 Setup

Consider an economy of $n = 1, ..., N$ countries. Each country is endowed with L_n unit of labor which is supplied inelastically and is allocated between manufacturing and non-manufacturing sectors. I assume that workers can freely move across sectors but migration to other countries is not allowed. Furthermore, I assume that there is a continuum of goods $u \in [0, 1]$ and perfect competition in each market. Consumers in country n maximize the following constant elasticity of substitution (CES) utility function:

$$U_n = \left(\int_0^1 Q_n(u)^{(\sigma-1)/\sigma} du \right)^{\sigma/(\sigma-1)}, \tag{6}$$

production combines labor and intermediates output with the former having a constant share of expenditure β. Moreover, I assume the presence of a non-tradable sector that is combined with manufacturing production to create the final consumption good using a Cobb-Douglas function in which the share of total expenditure for the tradable good is α. Similarly to Dekle et al.

[30] In trade literature, it is well-established that general equilibrium effects are important when analyzing changes in trade costs (Head and Mayer, 2014).

(2007), I define the exogenous deficit in manufacturing as the difference between production and imports: $D_n^{Ma} = X_n^{Ma} - Y_n^{Ma}$ while the overall, exogenous, trade deficit is defined as $D_n = X_n - Y_n$.

I extend the standard Ricardian models of trade by assuming the existence of $m = 1, ..., M$ distinct modes of transport. Let d_{ni}^m denote the iceberg trade costs for transporting goods from origin $i \in N$ to destination $n \in N$ using mode $m \in M$. Different costs by mode for the same origin-destination-product are often found in the data (Hummels, 2007). For instance, air transport is faster than sea shipping but incurs higher per-unit costs.

In the model, I assume a two-step decision process for consumers in each country. First, buyers select the source destination for goods, followed by the choice of transport mode. In making the first decision, consumers compare factory-gate prices and transport cost indices across all origins. Once the origin is chosen, consumers then select the mode of transport.

A key assumption throughout this paper is that factory-gate prices are independent of the transport mode. Specifically, producers are assumed to set prices based only on their productivity. Transport costs, which are borne by the importer, do not influence this pricing decision.[31] Another important assumption is the simultaneous availability of all modes without capacity constraints.This allows for the application of a discrete choice model, where the share of each mode is always positive. While this assumption may seem strong, empirical evidence suggests that many goods exhibit positive trade shares for both air and sea transport (see for example Figure 3).

I make a series of simplifying assumptions to focus on the substitution mechanism. First, I assume that all transport costs are mode-specific.[32] Second, I assume that all modes are equally substitutable among themselves.[33] I abstract from congestion costs; however, in Section 5, I develop an extension where the costs of a mode are endogenous to the share of trade and depend on the infrastructure available in the origin and destination countries.[34] Additionally, the transport sector is assumed to operate under perfect competition. This simplifies the model and allows focus on the primary mechanism of substitution between transport modes. Market power in transportation, which would introduce additional trade frictions, is excluded from this analysis, though it is an area the trade literature has recently begun to explore (Hummels et al., 2009; Asturias, 2020; Ignatenko, 2020).

This approach is similar to that of Allen and Arkolakis (2022), who address the problem of consumers choosing among multiple routes. There are two key distinctions between their work and the present study. First, they assume a countably infinite set of routes, while this model considers a finite, small number of transport modes. Additionally, in this model, the elasticities

[31] This assumption is commonly adopted in trade models, allowing trade costs to be expressed as a percentage of the total value of the good. In this framework, I extend this concept by proposing that the same principle applies to transport costs by mode.

[32] I will show that costs common across transport modes, such as tariffs, have no impact on the share of each mode.

[33] This assumption is supported by my empirical findings in the previous section on air and sea transport.

[34] I assume that all countries have sufficient infrastructure to accommodate trade flows by each possible mode. This is a common assumption in trade models where no capacity constraints exist. Rich et al. (2011) notes that structural rigidities can affect the substitutability of transport modes.

of substitution between locations (countries of origin) and routes (modes of transport) differ, and a methodology is provided to estimate the latter. Allen and Arkolakis (2014) use a discrete choice model to infer the relative geographic trade costs of each available mode (excluding air transport) in the United States. In contrast, this paper directly models the choice of transport mode. In Appendix G.3, I show that this nested structure for transport costs by mode can be applied to any model included in the "universal gravity" framework introduced by Allen et al. (2020). Fuchs and Wong (2024) adopt a similar way of modelling trade flows and the choice of the transport mode, but they study intra-country trade and substitution between rail and road transport.

4.2 Discrete Choice Model of Transport Modes

Assume that in each country, n, there is a continuum of importers. Conditional on choosing origin i to buy goods from, they need to choose across M modes of transport. I follow Anderson et al. (1987) to show that a CES demand function for transport can be derived via a nested logit model with a deterministic second stage.

In Appendix G.1, I solve the discrete choice problem to show that the price index faced by importers in country n when importing goods from origin i is given by:

$$p_{ni} = \left(\sum_{m=1}^{M} (p_{ni}^m)^{1-\eta} \right)^{1/(1-\eta)} = p_i \left(\sum_{m=1}^{M} (d_{ni}^m)^{1-\eta} \right)^{1/(1-\eta)} = p_i d_{ni}, \tag{7}$$

where I obtained the last part by substituting the definition of price by mode and exploiting the fact that the price index is homogeneous of degree 1.[35] In equation (7) it is possible to recognize that d_{ni} is the iceberg costs that are commonly used in the literature. I therefore call:

$$d_{ni} = \left(\sum_{m=1}^{M} (d_{ni}^m)^{1-\eta} \right)^{1/(1-\eta)}, \tag{8}$$

the transport costs index that will be paid when importing goods to country n from origin i.

This is the equivalent of the usual iceberg costs that are used in quantitative models of trade; the difference lies in the fact that in my model they are derived by aggregating costs by mode. I can therefore use d_{ni} as the relevant price that importers use in making their decision of where to source goods from. This will allow me to exploit a series of very well-established results in the literature while introducing an additional margin of adjustment. As mentioned before, I am assuming that there are no country-pairs additional costs, e.g. tariffs (τ_{ni}), however, if we want to include them in the price index (7) we would simply have $p_{ni} = p_i \tau_{ni} d_{ni}$.[36]

Finally, this demand system implies that the share of trade by mode between two countries

[35] Here we can see how the assumption that prices are independent of the transport mode is crucial since it allows us to treat prices as constant. I can then write: $p_i^m = p_i \; \forall \; m \in M$

[36] For the rest of the paper I will assume, $\tau_{ni} = 1$. Since later I solve the model in changes, all the constant variables are dropped so to assume a fixed level of tariffs or no tariffs is equivalent.

is given by:

$$\pi_{ni}^{m} = \frac{(d_{ni}^{m})^{1-\eta}}{\sum_{k}(d_{ni}^{k})^{1-\eta}} = \frac{X_{ni}^{m}}{X_{ni}}, \tag{9}$$

where X_{ni}^{m} is the value imported by n from i by mode m, X_{ni} is the total value imported, and η represents the elasticity of substitution between transport modes within country pairs. Given the assumptions of the CES demand system, we have the restriction that $\eta > 1$.

4.2.1 Elasticity of Substitution

Starting from equation (9) we can see that the share of trade by mode between two country pairs is a function of the relative trade costs by mode and the parameter η that governs the elasticity of substitution between transport modes. Therefore it is possible to interpret the Wald-DiD estimator results presented in the previous section as a structural parameter of the model. The estimated coefficient β_{DiD} can be then used to recover the underlying value of η. To see this, take logs of (9) to obtain:

$$\ln\left(\frac{X_{ni}^{m}}{X_{ni}}\right) = (1-\eta)\ln\left(\frac{d_{ni}^{m}}{d_{ni}}\right),$$

then, taking ratios between two generic modes m and s we obtain the model equivalent of equation (2):

$$\ln\left(\frac{X_{ni}^{m}}{X_{ni}^{s}}\right) = (1-\eta)\ln\left(\frac{d_{ni}^{m}}{d_{ni}^{s}}\right),$$

then, $(1-\eta)$ corresponds to the change in share of trade by mode for a given increase in the costs of that mode, which is exactly the same interpretation of the Wald-DiD estimator presented before. The value of the elasticity that I found using the increase in transport costs due to the Russian-Ukrainian conflict and the US West Coast port congestion is $\eta = 1.58$ and $\eta = 2.31$ respectively. Therefore, the model implies that the elasticity of substitution between transport modes is $\eta = 1 + \beta_{Did} \in (2.58, 3.31)$.

4.3 Production and Trade

The rest of the model is structured as a standard Ricardian model of trade based on Eaton and Kortum (2002). I assume that manufacturers' productivity in country n to produce a good u is $z_n(u)$. As common in these models, I assume that the efficiency of production is the realization of a random variable Z_n which is independently distributed across origins and takes the form of a Fréchet (Type II extreme value) distribution. In country n, the cost of an input is then $c_n = w_n^{\beta} p_n^{1-\beta}$. Where w_n and p_n are, respectively, the wage level and the price index in country n.

Each country sources goods from the cheapest location; thus, given the productivity distributions across nations, the price index in a location n is given by:

$$p_n = \gamma \phi_n^{-1/\theta} = \sum_{i=1}^{N} A_i (c_i d_{ni})^{-\theta}, \tag{10}$$

where A_i is the technology level, d_{ni} is the transport costs index, and θ is the shape parameter of the Fréchet distribution, which is also the elasticity of aggregate trade flows with respect to aggregate trade costs.

Given the price index in each location, the share of goods that country n buys from country i is given by:

$$\pi_{ni} = \frac{X_{ni}}{X_n^{Ma}} = \frac{A_n(w_n^{\beta} p_n^{1-\beta} d_{ni})^{-\theta}}{\Phi_n}. \tag{11}$$

4.4 Market Clearing

To close the model, the last ingredient needed is that the budget constraint condition is satisfied in equilibrium. To be closer to what is observed in the data, I assume that each country has a deficit D_n and D_n^{Ma}. I follow the national accounting in Dekle et al. (2007), and I define the GDP as $Y_n = w_n L_n$, while the gross production of manufacturing goods as $Y_n^{Ma} = X_n^{Ma} - D_n^{Ma}$. Since manufactures are used as the input both for production and final demand, I can write the demand for manufacturing goods as $X_n^{Ma} = \alpha_n X_n + (1-\beta_n) Y_n^{Ma}$, where α_n is the share of manufactures in the final demand and X_n is the final absorption.

The market clearing condition imposes that final absorptions and production equal in equilibrium:

$$Y_n^{Ma} = \sum_{i=1}^{N} X_{ni} = \sum_{i=1}^{N} \pi_{in} X_i^{Ma},$$

solving for manufacturing production and balance trade the final budget constraint is:[37]

$$w_n L_n + D_n - \frac{1}{\alpha} D_n^{Ma} = \sum_{i=1}^{N} \pi_{ni} \left[w_i L_i + D_n - \frac{1-\beta}{\alpha} D_n^{Ma} \right]. \tag{12}$$

4.5 General Equilibrium

Equation (6) tells that the final utility in country n depends on the consumption of each good u. We know that each good u can be sourced by the destinations with lower prices; therefore, we can rewrite the utility as a function of the quantity imported from each origin:

$$U_n = \left(\int_0^1 \left[\sum_{n=1}^{N} q_{ni}(u) \right]^{\frac{\sigma-1}{\sigma}} du \right)^{\frac{\sigma}{\sigma-1}},$$

now it is possible to insert in this equation the lower nest defined by equation (37) which regulates how quantities by origins are transported via different modes.

$$U_n = \left(\int_0^1 \left[\sum_{i=1}^{N} \left(\sum_{m=1}^{M} (q_{ni}^m)^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}} \right]^{\frac{\sigma-1}{\sigma}} du \right)^{\frac{\sigma}{\sigma-1}}, \tag{13}$$

[37] see Dekle et al. (2007) for an explicit derivation of the budget constraint

then given the technology, A, deficits, D, D^{Ma}, labour endowments, L and transport costs, d^m_{ni}, an equilibrium is a vector of prices, p, and wages w that satisfies the following system of equations:

share of expenditure

$$\pi_{ni} = \frac{X_{ni}}{X_n} = \frac{A_n \left(d_{ni} w_n^{\beta} p_n^{1-\beta}\right)^{-\theta}}{\sum_{h=1}^{N} A_h \left(d_{nh} w_h^{\beta} p_h^{1-\beta}\right)^{-\theta}},$$

price index

$$P_n = \left[\sum_{i=1}^{N} A_i \left(d_{ni} w_i^{\beta} p_i^{1-\beta}\right)^{-\theta}\right]^{-1/\theta},$$

share of mode m between importer n and exporter i

$$\pi^m_{ni} = \frac{X^m_{ni}}{X_{ni}} = \frac{(d^m_{ni})^{1-\eta}}{\sum_{m=1}^{M} (d^m_{ni})^{1-\eta}},$$

transport cost index between importer n and exporter i

$$d_{ni} = \left[\sum_{m=1}^{M} (d^m_{ni})^{1-\eta}\right]^{1/(1-\eta)},$$

and a market clearing condition

$$w_n L_n + D_n - \frac{1}{\alpha} D_n^{Ma} = \sum_{i=1}^{N} \pi_{ni} \left[w_i L_i + D_n - \frac{1-\beta}{\alpha} D_n^{Ma}\right].$$

Note that the usual assumption on parameters that require $\theta > \sigma$ is still required to derive the share of π_{ni}. In addition, given the choice mode, we also have the additional restriction that $\eta > \sigma$. However, there is no restriction on the relationship between θ and η. This stems from the assumption that factory gate prices are independent of the transport mode used to import goods so that when the origin is chosen the transport costs are already determined.

4.6 Response to Shock

The model has the common gravity structure that is usually obtained in the literature. Following Eaton and Kortum (2002) the gravity equation can be written as:

$$X_{ni} = \gamma^{-\theta} X_n Y_i d_{ni}^{-\theta} (P_n \Omega_i)^{\theta},$$

where now θ is the elasticity of trade flows with respect to changes in aggregate trade costs. I can then substitute the new definition of trade costs introduced above $\left(d_{ni} = (\sum_1^M (d^m_{ni})^{1-\eta})^{1/(1-\eta)}\right)$ to obtain:

$$X_{ni} = \gamma^{-\theta} X_n^{Ma} Y_i^{Ma} d_{ni}^{-\theta} (P_n \Omega_i)^{\theta},$$

finally, we can take logs to obtain the classic log-linear version of the gravity equation:

$$\ln X_{ni} = -\theta \ln \gamma + \ln X_n^{Ma} + \ln Y_i^{Ma} - \theta \ln d_{ni} + \theta \ln P_n + \theta \ln \Omega_i, \tag{14}$$

$$\ln X_{ni} = -\theta \ln \gamma + \ln X_n^{Ma} + \ln Y_i^{Ma} - \frac{\theta}{1-\eta} \ln \left(\sum_{m=1}^{M} (d_{ni}^m)^{1-\eta} \right) + \theta \ln P_n + \theta \ln \Omega_i. \tag{15}$$

Let's consider a shock to the transport network for a single mode, $s \in M$. In my model, this shock leads to an increase in d_{ni}^s for each country pair. Conversely, in a single-mode model, this shock would result in an increase in bilateral iceberg costs for each country pair, d_{ni}. To demonstrate that the loss in welfare is smaller in my model, I calculate the elasticity of trade flows for both models in response to a change in trade costs and compare the results. In an EK-style model, the change is equal to $-\theta$, as can be seen by taking the derivatives of equation (14). In my model, however, we must take the derivative of equation (15) with respect to $\ln d_{ni}^s$. Therefore, the elasticity of trade flow with respect to a change in costs for a single mode of transport is:

$$\frac{\partial \ln X_{ni}}{\partial \ln d_{ni}^s} = -\theta \frac{(d_{ni}^s)^{1-\eta}}{\sum_{m=1}^{M} (d_{ni}^m)^{1-\eta}} = -\theta \pi_{ni}^s > -\theta, \tag{16}$$

I can now compare the two responses to demonstrate that the elasticity of trade flows with respect to a trade shock on iceberg costs is smaller when multiple modes of transport are introduced. Using equation (9), it is clear that the response in (16) is always larger (closer to zero) than $-\theta$. Additionally, note that equation (16) depends on the value of η. This implies that, once multiple sectors are introduced, welfare gains or losses will vary depending on the substitutability of each good across transport modes.

An implication of this modified gravity equation is that when trade cost changes are mode-specific, the resulting change in aggregate trade will depend on the initial share of the affected mode. In practice, this introduces non-constant elasticities of aggregate trade flows with respect to mode-specific transport costs, which vary depending on the initial level of trade between country pairs. Consequently, even homogeneous shocks across country pairs can produce heterogeneous impacts.

However, for any cost shifter common to all modes—such as a bilateral tariff between countries—the response will mirror that of the standard gravity model. Moreover, this result suggests that estimating the trade elasticity θ using mode-specific transport costs could result in biased estimates.

4.7 System in Changes

To calculate the welfare change from a change in transport costs for a single mode I can apply the exact algebra approach introduced by Dekle et al. (2007). To do so, I assume that technology (A), labour (L), and aggregate deficits (D, D^{Ma}) across countries are constant. Further, I assume that the shocks come from a change in transport costs for a generic mode $s \in M$. I define a variable in changes as $\hat{x} = x'/x$, where x' is the after-shock value and x is the before-shock value.

The equations for the trade share between two countries, the price index and the market clearing conditions can be written in changes as follows:

$$\hat{\pi}_{ni} = \frac{\left(\hat{d}_{ni}\hat{w}_i^{\beta}\hat{p}_i^{1-\beta}\right)^{-\theta}}{\sum_{h=1}^{N}\pi_{nh}\left(\hat{d}_{nh}\hat{w}_h^{\beta}\hat{p}_h^{1-\beta}\right)^{-\theta}} \tag{17}$$

$$\hat{P}_n = \left[\sum_{i=1}^{N}\pi_{ni}\left(\hat{d}_{ni}\hat{w}_i^{\beta}\hat{p}_i^{1-\beta}\right)^{-\theta}\right]^{-1/\theta} \tag{18}$$

$$\hat{w}_n Y_n + D_n - \frac{1}{\alpha}D_n^{Ma} = \sum_{i=1}^{N}\frac{\pi_{ni}\left(\hat{d}_{ni}\hat{w}_i^{\beta}\hat{p}_i^{1-\beta}\right)^{-\theta}}{\sum_{h=1}^{N}\left(\pi_{nh}\hat{d}_{nh}\hat{w}_h^{\beta}\hat{p}_h^{1-\beta}\right)^{-\theta}}\left[\hat{w}_n Y_n + D_n - \frac{1-\beta}{\alpha}D_n^{Ma}\right] \tag{19}$$

The crucial variable through which the shock propagates in the economy is the aggregate trade costs between countries $\hat{d}_{ni}$.

Proposition 1. *For a change in transport costs for mode $s \in M$, between countries n and i. The change in the transport index is:*

$$\hat{d}_{ni} = \left[1 + ((\hat{d}_{ni}^{s})^{1-\eta} - 1)\pi_{ni}^{s}\right]^{1/(1-\eta)}. \tag{20}$$

Proof. See Appendix G.2

I can therefore calculate the change in aggregate trade costs without needing to know the initial level of transport costs by mode, d_{ni}^{m}, or the aggregate ones, d_{ni}. Interestingly, the change in aggregate trade costs by country pairs differs across nations even when the cost by mode is equal for all routes. This is because the final change depends on the pre-shock share of the mode used. In this sense, we can interpret the share as a measure of exposure to shock by each mode. Intuitively, the more a mode is used along a route, the more that pair is exposed to an increase in transport costs. These differential effects may be of interest as they may enhance cross-country differences. For example, developing nations rely more on trade by sea; therefore, an increase in sea trade costs will disproportionately affect economies that are already more fragile.

Proposition 2. *For $\eta > 1$, $\hat{d}_{ni}^{m} > \hat{d}_{ni} > 1$ if and only if $\hat{d}_{ni}^{m} > 1$*

Proof. See Appendix G.2.1

Proposition 3. *For $\eta > 1$, $\hat{\pi}_{ni}^{m} < 1$ if and only if $\hat{d}_{ni}^{m} > 1$*

Proof. See Appendix G.2.2

Propositions 2 and 3 imply that an increase in transport costs for a mode m between two countries n and i translates into a higher transport index, d_{ni}, and into a lower share of mode m,

π^m_{ni}, between the two countries. Instead,for the modes that are unaffected, the share will go up:

$$
\begin{aligned}
\hat{\pi}^s_{ni} &= \frac{\pi'^s_{ni}}{\pi^s_{ni}} \\
&= \frac{(d^s_{ni})^{1-\eta}}{d'^{1-\eta}_{ni}} \frac{d^{1-\eta}_{ni}}{(d^s_{ni})^{1-\eta}} \\
&= \frac{1}{\hat{d}^{1-\eta}_{ni}} > 1 \qquad \iff \qquad \hat{d}_{ni} > 1
\end{aligned}
$$

which again follows from Proposition 2.

These results imply that when a mode is affected by a shock, the share of trade via that mode will decrease, while the share of trade via other modes will increase. In addition, total transport costs will rise, which will further suppress trade. However, compared to a world without substitution across modes, the decrease in trade will be smaller. This mechanism aligns with the findings I presented in the empirical section regarding the Russian-Ukrainian conflict and the consequent sanctions.

Finally, I can also derive the welfare changes that are given by the change in the own trade share as common in this class of models (Arkolakis et al., 2012).

$$GT = \hat{\pi}_{nn}^{(\frac{1-\alpha}{\beta})(-\frac{1}{\theta})} \tag{21}$$

Note that the welfare formula does not change as the trade mechanism of the model is the same as the standard quantitative models of international trade.

5 Model with Congestion

In this section, extend the baseline model by introducing mode-specific congestion costs. In this new specification, transport costs are now determined by the demand for each transport mode between two countries. In the baseline specification of my model, I assumed that trade could be freely relocated between different transport modes. This is a strong assumption that may not hold in reality. The underlying intuition is that congestion will partially counteract the scope for substitution, as transport modes become more costly the more they are used.

Once I allow for mode-specific congestion costs, the transport index between two countries, d_{ni}, will now become an endogenous outcome of the model, based on the exogenous iceberg costs by mode and the endogenous level of trade between the two commercial partners. This adds an additional mechanism of adjustment to the model that is not present in the standard quantitative models of international trade. However, a richer model comes at the cost of a more complex system of equations to solve for.

In this section, I will show a stylized way to introduce congestion and a method to rewrite the equilibrium equations in changes, ensuring that the data requirements for the counterfactual remain the same as in the baseline under a set of reasonable assumptions.

5.1 Endogenous Transport Index with Congestion

Consider again an economy in which multiple modes of transport are available between each country pair. I assume the presence of mode-specific transport costs, d_{ni}^m, between countries i and n. However, the price now depends on a fundamental component, δ_{ni}^m, and a congestion component, Ξ_{ni}^m.

I model the congestion component Ξ_{ni}^m as having two elements. The first element is a function of the total value of trade by mode m between i and n which I write as $(X_{ni}^m)^\lambda$, with $0 < \lambda < 1$. The parameter λ is a measure of the sensitivity of the congestion costs to the level of trade. The higher λ is, the more trade costs will react to changes in trade flows by mode between country pairs. The second element is a function of a pair-mode specific component that intuitively can be thought of as the capacity, and/or quality, of the infrastructure that is used to transport the goods, which I define as $I_{ni} = I_n \times I_i$. This approach is akin to the one used in recent spatial models. (Fajgelbaum and Schaal, 2020; Allen and Arkolakis, 2022; Fuchs and Wong, 2024). The total costs of moving a good with mode m from country i to country n is then given by:

$$d_{ni}^m = \delta_{ni}^m \Xi_{ni}^m = \delta_{ni}^m \frac{(X_{ni}^m)^\lambda}{I_n I_i}, \tag{22}$$

where δ_{ni}^m is defined as the iceberg costs for mode m between i and n and d_{ni}^m is now the total costs to move goods with mode m. The mode-specific iceberg costs, δ_{ni}^m, can be thought of as all those pair-specific characteristics that affect costs other than infrastructure and congestion which are assumed exogenous to the economy.

For the rest of the paper, I will assume that infrastructure's capacity and quality are constant across countries and modes. This is a strong assumption that may not hold in reality. However, it is a reasonable starting point to understand the effect of congestion on the welfare of the countries.[38] At the end of this section, I will show that the level of infrastructure is not needed to calculate the counterfactuals in changes once it is assumed to be constant.

5.2 Discrete Choice Model with Congestion

As in the previous section, assume that in each country, n, there is a continuum of importers. Conditional on choosing origin i to buy goods from, they need to choose across M modes of transport. The main distinction is now that the costs of the mode are endogenous and depend on the level of trade. Since I am assuming that all importers have no impact on the market, I assume that congestion costs are externalities that importers take as given when choosing the mode.

The price index from the discrete random choice mode, which corresponds to the transport

[38] To add the endogenous choice of investment in infrastructure would increase the complexity of the problem and would require a more dynamic setting that is outside the scope of this current work.

costs index in the upper nest, is now given by:

$$d_{ni} = \left(\sum_{m=1}^{M} (d_{ni}^{m})^{1-\eta} \right)^{1/(1-\eta)} = \left(\sum_{m=1}^{M} (\delta_{ni}^{m})^{1-\eta} (\Xi_{ni}^{m})^{1-\eta} \right)^{1/(1-\eta)}, \tag{23}$$

and accordingly, now the share of mode s between importer i and exporter j is given by:

$$\pi_{ni}^{m} = \frac{(d_{ni}^{s})^{1-\eta}}{\sum_{m=1}^{M} (d_{ni}^{m})^{1-\eta}} = \frac{(\delta_{ni}^{s})^{1-\eta} (\Xi_{ni}^{s})^{1-\eta}}{\sum_{m=1}^{M} (\delta_{ni}^{m})^{1-\eta} (\Xi_{ni}^{m})^{1-\eta}}. \tag{24}$$

The main difference with the previous section is that now the share of mode used by each importer is a function of the level of trade and the difference in costs between the modes.

5.3 General Equilibrium with Congestion

With congestion, the transport index between two countries i and n, d_{ni}, is now an endogenous outcome of the model. However, the equilibrium system of equations is still the same as in the previous section. The only difference is that now d_{ni} is jointly determined with the wages and the price indexes in each country.

Consequently, the equilibrium is now a vector of prices, p, wages w, and transport costs, d, that satisfies equations (9)-(11)-(12)-(24).

5.4 System in Changes with Congestion

Similarly to the previous section, I can apply the exact algebra to simplify the equilibrium equations by eliminating all the variables that are not affected by the change in trade costs. To do so, I assume that technology (A), labour (L), deficits (D, D^{Ma}), and infrastructure (I) across countries are constant. Further, I assume that the shocks come from a change in transport costs for a generic mode $s \in M$. I define a variable in changes as $\hat{x} = x'/x$, where x' is the after-shock value and x is the before-shock one.

The main difference comes from the fact that now a change in costs for mode s will change the relative prices of the remaining modes via readjustment in the share of each mode used. In Appendix G.4 I show that the final effect on the transport index of a change $\hat{\delta}_{ni}^{s}$ can be written as:

$$\hat{d}_{ni} = \left[1 + \left((\hat{\delta}_{ni}^{s} (\hat{X}_{ni}^{s})^{\lambda})^{1-\eta} - 1 \right) \pi_{ni}^{s} + \sum^{-s} \pi_{ni}^{m} \left((\hat{X}_{ni}^{m})^{(\lambda)(1-\eta)} - 1 \right) \right]^{1/(1-\eta)}, \tag{25}$$

which requires information only on the pre-shock share of trade flows by mode between each importer and exporter. This is a key result as it implies that the data requirements for the counterfactual are the same as the baseline under a set of reasonable assumptions.

There are two key distinctions concerning the baseline scenario. First, now we have an additional parameter λ that measures the sensitivity of the congestion costs to the level of trade that needs to be estimated. Second, the final change in the transport index is determined jointly with the level of prices and wages in each country, equations (9)-(11)-(12). In Appendix G.5 I discuss the algorithm to solve for the general equilibrium in changes.

5.5 Treat on Identification due to Congestion

Since congestion affects the ability of agents to substitute it can also affect the interpretation of the parameter estimated in the previous section. Within this framework, I show that the share of each mode can be determined using equation (24). As a consequence, congestion costs could change the interpretation of the elasticity parameter, η, recovered in the previous section using equation (9).

However, the distortion introduced by congestion costs will downward bias the elasticity of substitution between modes. In fact, the congestion costs will make the mode that is used more expensive, and therefore less used, while the other modes will be used more. This will lead to a lower elasticity of substitution between modes. It is also possible to show this analytically by taking the ratio of equation (24) between two generic transport modes m and s by bringing the flows by transport mode on the right-hand side:

$$\ln\left(\frac{X_{ni}^m}{X_{ni}^s}\right) = \frac{1-\eta}{1-\lambda(1-\eta)} \ln\left(\frac{d_{ni}^m}{d_{ni}^s}\right),$$

moreover, we can see that for values of λ close to zero the bias will disappear. Since a value approaching zero for the congestion parameter is usually found in the literature (Allen and Arkolakis, 2022; Fuchs and Wong, 2024) I believe that the parameter identified is a good approximation of the true elasticity of substitution or at least a lower bound.

Using the estimated values, β_{did}, in the previous section and the congestion strength $\lambda = 0.092$ (Fuchs and Wong, 2024), we get values for the elasticity of substitution between modes, once congestion is taken into account, of $\eta \in (2.78, 3.96)$. [39]

6 Taking the Model to the Data

Two fundamental parameters in this model regulate how trade cost shocks are propagated: the elasticity of trade flows, θ, and the elasticity of substitution between modes of transport along the same route, η. Regarding the former, there exists extensive literature in international trade that addresses the challenges of recovering a reasonable estimate (Head and Mayer, 2014). Since the focus of this work is on substitutability across modes of transport, I chose to set $\theta = 4$.

On the other hand, there is little evidence on the elasticity of substitution across modes of

[39]To see this just solve for:

$$\hat{\beta}_{Did} = \frac{1-\eta}{1-\lambda(1-\eta)} \quad \rightarrow \quad \eta = 1 - \frac{\hat{\beta}_{Did}}{1+\hat{\beta}_{Did}\lambda}$$

transport in international trade. I estimate this parameter using the airspace closure, air to sea, and using congestion in ports, sea to air, and I find that the elasticity of substitution between modes of transport is between 1.58 and 2.31. I set it to be $\eta = 3$ as my baseline value. To calibrate the rest of the model, I need data on trade by transport mode between countries, GDP, and trade balances.

The choice of the sample is driven by the availability of data on trade flows by mode of transport between country pairs. I collect them from various sources: European data are collected from Eurostat, US data are taken from the US Census Bureau, Japan data are taken from the Japan Customs Authority, ASEAN members' data are taken from the ASEAN Secretariat, and Latin America and the Caribbean data are taken from the Inter-American Development Bank (IDB). I am also able to complement these datasets with ten more countries using trade flows by mode coming from the United Nations Statistical Division (UN Comtrade). A complete list of the countries used can be found in Table I.13. I aggregate the European Union into a single entity. So my final sample comprises 32 entities plus one that absorbs the rest of the world (RoW).

For all these countries, I use 2018 as the year of reference. However, for ASEAN countries, the only years available are 2021 and 2022, so I use the former as the year of reference for the share by mode. I use import-reported flows to build the import share by mode between these countries, and I use the export-reported flows to back out the share by mode for China and the RoW.[40]

Since most international trade, in terms of both value and quantity, is conducted via air and sea, I only keep these two modes of transport. Land trade is predominantly conducted between countries that share a border, so it generates many zero flows between country pairs that are not explained by the theory. Additionally, not all databases report trade via land, such as the US Census and Japan, which do not share a physical border with any of the countries in the sample. This is also why I chose to aggregate the European Union as a single block. In fact, most of the trade between the EU and the rest of the world is conducted via sea and air, while intra-EU trade is mostly conducted via land.

I only keep flows in the following ISIC3 sectors since they correspond to the trade in manufactures: *Chemicals* (23-24-25), *Food* (15-16), *Machines* (29-30-31-32-33), *Metals* (27-28), *Minerals* (26), *Other* (36), *Textiles* (17-18-19), *Vehicles* (34-35), and *Wood-Paper* (20-21-22). I make this choice so that I can use the same classification of goods used in the TradeProd (Mayer et al., 2023) database that reports internal trade flows.[41]

However, I use these datasets only to retrieve information on the share of each mode. To calculate aggregate trade flows, I use the UN Comtrade database. I do this to ensure homogeneity in the classification of goods, units of measurement, and partner countries. Since Comtrade does not always report internal trade, I use the TradeProd database to retrieve information on

[40] To include more countries in the sample it is also possible to predict the transport share based on observables like distance, GDP, contiguity, etc., as done in Shapiro (2016).

[41] Since in my source data, products are reported following the Harmonized System (HS) classification, I use the concordance tables from the UN WITS database to map between the two categorizations.

internal trade flows. Finally, I use the World Bank database to collect data on GDP while current accounts and deficits in manufactures are collected from the IMF. I use the UNCTAD database to gather data on the distance between country pairs by mode. Table I.12 provides a summary of the dataset used.

I assume that internal trade is carried out by a single mode that is not affected by the shock. I do not expect this additional margin to be particularly significant since internal trade is usually carried out via truck and/or train. It will matter however for the CO_2 calculation, in fact, I will not be able to calculate the impact of the rise in internal transport emissions.

Given the system in changes derived in the previous section, these are all the quantities required to calibrate the model. I then take α and β from Eaton and Kortum (2002). For the parameter that regulates the strength of congestion I pick $\lambda = 0.092$ from Fuchs and Wong (2024). While this parameter is derived from a spatial model and is based on congestion along roads, I believe it can serve as a good approximation for congestion in international trade. As a robustness check, I will show that qualitatively the results do not change for different values of λ.

7 Quantitative Experiments

This section uses the model to assess policy experiments highlighting transport mode substitution's role in transmitting cost shocks. I analyze welfare responses to transport cost increases, with and without substitution, to evaluate this adjustment's importance. I also show that substitution is important to study changes in emissions from the transport sector.

I start by studying two counterfactual scenarios: the closure of Russian-Ukrainian airspace and the closure of the Suez Canal.[42] These examples are an ideal setting for demonstrating the relevance of substitution because they affect a single transport mode at a time and illustrate how geopolitical events—becoming increasingly frequent—can significantly impact international trade via the transport sector.

Additionally, I show that studying substitution is not only relevant for welfare considerations but also crucial for understanding the carbon footprint of international trade. Transport-specific shocks affect the share of trade carried by each transport mode, which has a substantial impact on the sector's overall CO_2 emissions. To illustrate this, I assess the impact of a new International Maritime Organization (IMO) regulation aimed at reducing CO_2 emissions from sea transport. By mandating reduced vessel speeds, the policy decreases overall sea capacity and increases international sea costs.

For each experiment, I compare the results of the full model with endogenous transportation costs presented in Section 5 with the prediction of a model in which substitution is not allowed. In the appendix, I also present the results for the baseline model with no congestion. No substi-

[42]The first experiment is motivated by the war in Ukraine, which is referenced in the empirical section. However, here I abstract from other sanctions implemented during that period. The Suez Canal experiment is inspired by recent geopolitical instability in the Red Sea, which has significantly increased both journey length and transport costs.

tution is modelled by having Cobb-Douglas expenditure share for each mode between country pairs. The key equations of the model, both with and without congestion but incorporating Cobb-Douglas transport mode shares, are detailed in Appendices G.6 and G.7.

To compute aggregate emissions, I use the total weight traded as reported in the Comtrade database for all countries' flows. The average distance traveled is determined from the UNCTAD dataset. These two measures enable the calculation of aggregate CO_2 emissions by mode, using the modal production of CO_2 per tonne-kilometer from Shapiro (2016). The post-shock CO_2 emissions are calculated by assuming a constant weight-to-value ratio and using the average unit value between each country pair to convert post-shock values from dollars to tonnes. The same CO_2 production per tonne-kilometer is applied to estimate the new emission levels following the increase in sea transport costs.

It is important to note that, in this context, the reduction in CO_2 emissions stems solely from the decrease in trade due to increased transport costs. Therefore, it should be interpreted as the net change arising only from international transport. In practice, two additional factors are at play. First, higher transport costs lead countries to expand national production, increasing local CO_2 emissions. Second, increased domestic trade results in higher carbon emissions from internal transport (Shapiro, 2016; Copeland et al., 2022; Sogalla et al., 2024).

7.1 Impact of the Closure of the Russian and Ukrainian Airspace

The conflict in Ukraine caused a series of bilateral sanctions between Europe and Russia that included the closure of Russian airspace.[43] For the purposes of this exercise, I assume that the air route restrictions are the sole economic shocks affecting trade between Europe and Asia.[44] Consequently, the results presented here should be interpreted as the ceteris paribus effect of the airspace closure.

To quantify the magnitude of this impact, I use the coefficient of the average increase in flight time estimated in Section 3 using equation (1). This indicates an average increase in flight time of approximately 7.5% between European and Asian destinations. I assume that this corresponds to an equivalent increase in trade costs.

In the calibrated version of the model, the affected origins are: Brunei, China, Europe, Indonesia, Japan, Myanmar, Malaysia, Philippines, Singapore, Thailand, and Vietnam. As noted in the calibration section, Europe is treated as a single block to minimize zero trade flows and to allow for the assumption of frictionless trade between member states.

7.1.1 The Welfare Effects of Substitution

Table 3 presents the average welfare losses resulting from airspace closure for the set of countries directly affected by the shock. Table I.15 contains the detailed results for all the countries.

[43] for a more detailed description see section 3.1.

[44] Other sanctions more directly targeted economic activities, such as the ban on Russian oil and gas imports, which adversely affected the European economy and vice versa. However, since this paper focuses exclusively on transport shocks, I do not take them into consideration.

Table 3: Closure of Russian-Ukrainian Airspace: Average Welfare Changes Across Models

Model	No Substitution + Congestion	Substitution + Congestion
Avg Welfare change (%)	-0.055	-0.053 (+3.77%)

Notes: This table reports the average welfare change, in countries directly affected by the shock, across different models for the counterfactual that studies the permanent closure of the Russian and Ukrainian airspaces. The shock is modelled a as a 7.5% increase in air costs for routes connecting Europe with Asian destinations. Column 1 reports the average change for a model with congestion but no substitution (Section G.7). Column 2 reports the results for a model in which both congestion and substitution are present (Section 5). All the numbers are expressed in percentage change from the initial equilibrium.

Column 2 shows that welfare losses are smaller when we allow for substitution between transport modes. The ability to partially shift to alternative modes allows the recovery of around 4%, or 0.02 percentage points, of the welfare losses incurred by the increase in transport costs. While these numbers may appear small, they are in line with the magnitude of the effect of a major trade deal between developed economies (Caliendo and Parro, 2015, 2022). Therefore, even small changes in the percentage of welfare can have significant economic implications.

I find that the change in the ratio of trade flows by sea with respect to trade flows by air increased by around 15%. This is consistent with what was found in the empirical section, where I observed an average increase in the sea share of around 11% (Column (2) in Table 1). While the datasets on which the two exercises are performed differ, it is reassuring to see that the model can reproduce a magnitude similar to the effect observed empirically.

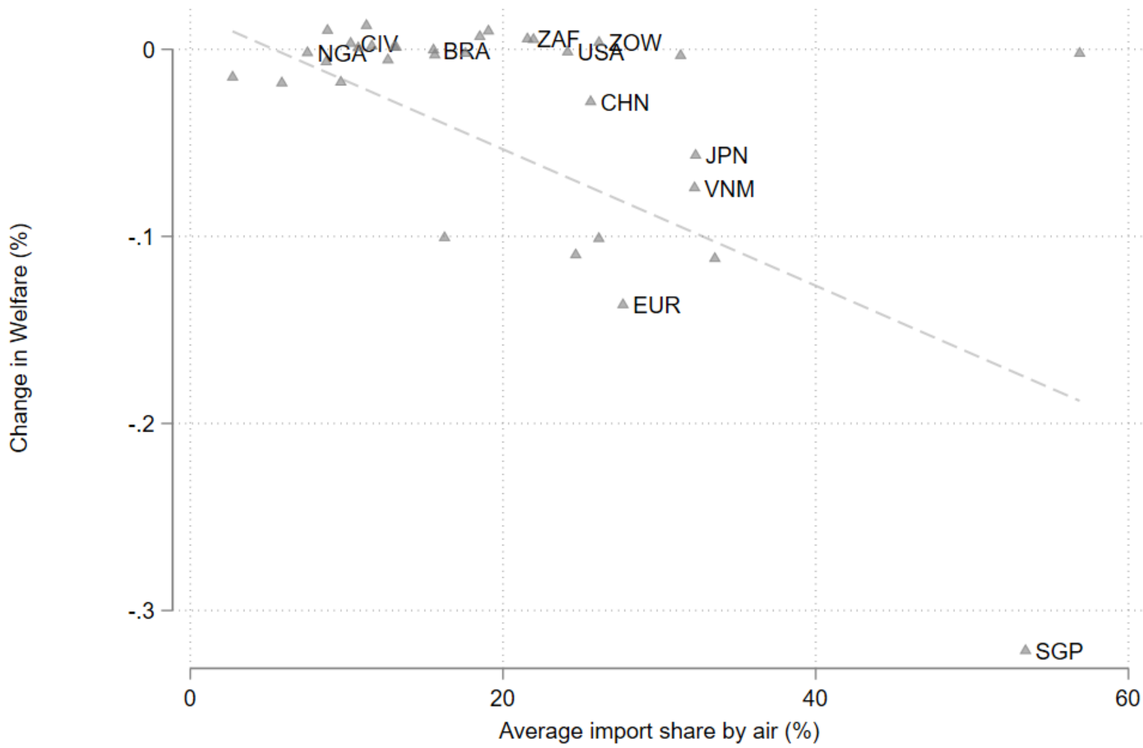
In Table I.14, I report the results for the model with no congestion. The gains from substitution are now higher (around 5%). Without congestion costs, the relative prices between modes do not change as agents start to switch to the cheaper mode. This leads to a larger increase in welfare. The average losses when congestion effects are not included are larger than in the baseline model. This is because the congestion channel affects not only substitution but also overall trade costs. As trade is decreased by the initial shock, the congestion costs are reduced, endogenously decreasing the trade costs between the affected countries.

Figure 7 illustrates how even a shock that is common across countries can have different impacts due to differential exposure to the shock. Countries that have a higher import share by air and are affected by the airspace closure suffer greater losses. We can see, for example, that Europe and Asia are the most affected regions.[45] Theoretically, this can be seen in equation (25), where the change in the bilateral trade cost is a function of the initial bilateral trade share by mode.

The heterogeneity in impact highlights the need for targeted and nuanced policy responses. For policymakers, it is important to consider the specific trade structure and modal dependencies of each country or region when designing mitigation strategies, sanctions, or negotiating trade agreements. Moreover, this differential exposure underscores the importance of diversifying trade routes and transport modes as a means of increasing economic resilience to future shocks,

[45] Singapore is the country that suffers the most due to its very high exposure to trade with Europe via air. However, this country is a crucial trade hub, so part of the trade reported could actually come from different nations.

Figure 7: Closure of Russian-Ukrainian Airspace: Change in Welfare and Air Share



Notes: This figure reports the welfare change by country caused by the closure of the Russian and Ukrainian airspaces. The results are for a model with substitution and congestion forces. The fitted line indicates that countries with a higher average import share by air that are exposed to the shock suffered greater losses. Countries' names are reported using the ISO3 code for the full names see Table I.13.

whether they are geopolitical, environmental, or technological in nature.

7.2 Permanent Closure of the Suez Canal

The Suez Canal is one of the major waterways on which the global trade system hinges, with approximately 20% of world sea trade flows passing through it.[46] This exercise is motivated by recent geopolitical events that have contributed to destabilizing the region.[47] In particular, a significant portion of sea trade routes has been diverted from their usual course and rerouted via the Cape of Good Hope, significantly increasing both the length of the journey and transport costs.

To quantify the increase in transport costs due to the closure of the Suez Canal, I use the estimates from Feyrer (2019), which calculate the increase in bilateral distance between country pairs due to the impossibility of passing through the channel. I calculate the percentage increase between country pairs and assume that transport costs increase accordingly, as I did for the closure of Russian airspace.

The shock is then modeled as an increase in sea costs, $\hat{d}_{ni}^{sea}$, which affects countries whose sea trade routes pass through the Red Sea. In my sample of countries, this represents an increase

[46]source Unctad (2024).

[47]The year 2024 saw an increase in attacks on sea carriers passing through the Strait of Hormuz.

Table 4: Closure of the Suez Canal: Average Welfare Changes Across Models

Model	No Substitution + Congestion	Substitution + Congestion
Avg Welfare change (%)	-0.587	-0.552 (+6.34%)

Notes: This table reports the average welfare change, in countries directly affected by the shock, across different models for the counterfactual that studies the permanent closure of the Suez Canal. Column 1 reports the average change for a model with congestion but no substitution (Section G.7). Column 2 reports the results for a model in which both congestion and substitution are active (Section 5). All the numbers are expressed in percentage change from the initial equilibrium.

in trade costs mostly between European and Asian/African countries. As a simplification, I assume the transport costs with the "rest of the world" block remain unchanged. As for all the counterfactuals, I assume that internal trade costs are constant.

7.2.1 The Welfare Effects of Substitution

The closure of the Suez Canal generates an average welfare change in the economy of -0.26% when I also allow for congestion. However, since the shock is localized to a subset of countries, the welfare changes are more pronounced in the affected regions. Table 4 reports the average welfare changes across different model specifications for the countries that are affected by the shock. Table I.16 contains the detailed results for all the countries.

The welfare losses are 6.34% lower when we allow for substitution between modes of transport. This is due to the fact that the substitution channel allows countries to partially offset the increase in transport costs by switching to other modes of transport.

As for the previous experiment, the introduction of congestion costs in the model further diminishes welfare losses, as trade diversions trigger a reduction in transport costs across all modes due to lower trade flows between the affected countries.[48]

Figure 8 illustrates the heterogeneous welfare changes across regions.[49] We can see that the regions that suffered the greatest losses due to the Suez Canal closure are Europe and Asia. Losses are greater in the model with no substitution, while the smaller effect is in the model in which both the congestion and the substitution channels are active.

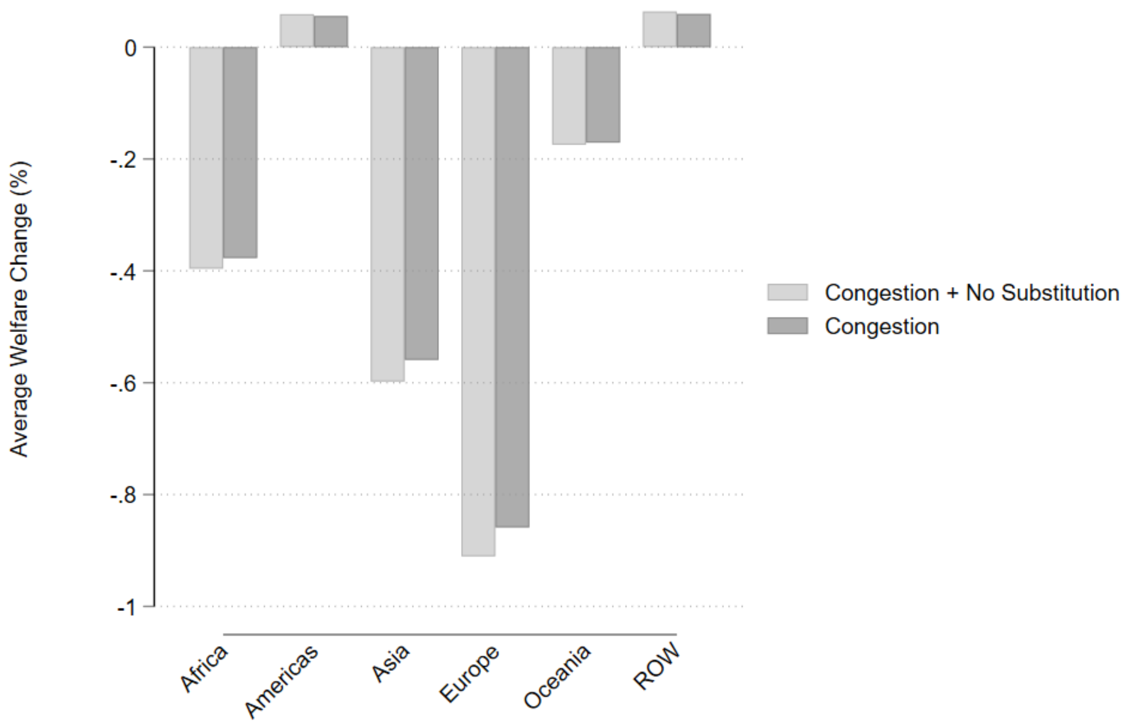
7.3 Substitution and Environmental policy: Impact of the IMO23

Substitution between transport modes in international trade affects not only welfare but also the environmental footprint of trade. Switching from a less polluting mode to a more polluting one increases the sector's overall emissions. Substitution can therefore significantly impact the effectiveness of environmental policies targeting the transport sector. To illustrate this additional margin, the last part of this paper examines the impact of the IMO23 regulation on the carbon footprint of international trade.

[48] See Table I.17 in the appendix for the results without congestion

[49] Since the shock is heterogeneous across countries the correlation with the exposure by mode is less clear. For more details see Figure H.8.

Figure 8: Impact of the Suez Canal Closure on Welfare by Region



Notes: This figure shows the results of the counterfactual that studies the permanent closure of the Suez Canal. It reports the average welfare change by region across the four model variants. We can see that the countries most affected are in Europe and Asia. Losses are smaller in the model with substitution thanks to the ability to switch to other modes of transport.

The IMO23 policy, introduced by the International Maritime Organization in July 2023, aims to reduce carbon emissions from sea trade (MEPC, 2023). It includes measures addressing ships' specific characteristics and carrier speeds. Lugovskyy et al. (2023) estimate that this measure likely causes an 8% decrease in shipping capacity across various countries, potentially increasing transport costs by the same magnitude. The authors also argue that this measure could lead to increased air transport usage, which, being more polluting, could potentially reverse the intended policy outcomes and increase total emissions. However, their model and applications consider only trade with the United States.

This experiment extends their analysis to a multi-country framework. Drawing on their findings, the IMO23 is modeled here as an increase in ocean transport costs due to capacity loss in the sector.[50] Furthermore, this study assumes that pollution is generated only through transport and not by production itself, a simplification compared to works such as Cristea et al. (2013) and Shapiro (2016).

I simulate the measure as a 10% increase in ocean transport costs, while the counterfactual CO_2 production level per tonne-kilometer is 7.3% lower for sea trade and unchanged for air trade.[51] The underlying assumption is that this analysis estimates the long-run impact of the

[50] This approach simplifies the overall policy impact to focus on its effect on modal shares.

[51] This figure is derived from Lugovskyy et al. (2023), which indicates it as the estimated fuel efficiency gain for the US.

Table 5: IMO23: Average Welfare and CO_2 Change Across Models

Model	No Substitution + Congestion	Substitution + Congestion
Avg Welfare change (%)	-1.950	-1.922 (+1.4%)
Avg CO_2 change (%)	-15.53	-12.01 (+29.4%)

Notes: This table reports the average changes in welfare and CO_2 across different models due to the introduction of the IMO23 regulation. The policy is simulated by increasing sea transport costs by 10% and by decreasing CO_2 emissions in sea transport by 7.3%. Column 1 reports the average change for a model with congestion but no substitution (Section G.7). Column 2 reports the results for a model in which both congestion and substitution are active (Section 5). All the numbers are expressed in percentage change from the initial equilibrium.

policy while holding infrastructure constant.

7.3.1 Impact on Welfare

Table 5 reports the average welfare change across different model specifications, confirming this effect in the present model. For detailed results by country, see Tables I.19 and I.20 in the appendix.

As before, substitution between transport modes mitigates welfare losses. However, the effect is less pronounced than in the previous examples, as the policy affects all countries, reducing the ability to find cheaper alternative partners. When comparing the numbers with a model without congestion, we can see that in this case, the latter has a larger effect on welfare. The global increase in costs reduces the trade flows across all country pairs, pushing down the demand for transport and its price (Table I.18).

Countries with higher reliance on sea trade before the cost increase are disproportionately affected. As shown in equation (20), a uniform cost increase across countries results in heterogeneous outcomes. Figure 9a illustrates this correlation by plotting welfare changes against the average import share by air.

Furthermore, since a higher share of sea transport negatively correlates with GDP,[52] the policy places a larger burden on more economically vulnerable nations (Figure 9b). In contrast, countries with a higher share of air trade experience a smaller welfare decline. Their limited exposure to the shock makes them relatively less expensive compared to their trading partners, enabling them to benefit more from international trade.

7.3.2 Effect on CO_2 Emissions from the Transport Sector

Changes in welfare are not the only aspect affected by substitution. The policy successfully reduces CO_2 emissions from the transport sector across all specifications, as shown in Table 5. Following the increase in sea costs, total emissions decreased by approximately 12.01%.

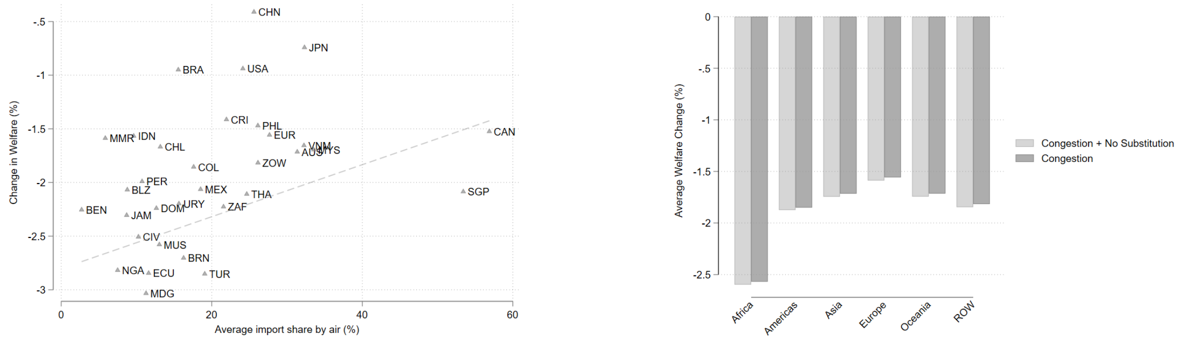
However, this reduction is primarily driven by the negative effect on trade volume rather than by making trade less polluting. Although substitution positively affects aggregate welfare by enhancing trade resilience, it negatively impacts emissions. Substitution decreases overall

[52] the correlation between GDP and the share of sea imports is approximately -0.50 in the sample

Figure 9: Impact of the IMO23 Regulation on Welfare

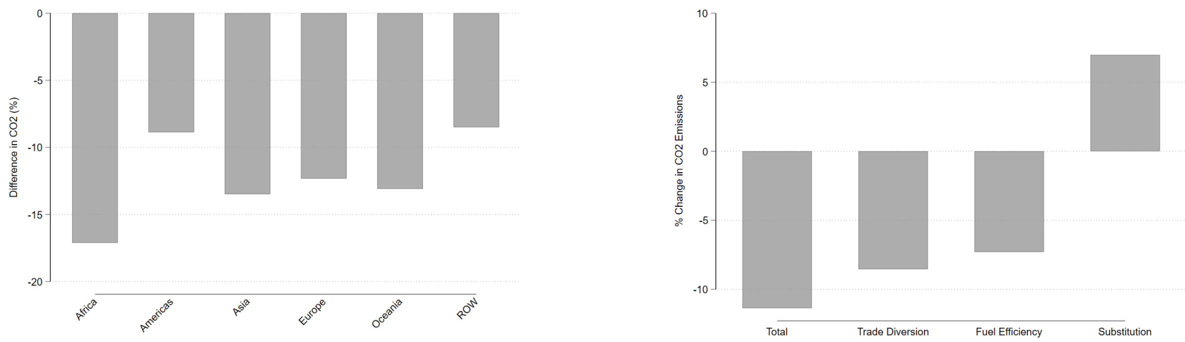
(a) Welfare Change and Air Share

(b) Welfare Change by Region



Notes: Panel (a) reports the welfare changes by country against the average import share by air.Welfare losses are decreasing with respect to the air share, since countries that rely more on ocean trade are more exposed to increases in sea costs. Panel (b) reports the average welfare change by region, substitution reduces welfare losses across all regions. However, some are more exposed to the measure given their pre-shock composition of trade by transport mode.

Figure 10: Impact of the IMO23 on CO_2 Emissions



(a) Change in Emissions by Region

(b) Decomposition of the Change in Emissions

Notes: Panel (a) reports the average change in CO_2 emissions by region. Panel (b) reports the decomposition of the change in CO_2 emissions by the different channels. The main takeaway is that substitution nearly entirely offsets the reduction in CO_2 emissions achieved through speed reduction and improved fuel efficiency.

policy efficiency by approximately 3.5 percentage points, or almost 30%, compared to a model with fixed shares. Notably, substitution nearly entirely offsets the reduction in CO_2 emissions achieved through speed reduction and improved fuel efficiency (Figure 10b).

The effect is asymmetric across countries due to varying degrees of exposure to the measure. Consistent with previous findings, countries with higher shares of air trade experience a smaller reduction in CO_2 emissions (Figure 10a). These results appear to contrast with those of Lugovskyy et al. (2023), who found that substitution forces in the United States are so strong that the policy increases emission levels. However, it is important to note that while their study delves more deeply into the technical details of the policy, the present analysis encompasses multiple countries, which may account for the divergence in results.

7.3.3 Sensitivity Analysis

Both substitution and congestion mechanisms contribute to mitigating welfare losses for nations more severely affected by increased sea costs. Tables I.21 and I.22 present sensitivity analyses of the results with respect to the elasticity of substitution and the congestion parameter, respectively. A higher elasticity of substitution (η) corresponds to lower welfare losses and higher CO_2 emissions, attributable to increased switching towards air trade. Similarly, a higher congestion parameter (λ) is associated with lower welfare losses and less CO_2 reduction, as trade flows demonstrate greater resilience to the shock under these conditions.

This study contributes to the trade literature by introducing substitution and congestion channels, which capture asymmetric effects absent in traditional models. These channels, alongside the standard trade diversion channel, reduce welfare losses in distinct ways. The substitution channel affects welfare by altering the relative share of each transport mode used, while the congestion channel influences welfare by changing transport costs for affected versus non-affected country pairs. By incorporating these two channels, we can observe more nuanced policy effects and examine a broader range of impacts not captured by standard trade models.

8 Conclusion

In this paper, I examine the relationship between changes in transport costs and changes in international trade patterns. In particular, I first look at the substitution between modes of transport in a reduced-form setting, using the closure of Russian airspace as a quasi-natural experiment. Second, I develop a Ricardian model of trade with endogenous transport costs which arise by including substitution between transport modes and congestion frictions. Finally, I use the model to quantify these additional margins of adjustment via three counterfactuals.

Using Eurostat data covering extra-European trade flows, I show that trade relies on multiple transport modes, even when accounting for origin-destination characteristics. Two main patterns emerge from the data: (1) over 50% of origin-destination-HS6 routes actively utilize at least two transport modes for trade, and (2) the share of each mode responds to changes in relative transport prices.

To identify the latter pattern, I exploit the Russian invasion of Ukraine as a quasi-natural experiment that caused an exogenous increase in air freight costs. The results show a significant increase in sea trade flows on affected routes, interpreted as evidence of substitution between transport modes. I use this exogenous shock to estimate an elasticity of substitution between air and sea transport within the same route. An alternative strategy using the 2021 congestion in US West Coast ports corroborates these findings. I can therefore study substitution from air to sea (airspace closure) and from sea to air (congestion in ports). I find a value for the elasticity of between 2.58 and 3.31.

I then develop a quantitative trade model with multiple transport modes and endogenous transport costs, embedding a discrete choice model for transport modes into a Ricardian framework akin to Eaton and Kortum (2002). When multiple modes are available, trade flows between two countries are less responsive to shocks on a single mode of transport since some trade can be shifted towards other modes. The empirical elasticity estimate is shown to be interpretable as a structural parameter through the model's lens. As an extension, I incorporate congestion costs, making transport costs between country pairs endogenous, as the price of each mode now depends on its level of utilization. Substitution forces and congestion costs represent novel channels in this literature, working in contrast to the usual trade diversion mechanism present in standard gravity frameworks.

To illustrate the quantitative importance of substitution and congestion forces in transmitting shocks to welfare, I perform two experiments: the permanent closure of the Suez Canal and the closure of Russian-Ukrainian airspace. I find that substitution helps in mitigating welfare losses arising from increases in mode-specific transport costs.

As a final exercise, I show that substitution can have implications not only for welfare analysis but also for the environmental footprint of international trade. I perform a counterfactual analysis of the IMO2023 regulation aimed at reducing carbon emissions from sea trade. I find that allowing for trade mode substitutability increases the resilience of trade flows, but by shifting trade from sea to air the environmental footprint of trade increases. This is an important result as it shows that policies aimed at reducing emissions from international trade may have unintended consequences.

The findings have important implications for policymakers, highlighting the significance of the elasticity of substitution across transport modes when designing policies targeting specific modes. Moreover, they demonstrate that allowing for trade mode substitutability increases the resilience of trade flows to localized transport shocks. My framework also opens up new potential applications, such as providing a novel perspective on the returns to infrastructure investments aimed at reducing transport costs and enhancing supply chain resilience.

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A Data Appendix

A.1 US trade data statistics

The US Census Bureau data on US imports is widely used in the literature to study the choice of transport modes in international trade (Hummels, 2007; Hummels and Schaur, 2013). Therefore, it serves as an appropriate benchmark for assessing the representativeness of the Eurostat data used in the main text.

Similar to European countries, the US also engages in substantial trade by air with the rest of the world. Approximately 25 percent of the total value imported into the United States is carried by air, with similar figures observed when examining manufacturers only.

Figure H.1c shows that the shares by mode of transport across origin-HS6 sectors are again polarized. There is a significant share of sector origins that use only sea transport. However, when we restrict the sample to observations that use both modes, we observe that the shares of the two transport modes are quite heterogeneous, as in the European data. Figure H.1e demonstrates that approximately 60 percent of the sector-origins use both modes of transport simultaneously.

These findings are consistent with the European data and indicate that the choice of transport mode is a relevant margin in international trade.

A.2 European trade statistics by product characteristics

Table I.1 reports some of the key statistics for Eurostat data on European Imports and Exports by mode of transport along several product characteristics. For each product dimension, the following statistics are reported: share of observations (origin-destination-HS6) that use both modes, share of total value carried via air, share of total volume carried by air, and the number of observations in the sample. The product characteristics along which the sample is split are the broad economic classification, the containerizability index, the temperature sensitivity index, the unit value, and a time cost index.

The Broad Economic Classification (BEC) is an indicator variable that categorizes products based on their final use and is composed of three main categories: Capital, Intermediate, and Consumption goods. Containerizability is an index that describes how easy it is for a good to be transported in a container. This measure is taken from Bernhofen et al. (2016). Temperature is an index that measures how sensitive a good is to temperature, and it takes values from 1 (low sensitivity) to 4 (high sensitivity). Unit Value is an index variable that contains unit value terciles based on the unit value distribution of each sector in 2019. The time costs index is a discretized version of the continuous index by Hummels and Schaur (2013).

We can see that the number of observations that use both modes is quite high across all dimensions, with the highest share for goods that have medium unit value. This is consistent with the idea that goods that are not too expensive nor too cheap are more likely to be transported by both modes. In terms of value by air, again the share is quite high across all dimensions. The lowest amount of value transported via air is found in those goods that are of difficult containerizability and those with low unit value. These products are more likely to be commodities that are transported by dry-bulk carriers via sea. Finally, as expected, the share of weight by air is low across all product characteristics.

B US Analysis and Identification Assumptions

This section presents similar checks on the identifying assumption for the effect of the 2021 port congestion on the US West Coast. The analysis replicates the steps followed in the study of the impact of Russian sanctions on EU countries, demonstrating that the assumptions required for a causal interpretation of the results are valid.

First, Table I.3 demonstrates that the treated and control groups were similar in terms of trade costs and trade values before the shock. Data from 2019 is used, as it precedes both the shock and the COVID-19 period. Trade flows and transport costs are similar across the two groups; this similarity should ensure that the results are not driven by the pre-shock composition of the sample.

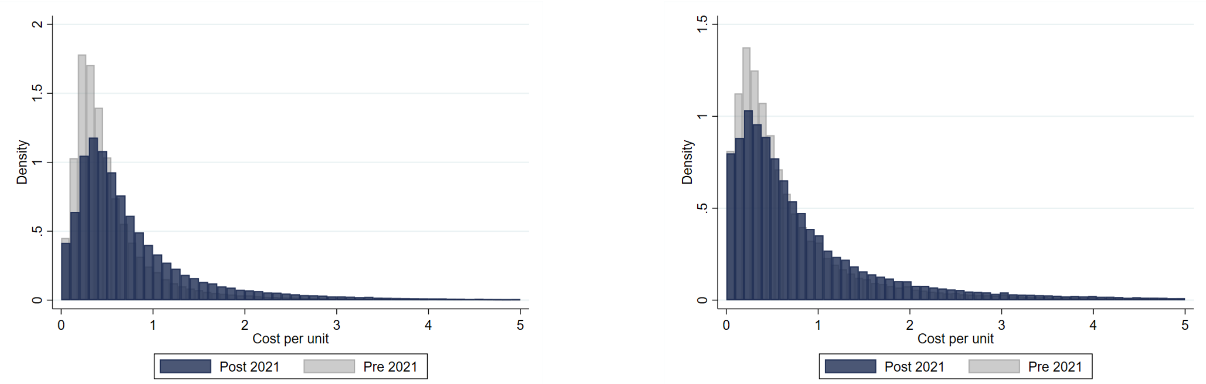
Second, Figure B.1 illustrates that the change in relative transport costs via sea increased disproportionately in the treated group compared to the control group. In the left panel, a clear shift in the distribution of sea costs toward the right is observable, implying higher per-unit costs for importing goods from Asian destinations. Conversely, the right panel shows that the distribution of costs for the control group remains more stable.

Finally, Figure B.2 demonstrates the effect of the congestion on relative trade costs and trade flows. The two panels are based on equations (4) and (5), where the dependent variables are the ratio of sea costs to air costs and the ratio of sea trade to air trade.

Both panels indicate that the congestion in US ports on the West Coast generated an increase in relative sea costs in the treated group and a decrease in sea trade. These results support the assumption of no pre-trend in the data and the causal interpretation of the findings. The left panel exhibits more volatility, which could be explained by the additional noise introduced by the post-Covid recovery. However, the overall trend is consistent with the main results.

Figure B.1: US Data: Change in sea Transport Costs

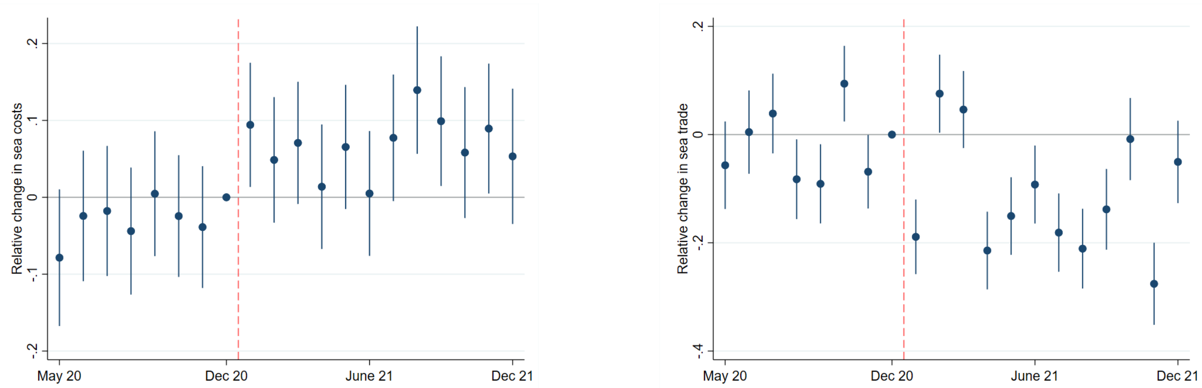
(a) Treated Countries (b) Non-Treated Countries



Notes: Panel (a) shows the distribution of sea costs in the treated group before and after the shock. Panel (b) shows the same for the control group. The treated group experienced a significant increase in sea costs compared to the control group.

Figure B.2: US Data: Event Studies

(a) sea Costs relative to Air Costs (b) sea Trade relative to Air Trade



Notes: Panel (a) reports the event study corresponding to equation (4), while panel (b) reports the event study corresponding to equation (5). The treated group is composed of US trading partners in Asia, while the control group is composed of European partners. We can see that after 2021 when congestion starts to engulf US West Coast ports there is a significant increase in the sea relative price in affected routes. Moreover, the relative trade flows by sea decrease significantly.

C Aggregate Effect of the Airspace Closure

In this section, I look at the effect of the closure of the Russian and Ukrainian airspace on the levels of trade flows by transport mode. In the main text, I show that the closure of the airspace led to an increase in the average flight time between European countries and Asian destinations. This increase in flight time can be used as a proxy for the increase in transport costs for air-freighted goods. I then show that the increase in transport costs led to a decrease in the relative share of air transport with respect to sea transport. I look at the effect on trade, first by transport mode and then aggregate.

To capture the effect of the airspace closure on trade flows, I estimate the following equation:

$$\ln X_{nihtm} = \beta \text{Post}_t \times \text{Treated}_{ni} + \mu_{nih} + \mu_{ht} + \epsilon_{nihtm}, \tag{26}$$

where $\ln X_{nihtm}$ is the trade flow, in value, between country n and i in sector h at time t with mode m, Treated_{ni}, Post_t, μ_{nih}, and μ_t are defined as in the main text. I first estimate equation (26) for air and sea transport separately, and then estimate it for the aggregate trade flow. The coefficient of interest is β, which captures the change in trade flows due to the increase in transport costs that followed the closure of the Russian Airspace.

Table C.1: Increase in air transport: aggregate effect

	(1) Air	(2) Sea	(3) All	(4) Aggregate
Post × Treated	-0.160***	-0.038	-0.099***	-0.091***
	(0.018)	(0.043)	(0.023)	(0.024)
Observations	2,472,709	2,472,709	4,958,592	2,472,709
R-squared	0.808	0.772	0.619	0.860
Origin-destination-HS6	Y	Y	Y	Y
Year-Month-HS6	Y	Y	Y	Y
Transport-HS6	N	N	Y	N

Notes: This table reports the results of the estimation of equation (26). In column (1) trade flows are by air and in column (2) are via sea. Column (3) reports the estimate for both which allow to include transport-date fixed effects (μ_{mt}). Column (4) report the results for the aggregate trade flows collapsed at the origin-destination-sector level. Standard errors are clustered at the origin-destination level. All the estimations are performed as OLS. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table C.1 reports the results of the estimation of equation (26).[53] In column (1) trade flows are by air and in column (2) are via sea. We can see that the closure of the airspace led to a decrease in the trade flows by air while the effect on sea trade is negative but not significant. The aggregate effect, columns (3) and (4), is also negative and significant. This result is consistent with the idea that the increase in transport costs led to a decrease in total trade and that substitution between modes is not enough to offset the increase in bilateral transport costs between affected countries.

[53]The table report the results for trade flows in euros. The results are quantitatively similar if I use trade flows measured in kilograms. This results are available upon request.

D Airspace Closure and Number of Modes Used

In this section, I look at the effect of the closure of the Russian airspace on the number of modes used between affected country pairs compared to the control group. The key point of this analysis is to show that the main effect of the sanctions has been a change in the share by mode rather than abandoning air transport altogether.

To study this effect, I estimate the following linear probability model:

$$\text{TwoMode}_{niht} = \beta \text{Post}_t \times \text{Treated}_{ni} + \mu_{nih} + \mu_{ht} + \epsilon_{nihtm}, \tag{27}$$

where TwoMode_{niht} is a dummy that takes value 1 if country n and i in sector h at time t used two modes and 0 otherwise. Treated_{ni}, Post_t, μ_{nih}, and μ_t are defined as in the main text. The coefficient β indicates the effect on the impact of the sanctions on the probability of having both modes at the same time.

Table D.2 reports the results of the estimation. The closure of the Russian and Ukrainian airspaces did not have meaningful impact on the number of modes used between origin-destination-sectors triplets compared to non-affected triplets. While the coefficient is negative and significant, it corresponds to a change in probability of only -1.5%. Therefore, I argue that the relevant margin of adjustment is the intensive margin, where we look at changes in the share of each mode between country pairs, rather than the extensive margin, where we look at the number of modes used.

Table D.2: Increase in air transport: Linear Probability Model

	(1) Number of Modes
Post × Treated	-0.015**
	(0.006)
Observations	6,869,061
R-squared	0.603
Origin-destination-HS6	Y
Year-Month-HS6	Y

Notes: This table reports the results of the estimation of equation (27). The dependent variable TwoMode_{niht} is an dummy that takes value 1 if country n and i in sector h at time t used two modes and 0 otherwise. Standard errors are clustered at the origin-destination level. All the estimations are performed as OLS. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

E Sectoral Heterogeneity

Product characteristics play a significant role in determining the modal share of transportation, suggesting that the elasticity of substitution between transport modes may vary across sectors. This section explores the sectoral heterogeneity in the elasticity of substitution between air and sea transport.

To investigate this, I re-estimate equation (2) by splitting the sample based on the product's HS sections.[54] In addition, I divide the sample along several indicator variables that capture sectoral characteristics of traded goods, including unit value, temperature sensitivity, containerizability (Bernhofen et al., 2016), broad economic classification, and time costs (Hummels and Schaur, 2013). In the first stage, where variation occurs at the country level, it is not feasible to estimate the differential impact on flight time by sector. For some statistics of the distribution of trade flows by volumes and values by subgroups, see Table I.1 in the appendix.

Figure E.3 presents the coefficients estimated using Wald-DiD for subsamples split along various product characteristics. Figure E.3a displays the results of the heterogeneity analysis by HS sections. The findings indicate that the effect of the war on the relative share of sea trade differs across products; however, no sections exhibit an increase in relative trade via air. The highest elasticity is observed in the textile and footwear sectors. While the vegetable products sector demonstrates an elasticity higher than average, the coefficient is imprecisely estimated due to a limited number of observations.

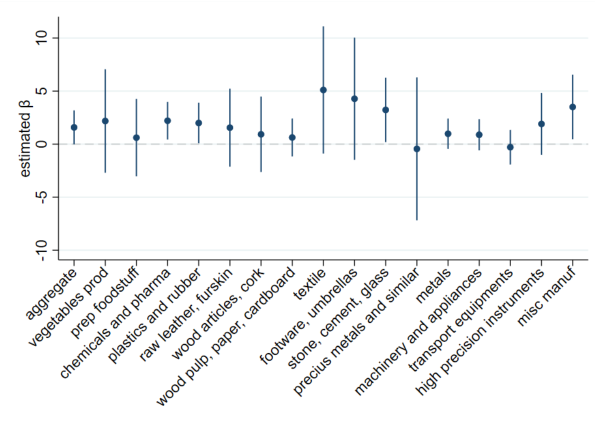
Figure E.3b reveals that the elasticity is higher for sectors with low and medium unit values, consistent with the notion that high-value/low-weight goods are predominantly transported via air. Figure E.3c illustrates that goods with some degree of containerizability exhibit higher substitution elasticity, possibly due to the ease of modal shift for these products. As expected, goods that are not easily containerizable demonstrate the lowest elasticity, reflecting the inconvenience of sea transport for such items.

When dividing the sample based on the Broad Economic Categories (BEC), consumption goods exhibit greater elasticity compared to intermediate and capital goods (Figure E.3d). Lastly, while temperature sensitivity does not significantly impact the substitution elasticity, goods with low time costs—indicating low time sensitivity—display higher elasticity of substitution (Figure E.3f) as one would expect since these goods will always be transported via air.

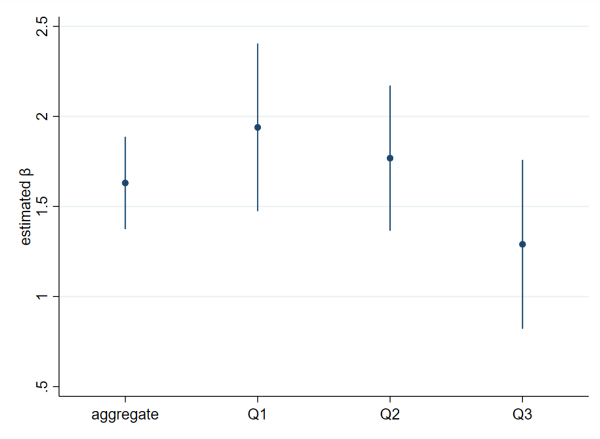
[54]The Harmonized System follows a hierarchical structure. The highest level of aggregation comprises 21 sections. For more information, see WCO (2018)

Figure E.3: Heterogeneity by Product Characteristics

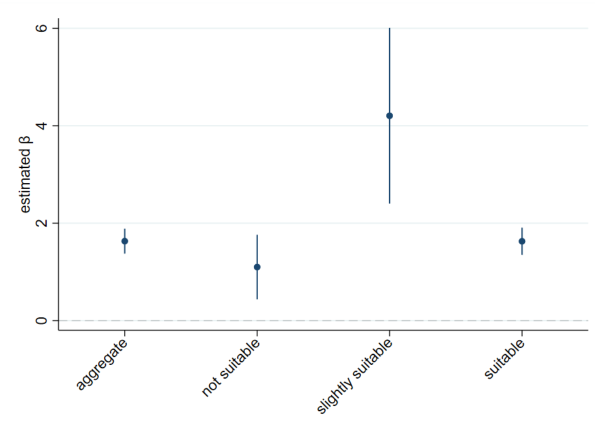
(a) HS Sections



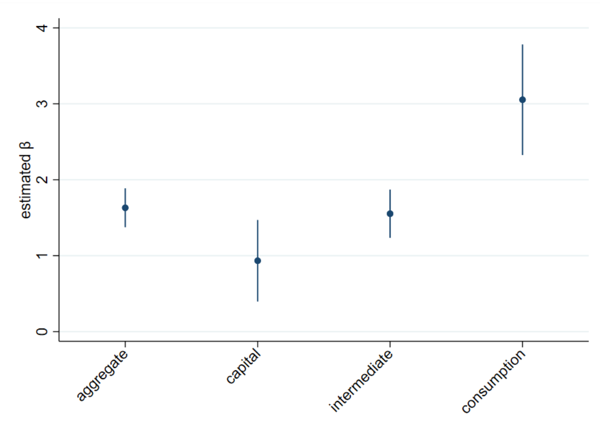
(b) Unit Value Bins



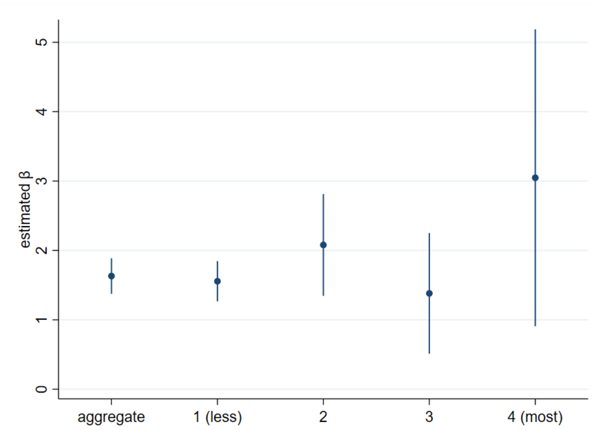
(c) Container Index



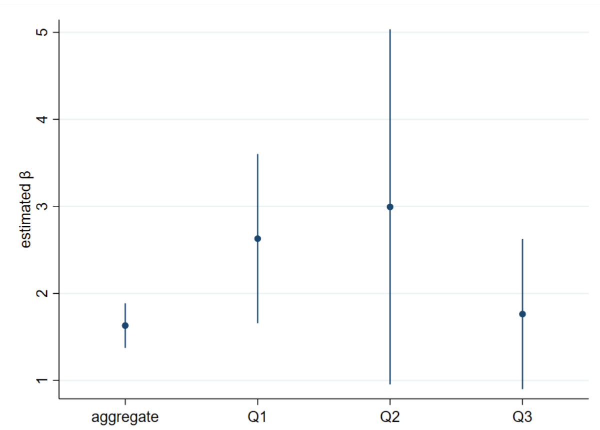
(d) Broad Economic Classification



(e) Temperature sensitivity



(f) Time Cost Bins



Notes: This figure reports the heterogeneity of the estimates for equation (2) along several product characteristics. Equation (1) is constant across sectors so is not reported. Panel (a) reports the estimates for the sample split by HS section (WCO, 2018). Panel (b) reports the estimate for the subsample based on the Unit Value tercile which is calculated by dividing the total value by the total weight in each 6-digit sector. Panel (c) contains the estimate for the sample divided according to the containerizability index (Bernhofen et al., 2016). Panel (d) reports the estimates based on the Broad Economic Classification (BEC). Panel (e) contains the estimates based on the temperature sensitivity of each sector. Panel (f) reports the estimate based on a discretized version of the time costs measure from Hummels and Schaur (2013).

F Short-term Elasticity of Substitution

In this section, I show how to estimate the elasticity of substitution between modes of transport in the short run. This strategy differs from the one used in the main text as the variation does not come from a single shock but the identification is given from the evolution of the transport costs by mode of transport and from cross-sectional differences between origins and sectors.

I propose a novel way to estimate this parameter from the relationship between trade shares and trade costs by the mode highlighted by equation (9):[55]

$$\frac{X_{ni}^m}{X_{ni}} = \frac{(d_{ni}^m)^{1-\eta}}{\sum_k (d_{ni}^k)^{1-\eta}}$$

taking log we obtain:

$$\ln\left(\frac{X_{ni}^m}{X_{ni}}\right) = (1-\eta)\ln d_{ni}^m - \ln\left(\sum_k (d_{ni}^k)^{1-\eta}\right)$$

The advantage of this approach is that I observe the left-hand side of the equation directly in the data.

In the model, there are no sectors and there is no dynamic but once I take this reduced form relationship to the data I can exploit these additional margins of variation to recover the elasticity of substitution across modes of transport and to study its heterogeneity. Therefore, I define the equation to be estimated as follows:

$$\ln X_{odmht} = \beta_\eta \ln d_{odmht} + \mu_{odht} + \mu_{mht} + \epsilon_{odmht} \tag{28}$$

Where the dependent variable is the log flow of trade from an origin o to a destination d at time t through the mode m in sector h. I also include a pair-sector-time variable, μ_{odh}, and mode-sector-time variables, μ_{mht}, to control for as many unobservable characteristics as possible.

Given this relationship, I can identify the elasticity of substitution between modes of transport as $\hat{\eta} = 1 - \hat{\beta}_\eta$. A challenge of this method is finding data on transport costs by transport mode. Specifically, for the purpose of this exercise, the optimal data would consist of a time series of trade costs by origin-destination mode of transport and sector ($\ln d_{odht}^m$). To the best of my knowledge, a dataset containing this information is not available. To overcome this limitation, I employ several approximations of $\ln d_{odht}^m$ as the relevant variation to identify η. A crucial assumption that I make with the costs used is that they can linearly map into variations in transport costs.

Regardless of the strategy employed, I expect the coefficient $\hat{\beta}_\eta$ to be negative since the theory predicts that higher transport costs by mode imply lower shares for that mode. Once I recover an estimate for β_η, I can define the elasticity of substitution between modes of transport with respect to trade costs as $\hat{\eta} = 1 - \hat{\beta}_\eta$. To be consistent with the theoretical assumptions of

[55]Note that Allen and Arkolakis (2014) have a similar approach to estimate the relative geographic trade costs of each mode. The crucial difference is that I interpret this parameter as the elasticity of substitution, η.

the model, we need to have $\eta > 1$, which implies that β_η must be smaller than zero.

To address potential concerns about the endogeneity of transport costs due to contemporaneity with trade flows, I instrument the current level of transport costs with the lagged value. In the baseline specification, I use the previous month's values, one lag, while as a robustness check, I show that the results are similar when using different time lags. The key requirement for the instrument to be valid is that the lagged value of the transport costs is correlated with the current value but not with the error term. This assumption is plausible since the transport costs are likely to be determined by factors that are not directly related to the current trade flows.

Note that, through this approach, I am assuming that the within-mode elasticity, i.e. how much the share of mode m reacts to changes in d_{ni}^m, and the cross-mode elasticity, i.e. how much the share of s reacts to changes in d_{ni}^m, are equal. I can directly test this by estimating the following equation:

$$\ln X_{od,t}^{s,h} = \beta_\eta^{cross} \ln d_{od,ht}^m + \mu_{odht} + \epsilon_{odh,t} \tag{29}$$

Where the only difference with the previous strategy is that the left-hand side is the log-trade flow for a mode s different than m. In this case I expect $\hat{\beta}_\eta^{cross} > 0$ since the elasticity is given by $\hat{\eta} = 1 + \hat{\beta}_\eta^{cross}$. From the theory I should expect $\hat{\beta}_\eta^{cross} = -\hat{\beta}_\eta$, while this can be difficult to show since I don't have a precise measure of trade costs, the crucial step is to find at least $\hat{\beta}_\eta^{cross} > 0$ which means that even if the cross-elasticity differs, there is an increase in the usage of alternative modes.

Another important determinant of the elasticity η could be the heterogeneity across sectors. As mentioned before, it is reasonable to believe that the intrinsic characteristics of each good, e.g. the weight-to-value ratio, can play a role in determining how much substitution is possible. To partially address this point, I repeat my analysis by interacting the four transport cost proxies with an indicator variable, UV_{low} that takes the value 1 if the good, h, has a unit value lower than the median value and 0 otherwise.[56] Then I estimate the following:

$$\ln X_{od,t}^{m,h} = \beta_\eta \ln d_{od,ht}^m \times UV_{low} + \mu_{odht} + \epsilon_{odh,t} \tag{30}$$

Caliendo and Parro (2015) introduced a new method to estimate the elasticity of substitution between goods using the trade shares and the trade costs. They show that the elasticity of substitution can be estimated by taking ratios between country-pair shares to eliminate the fixed effects. I can apply a similar methodology to recover estimates for the elasticity of substitution between modes of transport. Taking the ratio between the shares by mode between an origin o and a destination d, I can write the following:

$$\ln\left(\frac{X_{od}^m}{X_{od}^s}\right) = \beta_\eta \ln\left(\frac{d_{od}^m}{d_{od}^s}\right) + \epsilon_{od} \tag{31}$$

This strategy allows for controlling directly for unobservable characteristics that are not mode-

[56] To calculate the unit value I take the total value trade and divide it by the total weight between all country pairs.

specific. I can then compare the results obtained from this method with the ones obtained from the previous strategy to see if the estimates for η are consistent not only across different datasets but also across different methodologies. The drawback of equation (31) is that it does not allow for the estimation of cross elasticities between modes.

F.1 Baseline Specification: US Charges by Mode of Transport

To estimate the elasticity of substitution between modes of transport, I use the charges by mode of transport reported in the US merchandise dataset published by the US Census Bureau. This dataset reports monthly trade flows by mode of transport, origin, and 6-digit product categories from 2013 to 2022.[57] The modes of transport reported in this dataset are only air and sea, vessels and containers, as they represent the main mode of entry in the US from all the countries apart from Mexico and Canada. For this reason, I drop all the flows between these countries.

I define a route as an origin-HS6. To construct a measure of the monthly transport costs by mode of transport, I divide the monthly total charges paid for each mode along a route by the total volume transported by that mode. Given that the settings allow me to have a time series I can also exploit the time variation in the data. I therefore estimate the following equation:

$$\ln X_{odhmt} = \beta_\eta \ln d_{odhtm} + \mu_{oht} + \mu_{hmt} + \epsilon_{odhmt} \tag{32}$$

Where the dependent variable is the log trade flow from an origin o to the United States of America d at time t through the mode m in sector h. I employ origin-HS6-time (μ_{oht}) and mode-sector-time (μ_{mht}) fixed effects. This set of controls captures the unobservable characteristics that are mode, origin, and sector-specific as well as possible time trends. I expect $\hat{\beta}_\eta$ to be negative. The identifying variation in this case comes from the time-series charges by mode and sector and cross-sectional differences across country pairs. Standard errors are clustered at the origin-HS6 level, which is the level of variation in the data.

To address the problem of possible differences in the elasticities between modes, namely the fact that it is different to pass from air transport to sea transport and vice versa, I also estimate equation (F.1) separately for air and sea flows. In this case, I cannot use origin-hs6-time fixed effects as they would absorb all the variation, so instead I employ origin-hs4-time ones paired with sector-time fixed effects. I am also able to estimate the cross-elasticity between modes by estimating equation using log air (sea) flows as the dependent variable and sea (air) cost as the regressor.

A drawback of this dataset is that it only covers the US imports. In the next subsection, I will describe alternative data sources that allow me to test the robustness and the external validity of the results obtained.

[57]The data are available for earlier years but need to be acquired while I use the free APIs made available the the Census Bureau.

F.2 Results

Table F.1 reports the baseline estimates of the elasticity of substitution between modes of transport using the US Census Bureau data. Columns (1) to (3) report the results of equation (F.1) with the dependent variable as the log flows by air, sea, and both respectively. Columns (4) to (6) replicate the analysis instrumenting the transport costs with its lagged value from the previous month. Columns (7) and (8) report the results of the ratio approach, equation (31). Across all the specifications, I find that the estimated coefficient $\hat{\beta}_\eta$ is negative and significant, which is consistent with the theory requiring $\eta > 1$. Moreover, since the elasticity of substitution is given by $1 - \beta_\eta$, I find that the elasticity of substitution between modes of transport is around 1.2. This implies that the substitution between modes of transport is relatively low compared to the elasticity of trade flows with respect to trade costs, which is usually between 4 and 12 (Head and Mayer, 2014). This value is less than half of what I estimate in Section 2. This is due to the fact that in the short run, there is less room for substitution since the contracts are already signed and the availability of carriers may be limited.

The magnitudes reported in this first table are interpretable as the average effect across different product varieties. By employing origin-year and 4-digit product codes fixed effects, I am controlling for all the time-varying product characteristics that could affect the elasticity of substitution. However, the elasticity of substitution likely varies across sectors. In the next sections, I will further explore this heterogeneity to show how sectoral characteristics are important in determining the substitutability across modes of transport. However, recall that in this sample I am keeping only the 6-digit HS codes that use at least 5% of both modes of transport. Therefore, I am excluding sectors in which the elasticity of substitution between modes is probably very low or not possible. For example, this could be the case for dry-bulk shipping in which the per-unit value and the weight make it unfeasible to be transported by air. As robustness, I will also show the results for the full sample.

Given the level of observation in my data in Columns (1) and (2) I cannot employ origin-time-HS6 fixed effects since they would absorb all the variation. However, in Column (3) by including both modes in the analysis I can employ these fixed effects. The results are consistent across the different specifications and deliver almost identical estimates.

The results are in line with what is reported in Hummels and Schaur (2010) and Hummels and Schaur (2013) in which the authors find that increases in the mode-specific transport costs affect not only the flow of the mode itself but also generate a shift towards the alternative mode. The scope of these works is different from mine since their focus is to study how different modes are used to hedge against uncertainty and shipping time, I am interested in how feasible it is to substitute between modes. Consequently, both the dependent variables and the controls vary significantly across the papers; however, the qualitative results are consistent. The key difference is that in this work, throughout the lens of the model, I can interpret the coefficient as the elasticity of substitution between modes of transport.

Table F.1: Baseline estimates of η

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln X_{odht,air}$	$\ln X_{odht,sea}$	$\ln X_{odhtm}$	$\ln X_{odht,air}$ IV	$\ln X_{odht,sea}$ IV	$\ln X_{odhtm}$ IV	$\ln(X^{air}_{odht}/X^{sea}_{odht})$	$\ln(X^{air}_{odht}/X^{sea}_{odht})$ IV
Transport Costs	-0.178***	-0.131***	-0.173***	-0.286***	-0.245***	-0.361***		
	(0.005)	(0.006)	(0.003)	(0.016)	(0.016)	(0.011)		
$\ln(d^{air}_{odht}/d^{sea}_{odht})$							-0.137***	-0.239***
							(0.004)	(0.001)
Observations	1,256,587	1,256,587	3,721,368	1,116,389	1,042,399	2,859,920	1,256,587	951331
R-squared	0.808	0.761	0.823				0.696	
IV F-stat				7602.67	6571.20	1449.35		7463.93
Origin-year-month-HS4 FE	Y	Y	N	Y	Y	N	Y	Y
Year-month-HS6 FE	Y	Y	N	Y	Y	N	Y	Y
Origin-year-month-HS6 FE	N	N	Y	N	N	Y	N	N
Year-month-HS6-mode FE	N	N	Y	N	N	Y	N	N

Notes: In columns (1) to (3) are reported the baseline estimates of regression (F.1) with the dependent variable as the log flows by air, sea, and both respectively. Columns (4) to (6) replicate the analysis instrumenting the transport costs with its lagged value from the previous month. Columns (7) and (8) report the results of the ratio approach, equation (31). Across all specifications, the data come from the US Census Bureau and are monthly imports to the US from the year 2013 to the year 2022. Sectors are defined as 6-digit product categories. the elasticity of substitution between modes of transport can be recovered as $\eta = 1 - \beta_{eta}$.
Standard errors in each column are clustered at the origin-sector. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

F.2.1 Cross-elasticity and Sectoral Heterogeneity

I can directly test the assumption that the within-mode elasticity and the cross-mode elasticity are equal by estimating equation (29). Columns (1) and (2) of Table F.2 report the results of estimating the elasticity using respectively log-air flows and sea costs and log-sea flows and air costs. I find that when sea trade costs rise, air flows significantly increase. On the other hand, when air costs rise, sea flows also decrease to some extent. While the first result is consistent with the theory, the fact that sea costs decrease with air costs is contradictory. A possible explanation is the nature of the cost shifter that I am using. Since I am using monthly variation, it is possible that sea flows take more time to adjust so that the cross-elasticity is not captured in the short run.

To further address this issue and to study the effect of sectoral composition in columns (3)-(4) I estimate the elasticity coefficient by interacting it with a dummy that takes value 1 if the sector has a unit value lower than the median value and 0 otherwise, as described in equation 30. I find that there are differences between air and sea flows in the reaction to cost changes. In particular, I find that the elasticity of substitution of air trade is higher for sectors with a higher unit value, column (3), while the elasticity of substitution of sea trade is higher for sectors with a lower unit value, column (4). This is consistent with the idea that the weight-to-value ratio plays a role in determining the substitutability across modes of transport. Columns (5)-(6) report instead the cross-elasticity interacted with the unit value dummy. I do not find that there is substitution from sea flows to air flows when air costs rise. However, consistent with the previous results, I find that the cross-elasticity of air flows is higher for sectors that are above the median unit value.

F.2.2 Robustness Checks

I perform several robustness checks on my baseline specification to ensure the validity of the results. First, I exclude from my sample the COVID-19 periods as multiple shocks happen in the transport sectors, especially in the US. Secondly, I test my results by focusing only on the

Table F.2: Cross-Estimates and heterogeneity in η

	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln X^{air}_{odht}$	$\ln X^{sea}_{odht}$	$\ln X^{air}_{odht}$	$\ln X^{sea}_{odht}$	$\ln X^{air}_{odht}$	$\ln X^{sea}_{odht}$
Air costs		-0.064**	-0.187***	-0.068***		
		(0.013)	(0.005)	(0.006)		
Sea Costs	0.014***				0.016***	-0.115***
	(0.004)				(0.004)	(0.006)
Air Costs $\times$UV Low			0.046***	0.023*		
			(0.011)	(0.013)		
Sea Costs $\times$UV Low					-0.021*	-0.110***
					(0.011)	(0.016)
Observations	1,256,587	1,256,587	1,256,587	1,256,587	1,256,587	1,256,587
R-squared	0.805	0.760	0.808	0.760	0.805	0.761
Origin-year-month-HS4 FE	Y	Y	Y	Y	Y	Y
Year-month-HS6 FE	Y	Y	Y	Y	Y	Y

Notes: Standard errors in each column are clustered at the origin-sector. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

manufacturing sectors.[58] Thirdly, I test the sensitivity of the results to the choice of the lag used as an instrument. Table I.11 shows that across all the different specifications the results are quantitatively and qualitatively consistent.

[58]Defined as *Chemicals* (23-24-25), *Food* (15-16), *Machines* (29-30-31-32-33), *Metals* (27-28), *Minerals* (26), *Other* (36), *Textiles* (17-18-19), *Vehicles* (34-35), and *Wood-Paper* (20-21-22)

G Theoretical Results

G.1 Solution of the Discrete Choice Model

In this section, I show how to obtain the main equations of Section 4.2. In the first stage, the consumer chooses which good to consume, while in the second, she decides the quantity. Consider a mode $m \in M$ and denote the conditional direct utility of a consumer, in country n buying a good from country i using mode m as $u^m_{ni} = \ln q^m_{ni}$. The price that she will face is equal to $p^m_{ni} = p_i d^m_{ni}$. With p_i as the factory-gate price.

Maximizing this utility leads to demand q^m_{ni}. I can now write the indirect utility as

$$V(p^m_{ni}) = \ln p_i + \ln d^m_{ni} - \ln y_n, \tag{33}$$

where y_n is the total expenditure. In the first stage of the problem, I assume that the choice of mode m follows the stochastic utility approach:

$$u^m_{ni} = V(p^m_{ni}) + \mu\epsilon^m_{ni},$$

with $\mu > 0$ and ϵ^m_{ni} that follow an extreme value type I distribution (Gumbel). Since in this step the country-pair flow is already decided, I will drop the ni notation for the remaining of the subsection.

The probability density of ϵ^m is $f(\epsilon^m) = \exp(-\epsilon^m)\exp(-\exp(-\epsilon^m))$. The cumulative density function is $F(\epsilon^m) = \exp(-\exp(-\epsilon^m))$. The probability of choosing mode m instead of mode k is:

$$\begin{aligned} Pr(u^m > u^k) &= Pr(V^m + \mu\epsilon^m > V^k + \mu\epsilon^k) \\ &= Pr(V^m - V^k + \mu\epsilon^m > \mu\epsilon^k). \end{aligned}$$

While the conditional probability is

$$Pr(u^m > u^k|\epsilon^m) = F(V^m - V^k + \mu\epsilon^m),$$

and the conditional probability of choosing m given the other options is:

$$Pr(u^m > u^k \forall k \neq m|\epsilon^m) = \prod F(V^m - V^k + \mu\epsilon^m).$$

Finally, the unconditional probability of the mode m is given by

$$Pr(u^m > u^k \forall k \neq m) = \int_{-\infty}^{\infty} \prod_{k\neq m} F(V^m - V^k + \mu\epsilon^m) f(\epsilon^m) d\epsilon^m.$$

Now we have to substitute in the definitions of $F(\cdot)$ and $f(\cdot)$ and solve

$$
\begin{aligned}
Pr^m &= \int_{-\infty}^{\infty} \prod_{k\neq m} F(V^m - V^k + \mu\epsilon^m) f(\mu\epsilon^m) d\epsilon^m \\
&= \int_{-\infty}^{\infty} \prod_{k\neq m} \exp(-\exp(V^m - V^k + \mu\epsilon^m)) \exp(-\mu\epsilon^m) \exp(-\exp(-\mu\epsilon^m)) d\epsilon^m \\
&= \int_{-\infty}^{\infty} \prod_{k} \exp(-\exp(V^m - V^k + \mu\epsilon^m)) \exp(-\mu\epsilon^m) d\epsilon^m \\
&= \int_{-\infty}^{\infty} \exp(-\exp(-\mu\epsilon^m) \sum_k \exp(V^m - V^k)(-\exp(-\mu\epsilon^m) d\epsilon^m.
\end{aligned}
$$

Change of variable to $t = -\exp(-\mu\epsilon^m)$ and $(1/\mu)dt = \exp(-\mu\epsilon^m)$.

$$
Pr^m = \int_{-\infty}^{0} \exp(t \sum_k \exp(V^m - V^k)) \frac{1}{\mu} dt.
$$

We can now solve the integral to obtain:

$$
Pr^m = \frac{1}{\sum_k \exp\left(-\left(\dfrac{V^m}{\mu} - \dfrac{V^k}{\mu}\right)\right)} = \frac{\exp\left(\dfrac{V^m}{\mu}\right)}{\sum_k \exp\left(\dfrac{V^k}{\mu}\right)}, \tag{34}
$$

I can substitute equation (33) into equation (34) to have that

$$
\begin{aligned}
Pr^m &= \frac{\exp\left(V_{ni}^m/\mu\right)}{\sum_k \exp\left(V_{ni}^k/\mu\right)} \\
&= \frac{\exp\left(-\ln p_{ni}^m/\mu\right)\exp\left(-\ln y/\mu\right)}{\sum_k \exp\left(-\ln p_{ni}^k/\mu\right)\exp\left(-\ln y/\mu\right)} \\
&= \frac{(p_{ni}^m)^{-1/\mu}}{\sum_k (p_{ni}^k)^{-1/\mu}} \\
&= \frac{(p_i d_{ni}^m)^{-1/\mu}}{\sum_k (p_i d_{ni}^k)^{-1/\mu}} \\
\pi_{ni}^m &= \frac{(d_{ni}^m)^{-1/\mu}}{\sum_k (d_{ni}^k)^{-1/\mu}}.
\end{aligned} \tag{35}
$$

The share imported by destination n from origin i by mode m depends entirely on the relative costs that are specific to the modes. Since factory-gate prices and other pair-wise costs are constant across transport modes, they do not matter in determining the share. Define now the elasticity of substitution between modes of transport as $\eta = (\mu + 1)/\mu$ so that we can rewrite equation (**??**) as:

$$
\pi_{ni}^m = \frac{(d_{ni}^m)^{1-\eta}}{\sum_k (d_{ni}^k)^{1-\eta}} = \frac{X_{ni}^m}{X_{ni}}, \tag{36}
$$

where the assumption of $\mu > 0$ implies $\eta > 1$.

The share in equation (36) can be derived from a CES utility function:

$$u_{ni} = \left(\sum_{m=1}^{M} (q^m_{ni})^{(\eta-1)/\eta} \right)^{\eta/(\eta-1)}, \tag{37}$$

that is maximised under the budget constraint: $\sum^M q^m_{ni} p^m_{ni} = \sum^M X^m_{ni} = X_{ni}$. Where q^m_{ni} is the quantity imported by n from i by each mode, and X_{ni} is the total value imported.

G.2 Derivation of $\hat{d}_{ni}$

Proof. To derive equation (20), assume that the shock is a change in costs for mode $s \in M$ we have that

$$\begin{aligned}
\hat{d}_{ni} = d'_{ni}/d_{ni} &= \frac{\left((d'^s_{ni})^{1-\eta} + \sum_{-s} (d^m_{ni})^{1-\eta}\right)^{1/(1-\eta)}}{\left(\sum_{m=1}^M (d^m_{ni})^{1-\eta}\right)^{1/(1-\eta)}} \\
&= \left[\frac{\left((d'^s_{ni})^{1-\eta} + \sum_{-s} (d^m_{ni})^{1-\eta}\right)}{\left(\sum_{m=1}^M (d^m_{ni})^{1-\eta}\right)} \right]^{1/(1-\eta)} \\
&= \left[\frac{\left((d'^s_{ni})^{1-\eta} + (d^s_{ni})^{1-\eta} - (d^s_{ni})^{1-\eta} + \sum_{-s} (d^m_{ni})^{1-\eta}\right)}{\left(\sum_{m=1}^M (d^m_{ni})^{1-\eta}\right)} \right]^{1/(1-\eta)} \\
&= \left[1 + \frac{(d'^s_{ni})^{1-\eta} - (d^s_{ni})^{1-\eta}}{\left(\sum_{m=1}^M (d^m_{ni})^{1-\eta}\right)} \right]^{1/(1-\eta)}
\end{aligned}$$

Now I use equation (8) to write $\sum_{m=1}^M (d^m_{ni})^{1-\eta} = d^{1-\eta}_{ni}$ and I divide and multiply $(d'^s_{ni})^{1-\eta}$ by $(d^s_{ni})^{1-\eta}$ to simplify further the equation

$$\begin{aligned}
\hat{d}_{ni} &= \left[1 + \frac{(\hat{d}^s_{ni})^{1-\eta}(d^s_{ni})^{1-\eta} - (d^s_{ni})^{1-\eta}}{d^{1-\eta}_{ni}} \right]^{1/(1-\eta)} \\
&= \left[1 + \frac{((\hat{d}^s_{ni})^{1-\eta} - 1)(d^s_{ni})^{1-\eta}}{d^{1-\eta}_{ni}} \right]^{1/(1-\eta)} \\
&= \left[1 + ((\hat{d}^s_{ni})^{1-\eta} - 1)\pi^s_{ni} \right]^{1/(1-\eta)}
\end{aligned}$$

Where, in the last step, I make use of equation (9). *QED*

G.2.1 Proof of Proposition 2

Proof. Consider the definition of $\hat{d}_{ni}$ in equation (20), then I want to show that

$$\hat{d}^s_{ni} > \left[1 + ((\hat{d}^s_{ni})^{1-\eta} - 1)\pi^s_{ni} \right]^{1/(1-\eta)}$$

given that trade costs are always positive, $\hat{d}_{ni} > 0$, and $\eta > 1$, I can write

$$
\begin{aligned}
(\hat{d}^s_{ni})^{1-\eta} &< \left[1 + ((\hat{d}^s_{ni})^{1-\eta} - 1)\pi^s_{ni}\right] \\
(\hat{d}^s_{ni})^{1-\eta} - 1 &< ((\hat{d}^s_{ni})^{1-\eta} - 1)\pi^s_{ni}
\end{aligned}
$$

which is always true since $0 < \pi^m_{ni} < 1$.

Similarly, to show that $\hat{d}_{ni} > 1$, consider again equation (20). I now want to show that

$$
\begin{aligned}
\hat{d}_{ni} = \left[1 + ((\hat{d}^s_{ni})^{1-\eta} - 1)\pi^s_{ni}\right]^{1/(1-\eta)} &> 1 \\
((\hat{d}^s_{ni})^{1-\eta} - 1)\pi^s_{ni} &< 0 \\
(\hat{d}^s_{ni})^{1-\eta} &< 1 \\
\hat{d}^s_{ni} &> 1
\end{aligned}
$$

QED

G.2.2 Proof of Proposition 3

Proof. The change in the share of mode m given a change in transport costs $\hat{d}^m_{ni}$ is

$$
\begin{aligned}
\hat{\pi}^m_{ni} &= \frac{\pi'^m_{ni}}{\pi^m_{ni}} \\
&= \frac{(d'^m_{ni})^{1-\eta}}{d'^{1-\eta}_{ni}} \frac{d^{1-\eta}_{ni}}{(d^m_{ni})^{1-\eta}} \\
&= \frac{(\hat{d}^m_{ni})^{1-\eta}}{\hat{d}^{1-\eta}_{ni}}
\end{aligned} \tag{38}
$$

Given proposition 1, if $\hat{d}^m_{ni} > 1$ then:

$$
\hat{d}^m_{ni} > \hat{d}_{ni} \quad \Longrightarrow \quad (\hat{d}^m_{ni})^{1-\eta} < \hat{d}^{1-\eta}_{ni} \quad \Longrightarrow \quad \hat{\pi}^m_{ni} < 1
$$

QED

G.3 Compatibility with a Broader Set of Models

In the main text, I introduce multiple transport modes in a Ricardian model of trade based on the seminal work of Eaton and Kortum (2002). However, the same methodology can be applied to any model that falls into the "universal gravity" framework Allen et al. (2020). This is due to the fact that the transport part of the model influences the trade mechanism only through the transport index that replaces what is usually the bilateral iceberg costs. The key assumption to obtain this result is the independence of the factory gate price with respect to the choice of transport mode.

G.4 Derivation of $\hat{d}_{ni}$ with Congestion

Proof. To derive equation (25), assume that the shock is a change in costs for mode $s \in M$ we have that

$$\hat{d}_{ni} = d'_{ni}/d_{ni} = \frac{\left(\sum_{m=1}^{M}(d'^{m}_{ni})^{1-\eta}(\Xi'^{m}_{ni})^{1-\eta}\right)^{1/(1-\eta)}}{\left(\sum_{m=1}^{M}(d^{m}_{ni})^{1-\eta}(\Xi^{m}_{ni})^{1-\eta}\right)^{1/(1-\eta)}}$$

$$= \left(\frac{(d'^{s}_{ni})^{1-\eta}(\Xi'^{s}_{ni})^{1-\eta} + \sum^{-s}(d^{m}_{ni})^{1-\eta}(\Xi'^{m}_{ni})^{1-\eta} \pm \sum_{m=1}^{M}(d^{m}_{ni})^{1-\eta}(\Xi^{m}_{ni})^{1-\eta}}{\sum_{m=1}^{M}(d^{m}_{ni})^{1-\eta}(\Xi^{m}_{ni})^{1-\eta}}\right)^{1/(1-\eta)}$$

$$= \left(1 + \frac{(d'^{s}_{ni})^{1-\eta}(\Xi'^{s}_{ni})^{1-\eta} - (d^{s}_{ni})^{1-\eta}(\Xi^{s}_{ni})^{1-\eta}}{\sum_{m=1}^{M}(d^{m}_{ni})^{1-\eta}(\Xi^{m}_{ni})^{1-\eta}} + \frac{\sum^{-s}(d^{m}_{ni})^{1-\eta}(\Xi'^{m}_{ni})^{1-\eta} - \sum^{-s}(d^{m}_{ni})^{1-\eta}(\Xi^{m}_{ni})^{1-\eta}}{\sum_{m=1}^{M}(d^{m}_{ni})^{1-\eta}(\Xi^{m}_{ni})^{1-\eta}}\right)^{1/(1-\eta)}$$

$$= \left(1 + \frac{\left[(\hat{d}^{s}_{ni})^{1-\eta}(\hat{\Xi}^{s}_{ni})^{(1-\eta)} - 1\right](d^{s}_{ni})^{1-\eta}(\Xi^{s}_{ni})^{(1-\eta)}}{\sum_{m=1}^{M}(d^{m}_{ni})^{1-\eta}(\Xi^{m}_{ni})^{1-\eta}} + \frac{\sum^{-s}(d^{m}_{ni})^{1-\eta}(\Xi^{m}_{ni})^{(1-\eta)}\left[(\hat{\Xi}^{m}_{ni})^{(1-\eta)}\right]}{\sum_{m=1}^{M}(d^{m}_{ni})^{1-\eta}(\Xi^{m}_{ni})^{1-\eta}}\right)^{1/(1-\eta)}$$

$$= \left[1 + \left((\hat{d}^{s}_{ni}(\hat{X}^{s}_{ni})^{\lambda})^{1-\eta} - 1\right)\pi^{s}_{ni} + \sum^{-s}\pi^{m}_{ni}\left((\hat{X}^{m}_{ni})^{(\lambda)(1-\eta)} - 1\right)\right]^{1/(1-\eta)}$$

where in the last step I use the definition of the share of mode m in equation (24) and the fact that $\hat{\Xi}^{s}_{ni} = (\hat{X}^{s}_{ni})^{\lambda}$ since infrastructures are assumed to be constant. *QED*

G.5 Sketch of the Algorithm for Model with Congestion

In this section, I describe the algorithm used to conduct counterfactuals with the model with multiple modes and congestion. The solution is based on the following steps:

1. Initialise the model with the change in transport costs for mode $s \in M$, $\hat{d}^{s}_{ni}$.
2. Compute the implied equilibrium prices, wages, and trade shares using the Alvarez-Lucas algorithm.
3. Compute the implied changes in the aggregate trade costs, $\hat{d}_{ni}$, using equation (25).
4. Repeat until convergence.

Similarly to the model without congestion, the algorithm is very fast and using Matlab and a laptop it can solve each counterfactual in less than a minute.

G.6 Model with Cobb-Douglas Shares

With Cobb-Douglas share by mode, the transport costs index is given by the following:

$$d_{ni} = \prod_{m=1}^{M} (d_{ni}^{m})^{\pi_{ni}^{m}}$$

Since shares are constant and the change in costs affects only one mode, the counterfactual change in the aggregate trade costs is given by

$$\hat{d}_{ni} = (\hat{d}_{ni}^{s})^{\pi_{ni}^{s}}$$

where s is the mode shocked and the share π is constant. Note that the equations for the rest of the system in changes remain unchanged by this new definition of trade costs.

G.7 Model with Cobb-Douglas Shares and Congestion

With Cobb-Douglas share by mode and congestion as described in Section 6, the transport costs index is given by the following:

$$d_{ni} = \prod_{m=1}^{M} (d_{ni}^{m})^{\pi_{ni}^{m}} = \prod_{m=1}^{M} (\delta_{ni}^{m} \Xi_{ni}^{m})^{\pi_{ni}^{m}}$$

Since shares are constant and the change in costs affects only one mode, the counterfactual change in the aggregate trade costs is given by

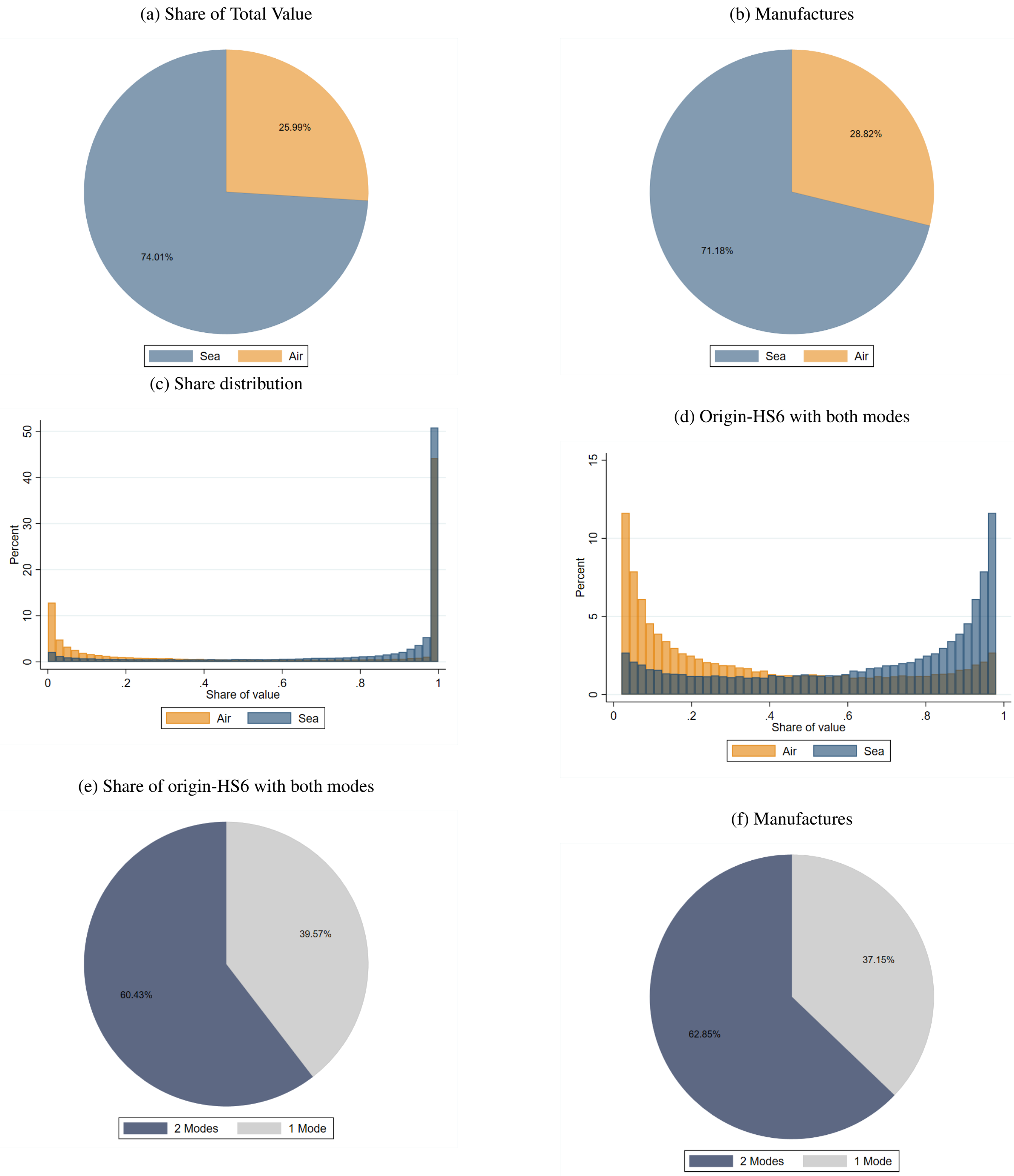
$$\hat{d}_{ni} = \left(\hat{\delta}_{ni}^{s} \left(\hat{X}_{ni}^{s}\right)^{\lambda}\right)^{\pi_{ni}^{s}} \prod_{m \neq s} \left(\left(\hat{X}_{ni}^{m}\right)^{\lambda}\right)^{\pi_{ni}^{m}}$$

where s is the mode shocked and the share π is constant. As for the previous case, the rest of the system is equal to the baseline case.

H Additional Figures

In this section are reported additional figures that complement the main text.

Figure H.1: Key statistics for US imports by mode of transport

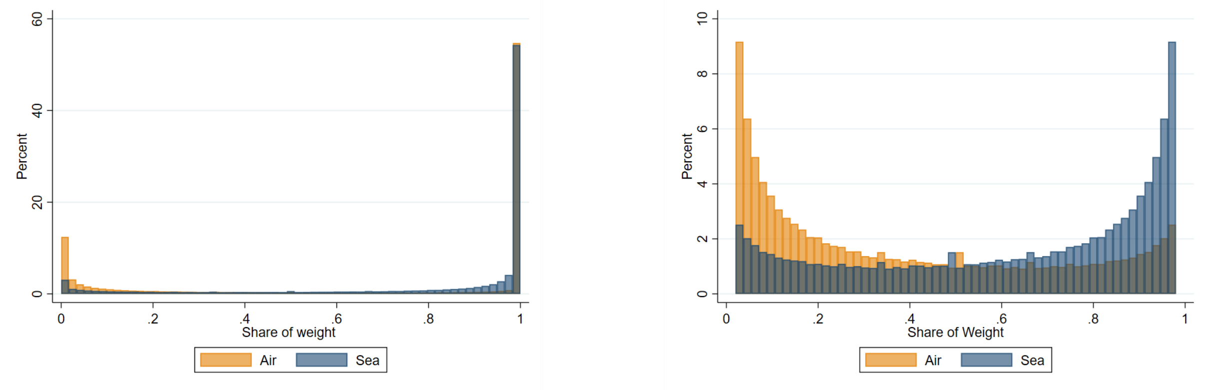


Notes: Panels (a) and (b) report the share of value transported via air and sea in the full sample and for the manufacturing sector only. Panels (c) and (d) show the distribution of the share of value transported by air in the full sample and in the subset of origin-HS6 sectors that use both modes. Panels (e) and (f) show the share of origin-HS6 sectors that use both modes of transport.

Figure H.2: Transport Mode Shares Distribution (weight)

(a) Full sample

(b) Origin-Destination-HS6 with both modes



Notes: Panel (a) shows the distribution of trade shares by transport mode in kilograms. Panel (b) shows the distribution of trade value shares across origin-destination-HS6 sectors that use both air and ocean transport. The sample consists of imports and exports of European Union members in 2019, collected from Eurostat.

Figure H.3: Transport Mode Share (Weight)

(a) Aggregate

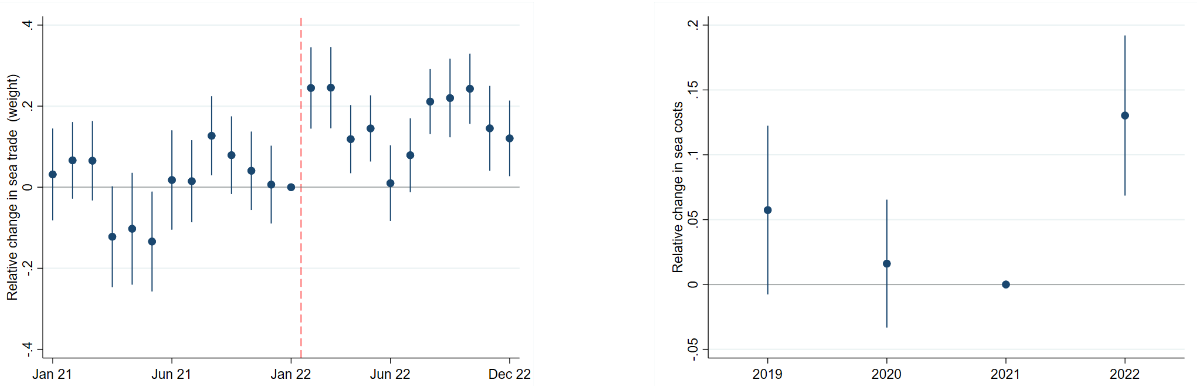
(b) Manufactures

Notes: Panel (a) reports the aggregate share of trade in kilograms by mode of transport. Panel (b) reports the same statistics for the manufacturing sector. The sample consists of imports and exports of European Union members in 2019, collected from Eurostat.

Figure H.4: Event Studies (Weight)

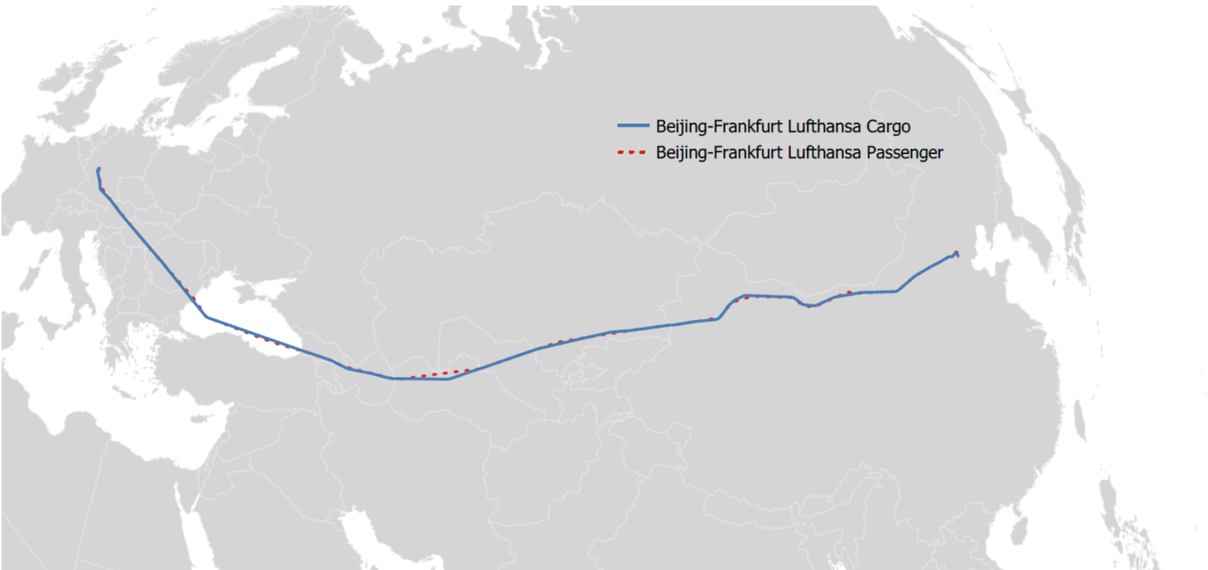
(a) sea Trade relative to Air Trade in weight

(b) sea Trade relative to Air Trade long



Notes: Panel (a) reports the estimate for equation (2) using the weight of the trade as the dependent variable. Panel (b) reports the estimate of the event study with the ratio of the trade flows by sector aggregate at the yearly level as the dependent variable. In both cases we can see that the pre-trends are not statistically significant.

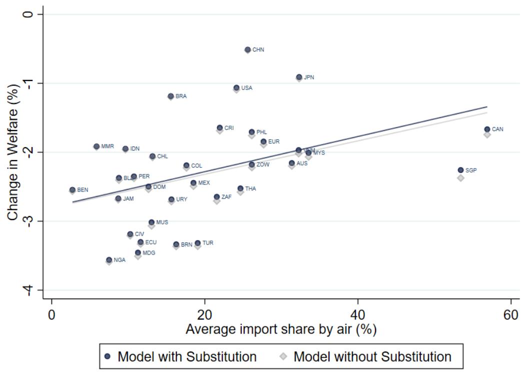
Figure H.5: Flight Path Cargo vs Passenger



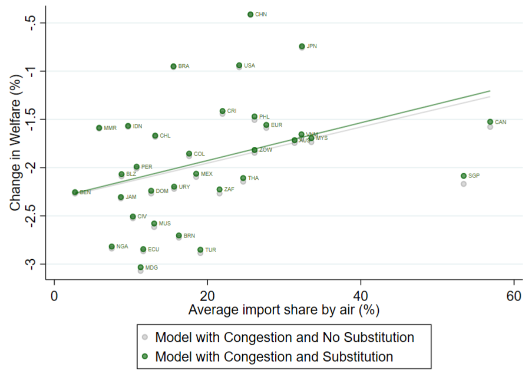
Notes: Flight route between Frankfurt and Beijing after the start of the Ukraine war for a passenger flight vs a cargo flight. Author's own calculation based on Flightradar24 data.

Figure H.6: IMO23 additional figures

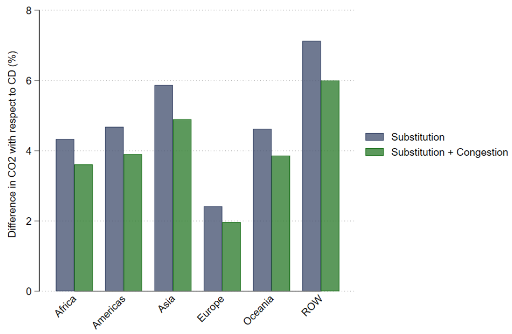
(a) Effect on Welfare without Congestion



(b) Effect on Welfare without Congestion

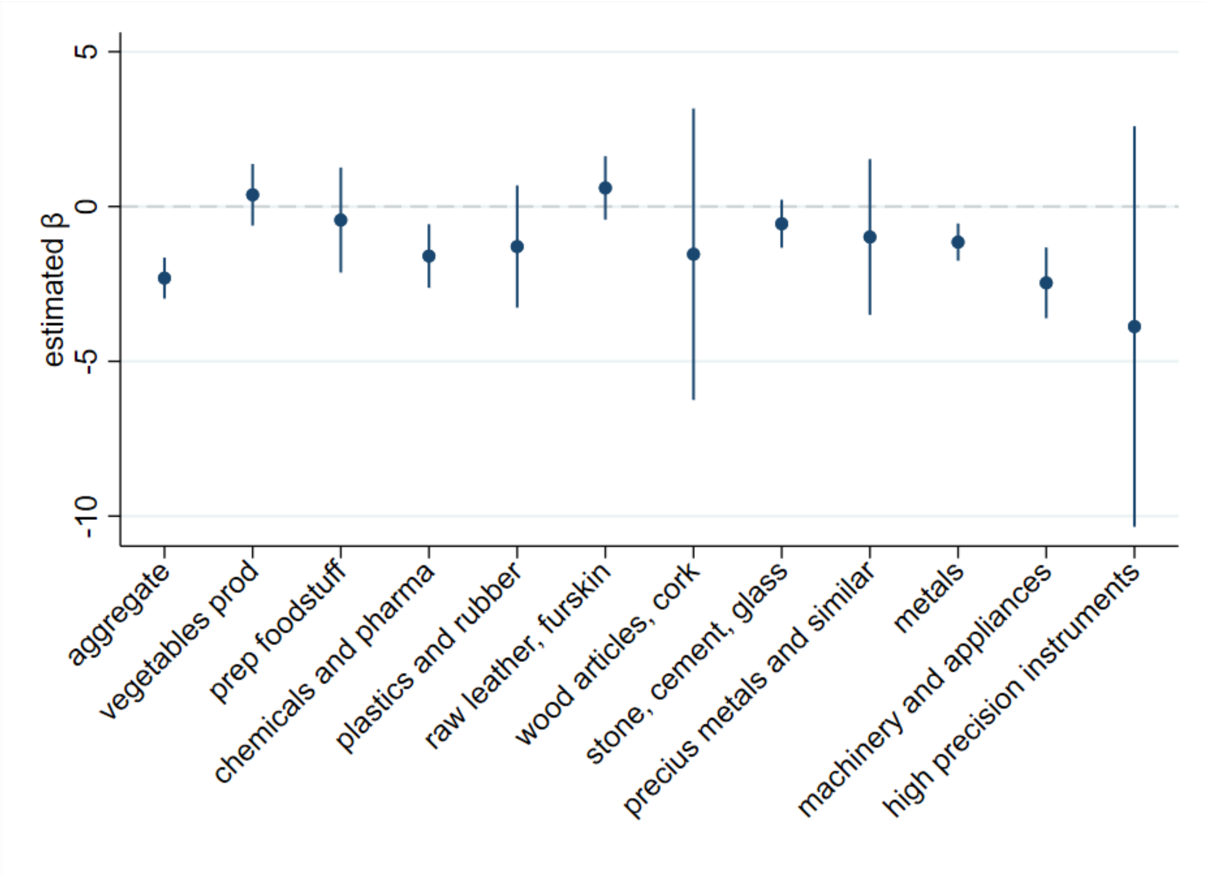


(c) Effect on CO_2 Emissions



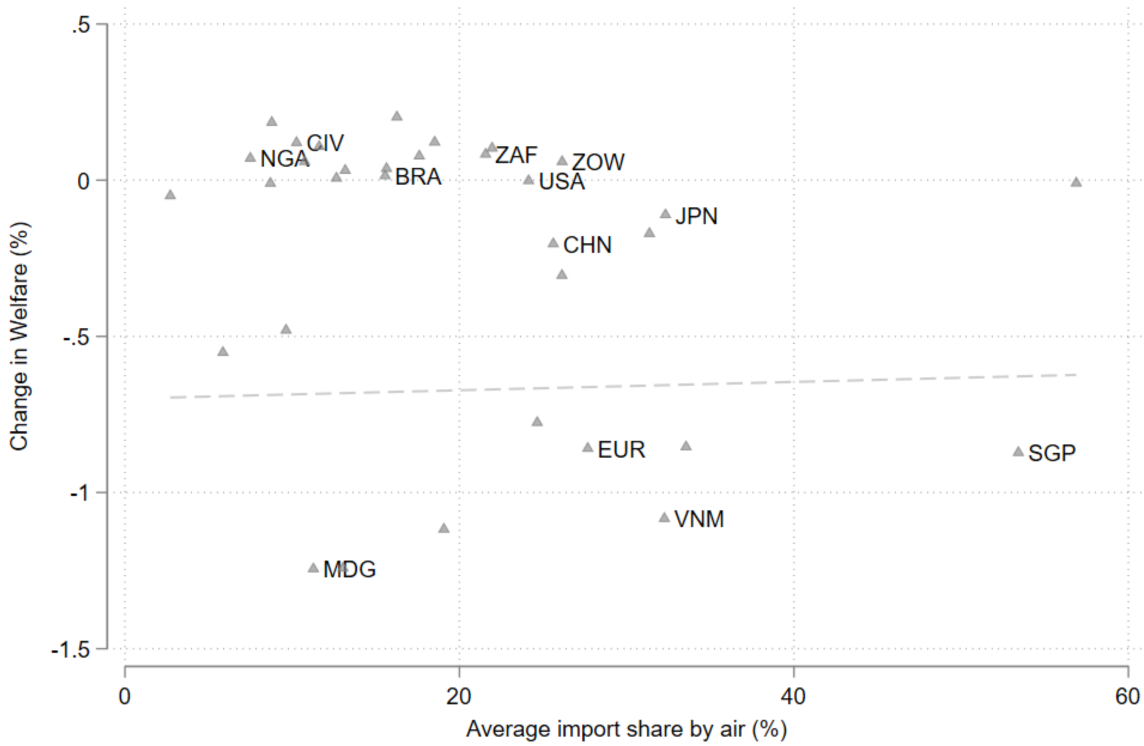
Notes: Panel (a) reports the counterfactual change in welfare in relationship with the air import share for the IMO23 experiment in the baseline mode with and without substitution. Panel (b) reports the estimates of the same policy but for the model with congestion costs with and without substitution. In both cases, the correlation with the air share remains. Substitution helps in mitigating the negative effects of the policy both in the model with and without congestion. Panel (c) reports the counterfactual relative change in CO_2 for the model with and without congestion with respect to the models with no substitution. Again in both scenarios, substitution across transport modes increases emissions.

Figure H.7: US Data: Sectoral Heterogeneity



Notes: This figure reports the estimates for Equation (5) for the sample split by HS section (WCO, 2018).

Figure H.8: Closure of the Suez Canal: Change in Welfare and Air Share



Notes: This figure reports the welfare change by country caused by the closure of the Suez Canal. The results are for a model with substitution and congestion forces. The fitted line indicates that countries with a higher average import share by air that are exposed to the shock suffered greater losses. Countries' names are reported using the iso3 code for the full names see Table I.13.

I Additional Tables

In this section, additional tables that complement the main text are reported.

Table I.1: air Trade and Product Characteristics

		% of observation with 2 modes	Value by Air (%)	Weight by Air (%)	Number of Obs
BEC					
Other	0	35.95	0.021	0.005	7710
Capital	1	53.79	0.390	0.060	377449
intermediate	2	54.38	0.271	0.004	1209396
Consumption	3	49.30	0.274	0.025	627600
Containerizability					
Not suitable	0	52.99	0.054	0.001	193,513
Slightly Suitable	1	44.35	0.202	0.010	151,770
Suitable	2	53.44	0.347	0.018	1876892
Temperature					
Low	1	53.61	0.242	0.005	1488940
Medium Low	2	54.63	0.285	0.006	433532
Medium High	3	48.78	0.515	0.015	178331
High	4	41.85	0.332	0.024	121372
Unit Value					
Low	1	46.41	0.014	0.002	424815
Medium	2	57.46	0.103	0.025	785724
High	3	51.83	0.445	0.098	1011604
Time Costs					
Low	1	47.56	0.405	0.011	653082
Medium	2	54.17	0.326	0.027	814913
High	3	55.80	0.085	0.003	754180

Notes: This table reports some key statistics of the Eurostat sample by product characteristics. The Broad Economic Classification (BEC) is an indicator variable that categorizes products based on their final use and is composed of three main categories: Capital, Intermediate, and Consumption goods. Containerizability is an index that describes how easy it is for a good to be transported in a container. This measure is taken from Bernhofen et al. (2016). Temperature is an index that measures how sensitive a good is to temperature, and it takes values from 1 (low sensitivity) to 4 (high sensitivity). Unit Value is an index variable that contains unit value terciles based on the unit value distribution of each sector in 2019. The time costs index is a discretized version of the continuous index by Hummels and Schaur (2013).

Table I.2: Treated and Control Groups Comparison

		Mean	Median	sd
	Air Trade			
Log Weight	Non-treated	8.392	8.56	2.26
	Treated	8.73	9	2.54
Log Value	Non-treated	12.66	12.83	2.64
	Treated	12.64	12.87	2.77
	Sea Trade			
Log Weight	Non-treated	9.35	9.75	3.25
	Treated	10.49	10.97	3.15
Log Value	Non-treated	12.35	12.76	2.99
	Treated	13.21	13.58	1.78

Notes: Comparison between the treated group and the control in order to exclude that the estimation's results are driven by the pre-shock composition of the trade flows. The treated group is composed of country pairs made by European countries and nations in eastern or southern Asia. Eurostat data for the year 2019. The unit of observation is the trade flows by air in a month between a country pair in a specific sector. Sectors are defined as 6-digit code product groups (HS6).

Table I.3: Treated and Control Groups Comparison for US Census

		Mean	Median	sd
	Air Trade			
Log Value	Non-treated	11.48	11.41	2.26
	Treated	11.86	11.85	1.45
Log Cost	Non-treated	1.19	1.29	1.25
	Treated	1.34	1.50	1.22
	Sea Trade			
Log Value	Non-treated	12.07	12.15	2.28
	Treated	13.53	13.68	2.44
Log Cost	Non-treated	-0.67	-0.59	1.47
	Treated	-0.63	-0.60	1.17

Notes: This table compares the treated group and the control in order to exclude that the estimation's results are driven by the pre-shock composition of the trade flows. The treated group is composed of US trading partners in Asia while the control group is composed of European partners. The unit of observation is the trade flows by mode in a month between a country pair in a specific sector. Sectors are defined as 6-digit code product groups (HS6). Data are based on the year 2019 since is pre-shock and pre-Covid.

Table I.4: Increase in air transport: aggregate effect

	(1)	(2)	(3)
	ln FlightTime	Ln Trade	Ln Trade
Post $\times$ Treated	0.073***	0.128***	
	(0.017)	(0.043)	
ln FlightTime			1.740**
			(0.757)
Observations	2,335,503	2,335,503	2,335,503
R-squared	0.844	0.612	-0.010
F-stat			18.709
Origin-destination-HS6	Y	Y	Y
Year-Month-HS6	Y	Y	Y

Notes: Column (1) reports the estimates for regression (1). The dependent variable is the log average flight time between two country pairs. Column (2) reports the estimates for regression (2) where the dependent variable is the ratio, in kilograms, between sea and air trade between a country n and a country i in sector h in month t. Treated is a dummy that takes values 1 if the origin/destination country is in Asia and 0 otherwise. Post is a dummy that takes value 1 after the start of the war (February 2022) and 0 otherwise. The Wald-DiD estimator, equation (3), is calculated via 2SLS and is equivalent to the ratio of the coefficients in columns (1) and columns (2). The coefficient of column (3) can be interpreted as the elasticity of substitution between transport modes. Standard errors are clustered at the origin-destination level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table I.5: IV results for alternative specifications

	(1) Baseline	(2) Manufacture	(3) March 22	(4) Share 1%	(5) Full	(6) No Outliers
lnftime	1.580**	1.565*	1.204*	1.632**	1.669**	1.863*
	(0.828)	(0.825)	(0.640)	(0.824)	(0.843)	(1.010)
Observations	2,297,813	2,183,732	2,297,813	2,363,391	2,492,003	2,157,246
IV F-Stat	18.71	17.41	18.71	16.93	15.95	18.89
Origin-Destination-HS6	Y	Y	Y	Y	Y	Y
Year-Month-HS6	Y	Y	Y	Y	Y	Y

Notes: This table reports the estimates for the Wald-Did estimator computed via IV-2SLS. The dependent variable is the ratio of sea trade with respect to air trade in euros between two country pairs. Column (1) reports the baseline estimates. Column (2) replicates the analysis using only manufacturing sectors. Column (3) reports the estimates with the dummy Post that takes value 1 from March 2022 onwards. Column (4) uses only origin-destination-sectors with at least 1% of trade by air. Column (5) uses the full sample. Column (6) uses the full sample but excludes observations with outliers in the average flight time. Standard errors are clustered at the origin-destination level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table I.6: Increase in air transport: Effect on Unit Values

	(1) Low	(2) Medium-low	(3) Medium-high	(4) High
ln FlightTime	2.274*	2.025**	1.639**	0.992
	(1.341)	(1.005)	(0.725)	(0.735)
Observations	269,771	549,279	786,240	730,209
R-squared	-0.022	-0.017	-0.010	-0.004
F-stat	10.725	16.842	21.927	20.055
Origin-destination-HS6	Y	Y	Y	Y
Year-Month-HS6	Y	Y	Y	Y

Notes: This table reports the estimates for the Wald-Did estimator computed via IV-2SLS across different subsample based on the ratio of the unit values by transport mode along the same origin-destination-sector triplet. Column (1) reports the results for the group in which the unit-value of the good transported via air and sea is the closest while column (4) reports it for those good in which is very different. Standard errors are clustered at the origin-destination level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table I.7: Increase in air transport: aggregate effect

	(1) UV ratio	(2) UV air	(3) UV sea
ln FlightTime	0.160	0.221	0.033
	(0.277)	(0.233)	(0.224)
Observations	2,335,503	2,395,071	2,401,609
R-squared	-0.000	-0.001	-0.000
F-stat	18.709	19.041	19.087
Origin-destination-HS6	Y	Y	Y
Year-Month-HS6	Y	Y	Y

Notes: This table reports the estimates for the Wald-Did estimator computed via IV-2SLS by unit values calculated it at the origin-destination-sector-transport level. Column (1) reports the results for the ratio between air and sea unit values within a common origin-destination-sector triplet. Columns (2) and (3) instead estimates the effect separately. Standard errors are clustered at the origin-destination level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table I.8: Flight-time: Naive OLS estimates

VARIABLES	(1) ln-trade	(2) ln-trade weight
lnftime	-0.066	-0.065
	(0.063)	(0.063)
Observations	2,335,503	2,335,503
R-squared	0.630	0.612
Origin-HS6	Y	Y
Year-Month-HS6	Y	Y

Notes: This Table reports the coefficients of the naive regression in which the dependent variable is the log-ratio of trade flows by air and sea in terms of value, column (1), and weight, column (2), and the independent variable is the bilateral flight time. Standard errors clustered at the origin-destination level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table I.9: US Transport Costs: Naive OLS estimates

	(1) Log Trade
lncost	-0.114***
	(0.004)
Observations	1,195,534
R-squared	0.710
Origin-HS6	Y
Year-Month-HS6	Y

Notes: This Table reports the coefficient of the naive regression in which the dependent variable is the log ratio of trade flows by air and sea in terms of value, and the independent variable is the ratio of transport costs from an origin i to the USA. Standard errors clustered at the origin-HS6 level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table I.10: Alternative specification η

	(1) OECD	(2) OECD IV	(3) CHL air	(4) CHL sea	(5) CHL	(6) CHL air IV	(7) CHL sea IV	(8) CHL IV	(9) CHL ALT
Transport Costs	-0.168***	-0.395***	-0.539***	-0.350***	-0.673***	-1.147***	-1.093***	-1.349***	
	(0.007)	(0.033)	(0.012)	(0.014)	(0.010)	(0.069)	(0.066)	(0.026)	
$\ln\left(d^{air}_{odht}/d^{sea}_{odht}\right)$									-0.378***
									(0.010)
Observations	664,918	467,949	570,537	570,537	1,724,722	455,483	455,483	1,106,114	570,537
R-squared	0.712	-0.000	0.795	0.753	0.800	-0.012	-0.012	0.049	0.697
Origin-destination-year-month-HS4 FE	Y	Y	N	N	N	N	N	N	N
Origin-year-month-HS4 FE	N	N	Y	Y	N	Y	Y	N	Y
Year-month-HS6 FE	Y	Y	Y	Y	N	Y	Y	N	N
Origin-year-month-HS6 FE	N	N	N	N	N	N	N	N	Y
Year-month-HS6-mode FE	N	N	N	N	Y	N	N	Y	N

Notes: Standard errors in each column are clustered at the origin-sector. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table I.11: Robustness checks η

	(1) No Covid Air	(2) No Covid Sea	(3) No Covid	(4) Manuf Air	(5) Manuf Sea	(6) Manuf	(7) lag t-2	(8) lag t-6	(9) lag t-12
Transport Costs	-0.196***	-0.137***	-0.188***	-0.198***	-0.138***	-0.190***	-0.283***	-0.319***	-0.340***
	(0.005)	(0.006)	(0.004)	(0.005)	(0.006)	(0.004)	(0.017)	(0.022)	(0.025)
Observations	903,928	903,928	2,679,116	876,250	876,250	2,519,496	1,103,843	1,062,456	1,010,593
R-squared	0.810	0.764	0.823	0.811	0.763	0.822			
Origin-year-month-HS4 FE	Y	Y	N	Y	Y	N	Y	Y	Y
Year-month-HS6 FE	Y	Y	N	Y	Y	N	Y	Y	Y
Origin-year-month-HS6 FE	N	N	Y	N	N	Y	N	N	N
Year-month-HS6-mode FE	N	N	Y	N	N	Y	N	N	N

Notes: Standard errors in each column are clustered at the origin-sector. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table I.12: Data and Parameters source for Counterfactual

Variable	Source	Currency	Exchange rate	Classification	Year
	Share by Mode				
Extra-European Trade	Eurostat	EUR	1.1069 (ECB)	CN8	2018
Japan	Trade Statistics of Japan	JPY	108.79 (IMF)	CN8	2018
USA	US Census Bureau	USD		CN8	2018
LATM countries	IDB database	USD		CN8	2018
Asean countries	Asean database	USD		CN8	2021
Others	Comtrade	USD		HS6	2018
China	Mirror Flows	Mirror Flows		Mirror Flows	2018
Row	Mirror Flows	Mirror Flows		Mirror Flows	2018
	Trade Flows				
International Trade	Comtrade	USD		HS6	2018
Intra-Country Trade	TradeProd Cepii	USD		ISIC3	2018
	Country Statistics				
GDP	World Bank	USD			2018
PPP	World Bank	USD			2018
BOP	IMF	USD			2018
	Parameters				
	Source	Value			
α	EK 02	0.188			
β	EK 02	0.312			
θ	Head and Mayer (2014)	4			
λ	Fuchs and Wong (2024)	0.092			
η	Own Calculation	3			

Notes: All data are for the year 2016. Share by mode for Latm is based on 2018 and for Asean countries for the year 2021 due to data availability. Trade data are converted to ISIC3 to ensure comparability with within-country trade flows. The Latin American countries are Brazil, Chile, Colombia, Costa Rica, the Dominican Republic, Ecuador, Jamaica, Mexico, Peru, and Uruguay. The Asean countries are Brunei, Cambodia, Indonesia, Malaysia, Myanmar, Philippines, Singapore, Thailand, and Viet Nam. The other countries are Australia, Benin, Bosnia, Belize, Canada, Côte d'Ivoire, Madagascar, Mauritius, Nigeria, El Salvador, Turkiye, and South Africa. Following the Trade-Prod dataset, only sectors related to industrial production are kept. The sectors used, with HS2 code in parenthesis, are: *Chemicals* (23-24-25), *Food* (15-16), *Machines* (29-30-31-32-33), *Metals* (27-28), *Minerals* (26), *Other* (36), *Textiles* (17-18-19), *Vehicles* (34-35), and *Wood-Paper* (20-21-22). Chinese trade flows by mode are inferred from other flows and converted accordingly. Intra-country trade flows are not reported by mode of transport. Trade flows by mode are restricted to air and sea only which accounts for more than 90% of total trade observed.

Table I.13: List of Country used

ISO code	Name	ISO code	Name
AUS	Australia	ITA	Italy
AUT	Austria	JAM	Jamaica
BEL	Belgium	JPN	Japan
BEN	Benin	LTU	Lithuania
BGR	Bulgaria	LUX	Luxembourg
BLZ	Belize	LVA	Latvia
BRA	Brazil	MDG	Madagascar
BRN	Brunei Darussalam	MEX	Mexico
CAN	Canada	MMR	Myanmar
CHL	Chile	MUS	Mauritius
CHN	China	MYS	Malaysia
CIV	Côte d'Ivoire	NGA	Nigeria
COL	Colombia	NLD	Netherlands
CRI	Costa Rica	PER	Peru
CYP	Cyprus	PHL	Philippines
CZE	Czechia	POL	Poland
DEU	Germany	PRT	Portugal
DNK	Denmark	ROU	Romania
DOM	Dominican Republic	SGP	Singapore
ECU	Ecuador	SLV	El Salvador
ESP	Spain	SVK	Slovakia
EST	Estonia	SWE	Sweden
FIN	Finland	THA	Thailand
FRA	France	TUR	Turkiye
GBR	United Kingdom	URY	Uruguay
GRC	Greece	USA	United States of America
HUN	Hungary	VNM	Viet Nam
IDN	Indonesia	ZAF	South Africa
IRL	Ireland	ROW	Rest of the Wolrd

Table I.14: Closure of Russian-Ukrainian Airspace: Average Welfare Changes Across Models

Model	No Substitution	Substitution
Avg Welfare change (%)	-0.064	-0.061 (+4.91%)

Notes: This table reports the average welfare change, in countries directly affected by the shock, across different models for the counterfactual that studies the permanent closure of the Russian and Ukrainian airspaces. The shock is modelled a as a 8% increase in air costs for routes connecting Europe with Asian destinations. Column 1 reports the average change for a model with congestion but no substitution (Section G.6). Colum2 2 reports the results for a model in which noth congestion and substitution are active (Section 4). All the numbers are expressed in percentage change from the initial equilibrium.

Table I.15: Change in welfare due to airspace closure and comparison with no-substitution model

		Model with Substitution		Model with Substitution and Congestion	
Country	Import Share by Air	Welfare Change (|%)	Δ Welfare	Welfare Change(%)	Δ Welfare
Australia	31.36	0.0029	-0.0001	-0.0033	0.0002
Benin	2.71	-0.0141	0.0007	-0.0149	0.0007
Belize	8.78	0.0185	-0.0015	0.0101	-0.0008
Brazil	15.55	0.0032	-0.0002	-0.0003	0.0000
Brunei Darussalam	16.26	-0.1227	0.0013	-0.1007	0.0013
Canada	56.88	0.0052	-0.0004	-0.0021	0.0000
Chile	13.17	0.0060	-0.0004	0.0011	-0.0001
China	25.61	-0.0364	0.0022	-0.0280	0.0014
Côte d'Ivoire	10.26	0.0198	-0.0015	0.0032	-0.0003
Colombia	17.60	0.0031	-0.0003	-0.0022	0.0000
Costa Rica	21.95	0.0133	-0.0010	0.0053	-0.0004
Dominican Republic	12.64	-0.0023	0.0000	-0.0056	0.0002
Ecuador	11.61	0.0080	-0.0007	0.0018	-0.0002
Europe	27.67	-0.1688	0.0094	-0.1365	0.0065
Indonesia	9.63	-0.0178	0.0015	-0.0176	0.0011
Jamaica	8.69	-0.0025	-0.0001	-0.0067	0.0002
Japan	32.32	-0.0725	0.0031	-0.0566	0.0021
Madagascar	11.26	0.0226	-0.0016	0.0127	-0.0009
Mexico	18.52	0.0163	-0.0011	0.0068	-0.0005
Myanmar	5.85	-0.0199	0.0016	-0.0180	0.0011
Mauritius	13.04	0.0123	-0.0011	0.0013	-0.0003
Malaysia	33.55	-0.1348	0.0067	-0.1118	0.0046
Nigeria	7.49	0.0138	-0.0011	-0.0018	-0.0001
Peru	10.74	0.0065	-0.0005	0.0008	-0.0001
Philippines	26.13	-0.1298	0.0059	-0.1012	0.0039
Singapore	53.42	-0.3755	0.0120	-0.3215	0.0089
Thailand	24.65	-0.1353	0.0070	-0.1099	0.0048
Turkey	19.07	0.0186	-0.0013	0.0098	-0.0006
Uruguay	15.64	0.0038	-0.0004	-0.0030	0.0000
United States of America	24.13	0.0033	-0.0003	-0.0014	0.0000
Viet Nam	32.25	-0.0897	0.0054	-0.0740	0.0037
South Africa	21.56	0.0149	-0.0010	0.0056	-0.0004
ROW	26.14	0.0125	-0.0007	0.0037	-0.0002

Notes: Change in welfare for baseline model with $\eta = 3$ and $d_{ni}^{air} = 1.08$ and comparison with Cobb-Douglas model. For the model with congestion $\lambda = 0.092$ is used. Δ Welfare is calculated as the percentage difference of the welfare changes between the version of the model with substitution and with Cobb-Douglas shares.

Table I.16: Change in welfare due to Suez Canal closure and comparison with no-substitution model

		Model with Substitution		Model with Substitution and Congestion	
Country	Import Share by Air	Welfare Change (|%)	Δ Welfare	Welfare Change(%)	Δ Welfare
Australia	31.36	-0.1943	0.0044	-0.1708	0.0038
Benin	2.71	-0.0208	0.0009	-0.0498	0.0024
Belize	8.78	0.2647	-0.0168	0.1849	-0.0104
Brazil	15.55	0.0406	-0.0028	0.0143	-0.0010
Brunei Darussalam	16.26	0.2681	-0.0217	0.2024	-0.0141
Canada	56.88	0.0412	-0.0047	-0.0093	-0.0012
Chile	13.17	0.0641	-0.0046	0.0313	-0.0021
China	25.61	-0.2508	0.0149	-0.2036	0.0113
Côte d'Ivoire	10.26	0.2784	-0.0171	0.1203	-0.0066
Colombia	17.60	0.1361	-0.0075	0.0774	-0.0038
Costa Rica	21.95	0.1727	-0.0106	0.1028	-0.0056
Dominican Republic	12.64	0.0410	-0.0028	0.0066	-0.0006
Ecuador	11.61	0.1631	-0.0098	0.1079	-0.0057
Europe	27.67	-0.9575	0.0656	-0.8588	0.0522
Indonesia	9.63	-0.6122	0.0083	-0.4801	0.0078
Jamaica	8.69	0.0367	-0.0027	-0.0100	0.0003
Japan	32.32	-0.1407	0.0073	-0.1108	0.0053
Madagascar	11.26	-1.4011	0.0808	-1.2444	0.0624
Mexico	18.52	0.1948	-0.0118	0.1218	-0.0066
Myanmar	5.85	-0.6514	0.0198	-0.5516	0.0183
Mauritius	13.04	-1.5020	0.0952	-1.2419	0.0674
Malaysia	33.55	-0.9929	0.0865	-0.8539	0.0698
Nigeria	7.49	0.2169	-0.0138	0.0702	-0.0041
Peru	10.74	0.1034	-0.0068	0.0595	-0.0034
Philippines	26.13	-0.3767	0.0547	-0.3050	0.0395
Singapore	53.42	-0.9678	0.1745	-0.8720	0.1382
Thailand	24.65	-0.9313	0.0769	-0.7760	0.0602
Turkey	19.07	-1.0627	0.0398	-1.1175	0.0461
Uruguay	15.64	0.0990	-0.0062	0.0374	-0.0020
United States of America	24.13	0.0315	-0.0040	-0.0015	-0.0014
Viet Nam	32.25	-1.2822	0.0592	-1.0832	0.0484
South Africa	21.56	0.1490	-0.0105	0.0832	-0.0056
ROW	26.14	0.1310	-0.0098	0.0593	-0.0044

Notes: This table reports the results of the second counterfactual experiment in which I simulate the impact of the closure of the Suez Canal. The elasticity of substitution between modes of transport is set to be $\eta = 3$ while the congestion strength is set to be $\lambda = 0.092$. Δ Welfare is calculated as the percentage difference of the welfare changes between the version of the model with substitution and without substitution.

Table I.17: Closure of the Suez Canal: Average Welfare Changes Across Models

Model	No Substitution + Congestion	Substitution + Congestion
Avg Welfare change (%)	-0.667	-0.624 (+6.89%)

Notes: This table reports the average welfare change, in countries directly affected by the shock, across different models for the counterfactual that studies the permanent closure of the Suez Canal. Column 1 reports the average change for a model with congestion but no substitution (Section G.6). Colum2 2 reports the results for a model in which noth congestion and substitution are active (Section 4). All the numbers are expressed in percentage change from the initial equilibrium.

Table I.18: IMO23: Average Welfare and CO_2 Change Across Models

Model	No Substitution	Substitution
Avg Welfare change (%)	-2.314	-2.277 (+1.6%)
Avg CO_2 change (%)	-17.911	-13.855 (+29.2%)

Notes: This table reports the average changes in welfare and CO_2 across different models due to the introductio of the IMO23 regulation. The policy is simulated by increasing sea transport costs by 10% and by decresing CO_2 emissions in sea transport by 7.3%. Column 1 reports the average change for a model with congestion but no substitution (Section G.6). Colum2 2 reports the results for a model in which noth congestion and substitution are active (Section 4). All the numbers are expressed in percentage change from the initial equilibrium.

Table I.19: Baseline Results IMO23 and comparison across models (Part 1)

		Model With Substitution			
Country	Impost Share by Air	Welfare Change (%)	CO_2 Imports (%)	Δ Welfare	Δ CO_2
Australia	31.36	-2.1567	-15.5312	0.0432	4.6237
Benin	2.71	-2.5451		0.0198	
Belize	8.78	-2.3726		0.0315	
Brazil	15.55	-1.1866	-29.8787	0.0111	2.0433
Brunei Darussalam	16.26	-3.3356	-21.4785	0.0308	7.8249
Canada	56.88	-1.6671	-2.7212	0.0775	3.5502
Chile	13.17	-2.0576	-18.8667	0.0166	8.8928
China	25.61	-0.5121	-20.6981	0.0083	9.0162
Côte d'Ivoire	10.26	-3.1872	-31.0030	0.0232	2.0252
Colombia	17.60	-2.1901	-13.0270	0.0365	4.1029
Costa Rica	21.95	-1.6445		0.0429	
Dominican Republic	12.64	-2.4990	6.0335	0.0383	12.7915
Ecuador	11.61	-3.3026	-11.6866	0.0282	2.4167
Europe	27.67	-1.8443	-13.9786	0.0454	2.4178
Indonesia	9.63	-1.9494	-19.4458	0.0111	11.8574
Jamaica	8.69	-2.6707	21.5019	0.0169	-0.0611
Japan	32.32	-0.9093	-15.9046	0.0212	7.9331
Madagascar	11.26	-3.4558	-13.1256	0.0532	1.3840
Mexico	18.52	-2.4437	-12.6300	0.0482	8.4275
Myanmar	5.85	-1.9153	-11.8003	0.0088	7.8908
Mauritius	13.04	-3.0153		0.0540	
Malaysia	33.55	-2.0090	-16.6525	0.0593	6.0125
Nigeria	7.49	-3.5613	-24.8471	0.0287	5.9969
Peru	10.74	-2.3507	-15.4192	0.0269	3.3923
Philippines	26.13	-1.7060	-10.1964	0.0520	5.1876
Singapore	53.42	-2.2583	-8.4191	0.1177	-0.2964
Thailand	24.65	-2.5245	-16.1565	0.0535	7.6365
Turkey	19.07	-3.3170	-17.0092	0.0471	-2.7392
Uruguay	15.64	-2.6835	-20.9832	0.0308	2.4816
United States of America	24.13	-1.0643	-9.3575	0.0294	3.4339
Viet Nam	32.25	-1.9693	-16.5354	0.0508	4.2319
South Africa	21.56	-2.6464	-12.0208	0.0607	7.9168
ROW	26.14	-2.1789	-9.9577	0.0429	7.1248

Notes: This table reports the results of the second counterfactual experiment in which I simulate the impact of the IMO23 regulation which I assumed to increase sea transport costs by $d_{ni}^{sea} = 1.1$. For this experiment I use the model described in Section 4. The elasticity of substitution between modes of transport is set to be $\eta = 3$ while the congestion strength is set to be $\lambda = 0.092$. Δ Welfare and Δ CO_2 are calculated as the percentage difference of the welfare changes and CO_2 imports between the version of the model with substitution and with Cobb-Douglas shares.

Table I.20: Baseline Results IMO23 and Comparison across Models (Part 2)

		Model with Substitution and Congestion			
Country	Impost Share by Air	Welfare Change (%)	CO_2 Imports (%)	Δ Welfare	Δ CO_2
Australia	31.36	-1.7149	-13.0916	0.0300	-13.0916
Benin	2.71	-2.2544		0.0147	
Belize	8.78	-2.0678		0.0228	
Brazil	15.55	-0.9495	-25.0053	0.0086	-25.0053
Brunei Darussalam	16.26	-2.7034	-18.0299	0.0232	-18.0299
Canada	56.88	-1.5245	-3.0035	0.0543	-3.0035
Chile	13.17	-1.6680	-15.4830	0.0128	-15.4830
China	25.61	-0.4109	-16.5173	0.0059	-16.5173
Côte d'Ivoire	10.26	-2.5067	-25.7889	0.0188	-25.7889
Colombia	17.60	-1.8551	-11.4365	0.0262	-11.4365
Costa Rica	21.95	-1.4133		0.0297	
Dominican Republic	12.64	-2.2399	4.8808	0.0286	4.8808
Ecuador	11.61	-2.8451	-10.6968	0.0221	-10.6968
Europe	27.67	-1.5572	-12.3300	0.0318	-12.3300
Indonesia	9.63	-1.5671	-15.3252	0.0094	-15.3252
Jamaica	8.69	-2.3053	14.3061	0.0141	14.3061
Japan	32.32	-0.7417	-12.9526	0.0148	-12.9526
Madagascar	11.26	-3.0330	-12.1150	0.0388	-12.1150
Mexico	18.52	-2.0634	-10.7656	0.0338	-10.7656
Myanmar	5.85	-1.5872	-10.0281	0.0071	-10.0281
Mauritius	13.04	-2.5788		0.0377	
Malaysia	33.55	-1.6945	-14.2949	0.0415	-14.2949
Nigeria	7.49	-2.8178	-20.1399	0.0218	-20.1399
Peru	10.74	-1.9905	-13.6110	0.0197	-13.6110
Philippines	26.13	-1.4703	-9.1771	0.0361	-9.1771
Singapore	53.42	-2.0856	-8.3384	0.0854	-8.3384
Thailand	24.65	-2.1082	-13.6695	0.0379	-13.6695
Turkey	19.07	-2.8516	-15.7029	0.0351	-15.7029
Uruguay	15.64	-2.1975	-17.9568	0.0233	-17.9568
United States of America	24.13	-0.9389	-8.8587	0.0205	-8.8587
Viet Nam	32.25	-1.6549	-14.3022	0.0358	-14.3022
South Africa	21.56	-2.2261	-10.4290	0.0423	-10.4290
ROW	26.14	-1.8166	-8.5001	0.0305	-8.5001

Notes: This table reports the results of the second counterfactual experiment in which I simulate the impact of the IMO23 regulation which I assumed to increase sea transport costs by $d_{ni}^{sea} = 1.1$. For this experiment I use the model described in Section 5. The elasticity of substitution between modes of transport is set to be $\eta = 3$ while the congestion strength is set to be $\lambda = 0.092$. Δ Welfare and Δ CO_2 are calculated as the percentage difference of the welfare changes and CO_2 imports between the version of the model with substitution and with Cobb-Douglas shares.

Table I.21: IMO23: Comparison across different elasticities (η)

		Welfare Change (%)					CO_2 Imports (%)				
Country	Import Air Share	Baseline	No Substitution	High	Low	Short	Baseline	No Substitution	High	Low	Short
Australia	31.36	-1.7149	-1.7444	-1.7107	-1.7204	-1.7410	-16.3220	-13.6987	-12.6239	-15.9566	
Benin	2.71	-2.2544	-2.2688	-2.2523	-2.2571	-2.2671					
Belize	8.78	-2.0678	-2.0901	-2.0646	-2.0720	-2.0876					
Brazil	15.55	-0.9495	-0.9580	-0.9482	-0.9511	-0.9570	-26.2392	-25.2412	-24.8224	-26.1023	
Brunei Darussalam	16.26	-2.7034	-2.7260	-2.7002	-2.7076	-2.7234	-23.0842	-19.0110	-17.2641	-22.5328	
Canada	56.88	-1.5245	-1.5779	-1.5170	-1.5342	-1.5716	-5.7949	-3.5286	-2.5990	-5.4797	
Chile	13.17	-1.6680	-1.6805	-1.6661	-1.6703	-1.6791	-21.3025	-16.5969	-14.6186	-20.6578	
China	25.61	-0.4109	-0.4168	-0.4101	-0.4120	-0.4161	-22.3215	-17.6259	-15.6579	-21.6770	
Côte d'Ivoire	10.26	-2.5067	-2.5250	-2.5041	-2.5102	-2.5230	-27.0396	-26.0284	-25.6030	-26.9011	
Colombia	17.60	-1.8551	-1.8808	-1.8514	-1.8599	-1.8779	-14.3384	-11.9899	-11.0078	-14.0155	
Costa Rica	21.95	-1.4133	-1.4426	-1.4092	-1.4188	-1.4392					
Dominican Republic	12.64	-2.2399	-2.2678	-2.2358	-2.2451	-2.2647	-5.2793	2.9117	6.4166	-4.1690	
Ecuador	11.61	-2.8451	-2.8666	-2.8419	-2.8491	-2.8642	-12.4624	-11.0360	-10.4332	-12.2676	
Europe	27.67	-1.5572	-1.5885	-1.5528	-1.5631	-1.5849	-14.0216	-12.6500	-12.0829	-13.8317	
Indonesia	9.63	-1.5671	-1.5763	-1.5657	-1.5688	-1.5753	-22.9825	-16.8105	-14.1662	-22.1465	
Jamaica	8.69	-2.3053	-2.3191	-2.3033	-2.3079	-2.3175	14.2656	14.2977	14.3128	14.2697	
Japan	32.32	-0.7417	-0.7564	-0.7396	-0.7445	-0.7547	-18.3693	-13.9985	-12.1380	-17.7748	
Madagascar	11.26	-3.0330	-3.0707	-3.0276	-3.0400	-3.0664	-13.1161	-12.3062	-11.9667	-13.0049	
Mexico	18.52	-2.0634	-2.0965	-2.0587	-2.0696	-2.0928	-16.6108	-11.8863	-9.8955	-15.9644	
Myanmar	5.85	-1.5872	-1.5942	-1.5862	-1.5886	-1.5935	-15.5776	-11.1036	-9.1892	-14.9711	
Mauritius	13.04	-2.5788	-2.6156	-2.5735	-2.5857	-2.6114					
Malaysia	33.55	-1.6945	-1.7354	-1.6887	-1.7021	-1.7307	-18.3855	-15.0829	-13.6818	-17.9353	
Nigeria	7.49	-2.8178	-2.8390	-2.8147	-2.8218	-2.8366	-23.9536	-20.8791	-19.5633	-23.5369	
Peru	10.74	-1.9905	-2.0098	-1.9877	-1.9941	-2.0076	-15.9754	-14.0656	-13.2575	-15.7148	
Philippines	26.13	-1.4703	-1.5058	-1.4652	-1.4768	-1.5017	-12.9243	-9.8913	-8.6237	-12.5071	
Singapore	53.42	-2.0856	-2.1691	-2.0740	-2.1008	-2.1594	-8.1002	-8.3038	-8.3619	-8.1339	
Thailand	24.65	-2.1082	-2.1453	-2.1029	-2.1151	-2.1410	-18.8438	-14.6621	-12.8985	-18.2717	
Turkey	19.07	-2.8516	-2.8857	-2.8467	-2.8581	-2.8819	-13.7077	-15.3359	-15.9833	-13.9387	
Uruguay	15.64	-2.1975	-2.2203	-2.1942	-2.2018	-2.2177	-19.6064	-18.2721	-17.7122	-19.4234	
United States of America	24.13	-0.9389	-0.9592	-0.9361	-0.9427	-0.9569	-11.3571	-9.3383	-8.4862	-11.0812	
Viet Nam	32.25	-1.6549	-1.6901	-1.6499	-1.6614	-1.6861	-17.2211	-14.8594	-13.8702	-16.8966	
South Africa	21.56	-2.2261	-2.2675	-2.2202	-2.2339	-2.2628	-15.9423	-11.4755	-9.6198	-15.3258	
ROW	26.14	-1.8166	-1.8465	-1.8123	-1.8221	-1.8431	-13.6779	-9.4879	-7.7347	-13.1022	

Notes: Change in welfare and total emission across models with different elasticity of substitution between modes of transport. In the baseline $\eta = 3$ and $d_{ni}^{sea} = 1.1$. In the high scenario $\eta = 3.3$, in the low $\eta = 2.58$, and in the short $\eta = 1.2$.

Table I.22: Comparison across different λ

		Welfare Change (%)			CO_2 Imports (%)		
Country	Import Air Share	Baseline	Low	High	Baseline	Low	High
Australia	31.36	-1.7149	-2.0988	-1.3706	-13.0916	-15.2117	-11.1922
Benin	2.71	-2.2544	-2.5074	-2.0232			
Belize	8.78	-2.0678	-2.3333	-1.8217			
Brazil	15.55	-0.9495	-1.1554	-0.7660	-25.0053	-29.2256	-21.3671
Brunei Darussalam	16.26	-2.7034	-3.2539	-2.1970	-18.0299	-21.0202	-15.4210
Canada	56.88	-1.5245	-1.6516	-1.3767	-3.0035	-2.7707	-3.0845
Chile	13.17	-1.6680	-2.0065	-1.3641	-15.4830	-18.4097	-13.0097
China	25.61	-0.4109	-0.4987	-0.3338	-16.5173	-20.1218	-13.5861
Côte d'Ivoire	10.26	-2.5067	-3.0958	-1.9980	-25.7889	-30.2948	-21.9881
Colombia	17.60	-1.8551	-2.1467	-1.5881	-11.4365	-12.8170	-10.2158
Costa Rica	21.95	-1.4133	-1.6154	-1.2199			
Dominican Republic	12.64	-2.2399	-2.4661	-2.0250	4.8808	5.8973	3.8276
Ecuador	11.61	-2.8451	-3.2440	-2.4721	-10.6968	-11.5597	-9.8933
Europe	27.67	-1.5572	-1.8074	-1.3247	-12.3300	-13.7652	-11.0155
Indonesia	9.63	-1.5671	-1.8988	-1.2729	-15.3252	-18.8733	-12.4846
Jamaica	8.69	-2.3053	-2.6228	-2.0196	14.3061	20.4329	9.9822
Japan	32.32	-0.7417	-0.8875	-0.6094	-12.9526	-15.4993	-10.8608
Madagascar	11.26	-3.0330	-3.4034	-2.6670	-12.1150	-12.9988	-11.2565
Mexico	18.52	-2.0634	-2.3951	-1.7522	-10.7656	-12.3820	-9.3588
Myanmar	5.85	-1.5872	-1.8723	-1.3314	-10.0281	-11.5574	-8.7715
Mauritius	13.04	-2.5788	-2.9592	-2.2249			
Malaysia	33.55	-1.6945	-1.9695	-1.4283	-14.2949	-16.3431	-12.4594
Nigeria	7.49	-2.8178	-3.4605	-2.2712	-20.1399	-24.1902	-16.8929
Peru	10.74	-1.9905	-2.3045	-1.6992	-13.6110	-15.1843	-12.1853
Philippines	26.13	-1.4703	-1.6766	-1.2687	-9.1771	-10.0686	-8.3222
Singapore	53.42	-2.0856	-2.2413	-1.8802	-8.3384	-8.4291	-8.0256
Thailand	24.65	-2.1082	-2.4716	-1.7636	-13.6695	-15.8267	-11.7754
Turkey	19.07	-2.8516	-3.2586	-2.4564	-15.7029	-16.8571	-14.4674
Uruguay	15.64	-2.1975	-2.6197	-1.8192	-17.9568	-20.5814	-15.6565
United States of America	24.13	-0.9389	-1.0489	-0.8293	-8.8587	-9.3058	-8.3233
Viet Nam	32.25	-1.6549	-1.9295	-1.3921	-14.3022	-16.2470	-12.5118
South Africa	21.56	-2.2261	-2.5933	-1.8760	-10.4290	-11.8139	-9.1690
ROW	26.14	-1.8166	-2.1322	-1.5238	-8.5001	-9.7651	-7.3871

Notes: Change in welfare and total emission across models with congestion and different λ. In the baseline $\lambda = 0.092$ and $d_{ni}^{sea} = 1.1$. In the Low scenario $\lambda = 0.01$, and in the high scenario $\lambda = 0.2$. The main takeaway is that welfare losses and CO_2 changes are amplified when congestion frictions are lower and the resulting equilibrium is closer to the model without congestion costs.