Shock Risks and Chokepoint Overreliance

Empirical Evidence from the Ever Given Incident

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Abstract

In March 2021, the container ship Ever Given crashed in the Suez Canal blocking traffic through it for six days. This paper explores the trade implications of this event at a port and country-level. We find that countries and ports with more trade routed to them through the Canal were affected more immediately after the incident, with imports slowing down by between 70% and 90%. We also find that the event caused propagation effects that applied to a wide range of would-be-unaffected countries and impacted, on average, at least 0.1% of country's final use of goods per year.

1 Introduction

On March 23, 2021, the Ever Given, one of the largest container ships in the world, was grounded in the Suez Canal. The ship was stranded for six days, during which all trade through the Canal was blocked (Yee and Glanz 2021). Every day, the blockage held up an estimated $10 billion worth of trade (Harper 2021). Freeing the ship took a multinational effort with 14 tugboats rotating the Ever Given in the water and dredgers digging up the sand the ship was stuck in on the shore (Hincks 2021).

*Data and replication files for the document and analysis are available at https://github.com/GavinEngelstad/IntlTradeSuezCanal. If you have questions, contact gengelst@maclester.edu.

The Suez Canal is one of a handful of maritime chokepoints. Most maritime trade travels through at least one of these chokepoints, which include other canals like the Panama Canal and areas with high levels of political instability like the East China Sea, demonstrating their central role in globalization (EIA 2017). Due to their importance, the risk of a blockage has been highlighted a number of times (Pratson 2023; Wang, Du, and Peng 2024; Xiao et al. 2022). Still, because of the rarity of such an event, there are few empirical studies on the implications a blockage would have.

This paper seeks to analyze the risks from marine chokepoint blockages on trade and the economy for individual geographies through analysis of the blockage caused by the Ever Given. We find that the blockage had extremely significant direct effects on ports that route significant amounts of trade through the canal and propagation effects that spread through global production processes impacting other countries that would have been otherwise unaffected.

The rest of the paper proceeds as follows: Section 2 gives a review of relevant literature and related work that we build on. Section 3 outlines the theoretical model we use for estimation. Section 4 explains the empirical model we use for estimation. Section 5 explores the data sources we use in our analysis. Section 6 estimates the direct effects of the blockage immediately during and after the event. Section 7 creates a lower bound on the propagation effects of the blockage. Section 8 concludes.

2 Lit Review

2.1 Maritime Trade and Chokepoints

By volume, about 80% of international trade happens by sea (Sirimanne et al. 2023). Most of this maritime trade travels through at least one marine chokepoint, or narrow, heavily trafficked passageway that connects two oceans or seas (Pratson 2023). Many of these chokepoints are located in regions with rampant political instability or are vulnerable to emerging global threats. In Yemen, Houthis recently started attacking ships traveling through the Red Sea (Bigg, Shankar, and Fuller 2024). In Central America, the effects of climate change are causing trade flows through the Panama Canal to drop by 50% (Arslanalp et al. 2023).

Trade flows through these chokepoints are essential for global food and energy security. Approximately 80% of maritime oil trade, 50% of the global oil supply, travels through one of just seven chokepoints, including the Suez Canal (EIA 2017). Additionally, 55% of food imports pass through one of these same choke points (Bailey and Wellesley 2017). The Suez Canal specifically is the shortest maritime route from east to west, and therefore plays an important role in trade initiatives between Asia, Africa, and Europe, including the Chinese Belt and Road Initiative (Rakha and El-Aasar 2024)

Major disruptions to these chokepoints would have far-reaching ramifications. Pratson 2023 found that an extended closure of any major chokepoint would cause significant increases in trade costs and force ships to reroute in ways that would affect every other chokepoint. Using AIS data that let them analyze the tracked movement of ships, Wang, Du, and Peng 2024 found that much of the world, especially in the Northern Hemisphere and global east, is reliant on just a handful of these checkpoints. Using an agent-based-model, Meza et al. 2022 found that a chokepoint blockade would be immediately impactful, especially on energy markets. Additionally, Xiao et al. 2022 found that the geography of chokepoints are exceptionally vulnerable to a wide variety of threats.

Despite these theoretical studies, empirical studies on the impacts of closing chokepoints are rare, since chokepoints are kept open. Between 1967 and 1975, the Suez Canal was shut down by the Egyptian Government, which had significant impacts on trade and output, but this type of shock is very different from the shorter term and less preventable shock we saw with the Ever Given (Feyrer 2021). The Ever Given incident gives us an opportunity to verify theoretical findings with an empirical study of a real, sudden chokepoint closure.

2.2 Maritime Trade as a Network

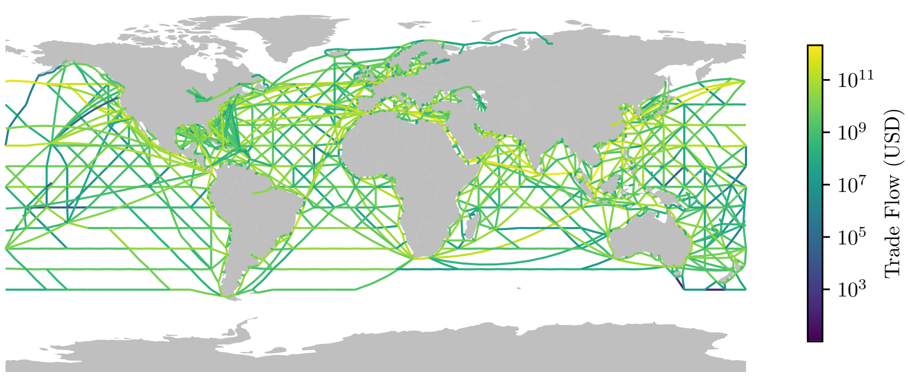
Using trade volumes as edge weights between node countries, international trade can be modeled using a web-like network structure (Bhattacharya et al. 2008). This sort of analysis can reveal a number of patterns in trade, including a power law in GDP and a “rich club” dynamic where trade is majority controlled by an ever smaller group. On the network, a properly specified gravity model can accurately predict edge weights and replicate the topological properties of the global trade network (Bhattacharya et al. 2008; Dueñas and Fagiolo 2013).

Using this same process on maritime trade networks specifically can reveal important structures in seaborne trade. Using nodes as ports and edges as voyages between ports, this type of analysis finds that the networks formed, especially by bigger ships, are very well-connected and fairly stable (Carlini et al. 2021). Over longer time periods, these networks tend to keep a constant diameter, or maximum network traversal distance, even as more ports are added and become more navigable (Kosowska-Stamirowska, Ducruet, and Rai 2016). When shocks occur and individual ports shut down, the network skips over the shutdown port instead of changing its topology completely (Kosowska-Stamirowska 2020).

A chokepoint closure would act very differently. By their very nature, a chokepoint can't be easily skipped over. Therefore, it is important to understand what happens to this network when chokepoints are blocked instead of a single port being shut down.

One network in particular, constructed in (Verschuur, Koks, and Hall 2022), will be of particular importance in this paper. Using 2015 data, the authors connected ports via their routes and trade volumes in a web-like trade network (Figure 2.1). Key for this study, the network also includes the volume on each edge that had, at some point in its route, traveled through the Suez Canal. This greatly simplifies our process, since we can use this pre-created network instead of having to construct our own.

Figure 2.1: The Verschuur, Koks, and Hall 2022 Maritime Trade Network.



Routes colored based on the total value of goods transported along the route in 2015.

2.3 Supply Chain Shocks and Intertemporal Propagation

Global supply chains have evolved to be exceptionally complex. This complexity can lead a shock in intermediate goods markets to cause disproportionately large economic disruptions and have feedback effects that cause long-run disruptions (Elliott and Jackson 2023; Ganapati and Wong 2023; Heiland et al. 2019). Elliott and Jackson 2023 also shows that as the amount of trade increases across these complex trade networks, the potential for these shocks to have greater impacts around the globe increases.

Empirically, firm-level analysis can show these sorts of shocks occurred after a 2011 earthquake in Japan, where US output was significantly affected by the shock (Boehm, Flaaen, and Pandalai-Nayar 2019). Colon, Hallegatte, and Rozenberg 2019 found that transportation shocks specifically could have propagating affects through a country's economy, and have indirect impacts on groups not typically affected by disasters. Using AIS data on container ship movement, Bai et al. 2024 found that supply chain disruptions cause macroeconomic effects, including inflation.

Analysis of the Suez Canal incident specifically found that it had similar ripple effects. Lee and Wong 2021 found that the supply chain effects of the incident caused oil and gas prices to surge, insurance companies to suffer a $31 billion loss, and stopped 12% of global trade. Özkanlisoy and Akkartal 2022 found that the blockage had ripple effects on global supply chains that persisted for more than three months after the blockage was resolved. Wan et al. 2023, using a network, found that these effects were mostly located in Africa, but the blockage also significantly affected Europe and Asia as well as made the overall global trade network significantly less navigable. A general equilibrium modeling approach in Gokan et al. 2024 found that the net negative effects of the blockage totaled to about 0.1% of the global GDP.

One common way of analyzing this propagation uses input-output (IO) tables. Originally presented in Leontief 1951, these tables allow us to track what intermediate goods different industries use and where they get them from. Using IO tables, Los, Timmer, and Vries 2015 presents an approach to figuring out where value comes from at every level of production for a final good.

This paper will use this value-added IO table approach to analyze how the shutdown of the canal and temporary severing of connections affects the value chains of final goods on both sides of the canal.

3 Theoretical Model

The theoretical model presented in this paper will attempt to capture both the direct and propagation effects that the blockage will cause. The first part of the model will look at how ships travel through the network and what the potential direct effects of the blockage could be. The second part will model how these goods are used and how propagation effects could spread through the network.

For this paper, the trade network will be constructed using ports as vertices and shipping lanes between ports as links. In this way, we get a directed network that represents all maritime trade.

This network transports a variety of goods. The set G contains the types, or industries, of these goods, where $g \in G$ represents goods from one industry.

For a port $i \in P$, there is vector of goods that are imported $\mathbf{x}_i^{\text{in}}$ and exported $\mathbf{x}_i^{\text{out}}$. The gth row of the vector, x_{ig}^{in}, represents the value of goods of type g that are imported into port i. Similarly, x_{ig}^{out} is the value of goods of type g that are exported from port i.

Along the network, a connection exists between port $i \in P$ and $j \in P$ if there exists a shipping lane connecting the two. This route takes a certain amount of time, t_{ij} to traverse and transports a vector of goods $\mathbf{x}_{ij}$. The gth row, x_{ijg}, represents the value of good g transported from i to j.

To allow the network to respond to shocks, we'll add a time dimension. Therefore, the import and export vectors for port i at time t become $\mathbf{x}_{i,t}^{\text{in}}$ and $\mathbf{x}_{i,t}^{\text{out}}$ respectively. The transport vector $\mathbf{x}_{ij,t}$ represents the vector of goods shipped at time t from node i en route to node j. Since it takes t_{ij} for the goods to travel along the shipping lane, these goods arrive at port j at time $t + t_{ij}$. At a good level, $x_{ig,t}^{\text{in}}$, $x_{ig,t}^{\text{out}}$, and $x_{ijg,t}$ represent the value of good g at time t imported into i, exported from i, and en route from i to j respectively.

Since the value of a port's exports is equal to the sum of the value of shipping routes from the port, we get the relationship

$$\mathbf{x}_{i,t}^{\text{out}} = \sum_{j \neq i} \mathbf{x}_{ij,t}, \tag{3.1}$$

meaning the exports from a port is equal to its out-degree centrality in the network. Similarly, since the value of a port's imports is equal to the sum of the value of shipping routes entering the port once they've traveled across the shipping lane, we get the relationship

$$\mathbf{x}_{j,t}^{\text{in}} = \sum_{i \neq j} \mathbf{x}_{ij,t-t_{ij}}, \tag{3.2}$$

meaning the imports into a port is equal to its in-degree centrality in the network t_{ij} periods in the future.

Within a country $c \in C$, there is some set of ports $P_c \subset P$ such that every $i \in P_c$ is a port in country c.

For a pair of countries $c, d \in C$, exports from c to d at time t, $\mathbf{x}_{cd,t}^{X}$, is defined as exports from any port in c to any port in d plus non-maritime exports, meaning

$$\mathbf{x}_{cd,t}^{X} = \sum_{i \in P_c} \sum_{j \in P_d} \mathbf{x}_{ij,t} + \mathbf{x}_{cd,t}^{oX}, \tag{3.3}$$

where $\mathbf{x}_{cd,t}^{oX}$ is other, non-maritime exports from c to d. Similarly, imports to c from d at time t, $\mathbf{x}_{cd,t}^{M}$, is defined as imports to any port in c from any port in d, meaning

$$\mathbf{x}_{cd,t}^{M} = \sum_{j \in P_c} \sum_{i \in P_d} \mathbf{x}_{ij,t-t_{ij}} + \mathbf{x}_{cd,t}^{oM}, \tag{3.4}$$

where $\mathbf{x}_{cd,t}^{oM}$ is non-maritime imports to c from d.

Therefore, c's total exports at time t, $\mathbf{x}_{c,t}^{X}$, and is defined as

$$\begin{aligned}
\mathbf{x}_{c,t}^{X} &= \sum_{d \neq c} \mathbf{x}_{cd,t}^{X} && (3.5)\\
&= \sum_{i \in P_c} \left(\mathbf{x}_{i,t}^{\text{out}} - \sum_{j \in P_c, j \neq i} \mathbf{x}_{ij,t} \right) + \mathbf{x}_{co,t}^{X} && (3.6)\\
&= \sum_{i \in P_c} \sum_{j \notin P_c} \mathbf{x}_{ij,t} + \mathbf{x}_{co,t}^{X} && (3.7)
\end{aligned}$$

where $\mathbf{x}^X_{co,t}$ is the total exports from country c through other, non-maritime routes. Similarly, d's imports at time t, $\mathbf{x}^M_{d,t}$, are defined as

$$\mathbf{x}^M_{d,t} = \sum_{d \neq c} \mathbf{x}^M_{cd,t} \tag{3.8}$$

$$= \sum_{j \in P_d} \left(\mathbf{x}^{\text{in}}_{j,t} - \sum_{i \in P_d, i \neq j} \mathbf{x}_{ij,t-t_{ij}} \right) + \mathbf{x}^M_{do,t} \tag{3.9}$$

$$= \sum_{j \in P_d} \sum_{i \notin P_d} \mathbf{x}_{ij,t-t_{ij}} + \mathbf{x}^M_{do,t} \tag{3.10}$$

where $\mathbf{x}^M_{do,t}$ is the imports to country d through non-maritime routes.

c's imports along with its output, $\mathbf{x}^Y_{c,t}$, are used as final goods domestically, $\mathbf{x}^F_{c,t}$, intermediate goods domestically, $\mathbf{x}^I_{c,t}$, or are exported to be used as final or intermediate goods in a foreign country. Therefore, we get

$$\mathbf{x}^Y_{c,t} + \mathbf{x}^M_{c,t} = \mathbf{x}^F_{c,t} + \mathbf{x}^I_{c,t} + \mathbf{x}^X_{c,t}. \tag{3.11}$$

Rearranging this gets the expression

$$\mathbf{x}^I_{c,t} = \mathbf{x}^Y_{c,t} + \mathbf{x}^M_{c,t} - \mathbf{x}^F_{c,t} - \mathbf{x}^X_{c,t}. \tag{3.12}$$

Intuitively, this suggests intermediate goods to be used in production processes in c in the next period include everything imported or produced minus everything exported or used as a final good.

These intermediate goods are used within the country to produce output in the period based on some production function $F_{ct} : \mathbb{R}^{\|G\|} \to \mathbb{R}^{\|G\|}$. Therefore, we have

$$\mathbf{x}^Y_{c,t} = F_{ct}(\mathbf{x}^I_{c,t-1}, z_{c,t}), \tag{3.13}$$

The production function F_{ct} is assumed to be increasing with respect to all inputs, so $\frac{\partial F_{ct}}{\partial x^I_{cg,t}} > 0$ for all $g \in G$. This output is then exported, used as final goods, and used as intermediate goods in the next period.

3.1 Model Predictions

Based on the model, shocks will affect the network in two ways.

Direct, first-order effects will cause immediate changes in the network. A port shutting down will change the network by removing shipping routes to that port, causing that port's would-be imports to either not be exported or to go somewhere else, consistent with what was observed in Kobe in Kosowska-Stamirowska 2020. Similarly, the port's would-be exports will have to be either used domestically or exported using some other port within the country.

For a chokepoint, these direct effects will be significant in the periods directly after a shutdown. Letting ij be a shipping route that goes through a chokepoint s t_{is} periods into its route and t_{sj} periods before the route ends so that $t_{is} + t_{sj} = t_{ij}$ and having the chokepoint shutdown at time t^s and open at time t^o, the traversal time from i to j for a ship leaving at time t becomes

$$t'_{ij,t} = \begin{cases} t_{ij} & \text{if } t < t^s - t_{is} \\ t_{sj} + t^o - t & \text{if } t^s - t_{is} \leq t < t^o - t_{is} \\ t_{ij} & \text{if } t \geq t^o - t_{is} \end{cases} \tag{3.14}$$

where the first and last parts of the equation say that if a ship arrives at the canal before or after the blockage, the trip will take the normal amount of time and the second part of the equation says that if the ship does get held up by the blockage, the trip will last as much time as it takes for the blockage to clear plus its normal length. Therefore, shipments that leave at time t are received at

$$t^r_{ij,t} = \begin{cases} t + t_{ij} & \text{if } t < t^s - t_{is} \\ t_{sj} + t^o & \text{if } t^s - t_{is} \leq t < t^o - t_{is} \\ t + t_{ij} & \text{if } t \geq t^o - t_{is} \end{cases} . \tag{3.15}$$

where the first and third equations represent the shipping route taking the normal amount of time and the second represents the shipment going through the chokepoint once the blockage clears. Assuming the shock only affects transport and exports are unaffected by the shutdown, total imports over time stay constant. However, there is a period of time between $t^s + t_{sj}$ and $t^o + t_{sj}$

where no goods are received at j from the route.

Therefore, the temporary direct effects for a port's imports can be calculated using

$$\Delta \mathbf{x}_{j,t}^{\text{in}} = \mathbf{x}_{j,t}^{\text{in}\prime} - \mathbf{x}_{j,t}^{\text{in}} = -\sum_{t=t^s+t_{sj}}^{t^o+t_{sj}} \sum_{i \neq j} \mathbf{x}_{ij,t-t_{ij}}. \tag{3.16}$$

These effects can be further aggregated to a country level using equation 3.10. Altogether, the model predicts a chokepoint shutdown shock would have significant, but temporary, negative direct effects on imports. These effects depend on the route going through the canal, so their magnitude is related to the portion of trade into the port that goes through the canal. Additionally, because of the time it takes to get from the chokepoint to the canal, t_{sj}, the timing of these effects will depend on the port's distance from the canal.

Second, indirect, propagation effects will exacerbate these immediate changes and cause them to persist over time. Since F_{ct} is assumed to be an increasing function, some shock that causes a decrease in intermediate goods from $\mathbf{x}_{c,t-1}^{I}$ to $\mathbf{x}_{c,t-1}^{I\prime} < \mathbf{x}_{c,t-1}^{I}$, we know that

$$\mathbf{x}_{c,t}^{Y} = F_{ct}(\mathbf{x}_{c,t-1}^{I}) > F_{ct}(\mathbf{x}_{c,t-1}^{I\prime}) = \mathbf{x}_{c,t}^{Y\prime}. \tag{3.17}$$

Assuming other countries exports are relatively unchanged by the shock, using equation 3.11, we know

$$\mathbf{x}_{c,t}^{I} + \mathbf{x}_{c,t}^{F} + \mathbf{x}_{c,t}^{X} = \mathbf{x}_{c,t}^{Y} + \mathbf{x}_{c,t}^{M} > \mathbf{x}_{c,t}^{Y\prime} + \mathbf{x}_{c,t}^{M} = \mathbf{x}_{c,t}^{I\prime} + \mathbf{x}_{c,t}^{F\prime} + \mathbf{x}_{c,t}^{X\prime} \tag{3.18}$$

Meaning the total of intermediate goods, final goods, and exports must decrease in the period following the intermediate goods shock. Letting these effects be distributed across all three factors, that means decreased intermediate goods persist intertemporally and propagate into c's trade partners.

Using equation 3.5, we have that when total exports decrease, exports to at least one country d must decrease. Letting i be the port with affected exports in country c and j be the receiving port in country d, we have

$$\mathbf{x}_{ij,t}^{\prime} < \mathbf{x}_{ij,t}, \tag{3.19}$$

which, using 3.2 means that

$$\mathbf{x}^{\text{in}\prime}_{j,t+t_{ij}} < \mathbf{x}^{\text{in}}_{j,t+t_{ij}}. \tag{3.20}$$

Using 3.8, this means

$$\mathbf{x}^{M\prime}_{d,t} < \mathbf{x}^{M}_{d,t} \tag{3.21}$$

which, like what happened in country c, causes a decrease in intermediate goods, and therefore outputs. This same effect will, then, continue to propagate intertemporally in d and within the network through d's trade partners. The magnitude of this indirect effect will depend on the extent to which $\mathbf{x}^{F}_{c,t}$ is affected instead of future intermediate goods and the scale effects of F_{ct}, with lower returns to scale causing output to recover faster since they are able to produce closer to the original level of output with the decreased amount of inputs.

Therefore, we get the intercountry propagation described in Boehm, Flaaen, and Pandalai-Nayar 2019 and the total economic effects described in Colon, Hallegatte, and Rozenberg 2019.

This model is very simplistic and ignores a number of possible impacts of the blockage, like rerouting and congestion slowing down trade through the canal when it opens up. Future work could expand this theory to account for these factors and give a basis to empirically test for these effects. Still, this provides a good starting point for the analysis in this paper.

4 Empirical Approach

4.1 Building a Trade Network and Estimating Direct Effects

Both for simplicity and due to availability constraints for the data required to make our own network,[1] this paper will base its analysis on the network constructed in Verschuur, Koks, and Hall 2022. Using this network, we have trade flows between ports (Figure 2.1) and flows along routes that have been through the Suez Canal.

From this network, we can also approximate the distance of a route between ports assuming

1. Other papers use Lloyd's Shipping Index (Kosowska-Stamirowska, Ducruet, and Rai 2016; Kosowska-Stamirowska 2020) or AIS data (Wang, Du, and Peng 2024). These databases all have significant paywalls making them infeasible.

ships travel across the shortest possible path.[2] This gives us a predicted maritime distance for any route $\hat{d}_{ij}$ between i and j.

Traversal time, t_{ij}, will be estimated using the average speed of shipping vessels, $\overline{v}$. Using this, we can say

$$t_{ij} \approx \frac{d_{ij}}{\overline{v}} = \hat{t}_{ij}. \tag{4.1}$$

Using this same reasoning, time to get from the Suez Canal s to j becomes

$$\hat{t}_{sj} = \frac{d_{sj}}{\overline{v}}. \tag{4.2}$$

From this shipping network, we can also estimate each port's reliance on the Suez Canal as the ratio of trade into the port that goes through the Suez Canal to overall trade into the port. Therefore, port j's exposure s_j is calculated as

$$s_j = \frac{\sum_t \sum_{i \neq j} s_{ij} f_{ij,t}}{\sum_t \sum_{i \neq j} f_{ij,t}}, \tag{4.3}$$

where $f_{ij,t}$ is the total amount of trade along routes from i to j and

$$s_{ij} = \begin{cases} 1 & \text{if the route from } i \text{ to } j \text{ goes through the Suez Canal} \\ 0 & \text{otherwise} \end{cases}. \tag{4.4}$$

Based on the theoretical model presented in 3, we expect port j to be affected by a canal shutdown $\hat{t}_{sj}$ periods delayed. Based on equation 3.16, we also expect the direct effects to be proportional to j's exposure, or the percent of trade that goes through the canal, times the quantity of trade into j without the canal shutdown. Therefore, we have

$$M_{j,t} = (1 - s_j \times c_{t-\hat{t}_{sj}})\overline{M}_{j,t}\varepsilon_{j,t} \tag{4.5}$$

where c_t is an indicator variable representing whether the canal is closed at time t, $M_{j,t}$ is port j's

2. In reality, ships adjust their path to follow "climatological routes" based on currents and wind, but these routes are close enough to the shortest paths that we can make the approximation (Zissis et al. 2020; Heiland et al. 2019).

imports in period t such that $M_{j,t} = \|\mathbf{x}^{\text{in}}_{j,t}\|_1$, and $\overline{M}_{j,t}$ is the normal amount of trade at time t. To get an expression we can estimate, we log both sides to get

$$\log M_{j,t} = \log(1 - s_j \times c_{t-\hat{t}_{sj}}) + \log \overline{M}_{j,t} + \varepsilon_{j,t}. \tag{4.6}$$

Since, in general s_j is small and $\log(1-x) \approx x$ when x is small, we say $(\log(1 - s_j \times c_{t-\hat{t}_{sj}})) = s_j \times c_{t-\hat{t}_{sj}}$. Therefore, this becomes the model

$$\log M_{j,t} = \alpha_0 + \alpha_1 c_{t-\hat{t}_{sj}} + \alpha_2 \left(c_{t-\hat{t}_{sj}} \times s_j\right) + \alpha_3 \log \overline{M}_{j,t} + \varepsilon_{j,t}. \tag{4.7}$$

α_1 captures any larger trends in shipping caused by the blockage, which we assume to be close to zero. α_2 captures how much more the blockage affects ports more reliant on the Suez Canal.

Since propagation effects have a delay before they have an impact, using higher frequency data and observing limited time periods after the event can eliminate some endogeneity from propagation effects and help identify only the direct effects from the shock. To allow for this, we shift the times in the model forward $\hat{t}_{sj}$ to get the estimated equation

$$\log M_{j,t+\hat{t}_{sj}} = \alpha_1 c_t + \alpha_2 \left(c_t \times s_j\right) + \beta_j. \tag{4.8}$$

Because of the smaller period the model is designed for, we assume $\log \overline{M}_{j,t}$ will stay more or less constant over time and is therefore lumped into the port fixed effects term β_j. This model excludes any time fixed effects term, so it can't control for trends in trade over time. However, these are less applicable since the model is meant to be used with higher frequency data in a smaller time period, meaning there will be less intertemporal variation.

Finally, we'll also estimate the effects at a country level. Letting $\hat{t}_{sc}$ and s_c represent the average of $\hat{t}_{sj}$ and s_j respectively for all ports j in country c weighted by share of imports, we get the model

$$\log M_{c,t+\hat{t}_{sc}} = \alpha_1 c_t + \alpha_2 \left(c_t \times s_c\right) + \beta_c. \tag{4.9}$$

Figure 4.1: Example World Input-Output Table.

$$
\begin{array}{rccc}
 & \text{Outputs} & \text{Final Demand} & \text{Total Output} \\
\text{Inputs} & \begin{pmatrix} \mathbf{Z}_{11} & \dots & \mathbf{Z}_{n1} \\ \vdots & \ddots & \vdots \\ \mathbf{Z}_{n1} & \dots & \mathbf{Z}_{nn} \end{pmatrix} & \begin{pmatrix} \mathbf{F}_{11} & \dots & \mathbf{F}_{n1} \\ \vdots & \ddots & \vdots \\ \mathbf{F}_{n1} & \dots & \mathbf{F}_{nn} \end{pmatrix} & \begin{pmatrix} \mathbf{x}_1^Y \\ \vdots \\ \mathbf{x}_n^Y \end{pmatrix} \\
\text{Value Added} & \begin{pmatrix} \mathbf{V}_1^\top & \dots & \mathbf{V}_n^\top \end{pmatrix} & & \\
\text{Total Output} & \begin{pmatrix} \mathbf{x}_1^{Y\top} & \dots & \mathbf{x}_n^{Y\top} \end{pmatrix} & &
\end{array}
$$

4.2 Propagation Effects

To estimate the propagation effects, we'll assume F_{ct} in section 3 is a linear transformation per Leontief 1951. Using Leontief techniques, we can follow value chains backwards through production processes to estimate what portion of all final use, not just imports, was affected by the blockage.

Leontief input-output analysis uses input-output tables to model production processes. Figure 4.1 shows a stylized version of one of these tables. $\mathbf{Z}$ shows what intermediate goods are used in the production of outputs. $\mathbf{Z}_{cd}$ contains the intermediate goods from country d used in the production of outputs in c where $z_{cd,k\ell}$ has the intermediate goods from industry ℓ used in the production of outputs in industry k. The final demand matrix $\mathbf{F}$ includes all uses for goods that aren't intermediate production processes, like consumption. $\mathbf{F}_{cd}$ shows the final goods from c used in d and $f_{cd,k\ell}$ shows the final goods from industry ℓ used for k. The value-added matrix $\mathbf{V}$ demonstrates where value is added to products without consuming intermediate goods. These include wages, profits, and taxes. $\mathbf{V}_c$ is the value added in country c and $v_{c,k\ell}$ is the value added in industry ℓ from k. The $\mathbf{x}^Y$ vector along the right and bottom are equal and contain the total output from each production process. $\mathbf{x}_c^Y$ is the total output in country c and $x_{c,\ell}$ is the total output in industry ℓ. In our model, we aggregate final use and value added into a single vector $\mathbf{x}^F = \mathbf{F1}$ and $\mathbf{x}^V = \mathbf{V1}$ where $\mathbf{1}$ is the vector of all 1s, essentially summing all possible types of final use and value added within a country-industry together.

Using these matricies, we divide each column i in $\mathbf{Z}$ by their associated value x_i^Y in $\mathbf{x}^Y$ to get the inputs used per unit of output matrix $\mathbf{A}$, and we divide each column i in $\mathbf{x}^V$ by x_i^Y to get the value added per unit of output vector $\mathbf{W}$.

From these, we know

$$\mathbf{x}^Y = \mathbf{A}\mathbf{x}^Y + \mathbf{x}^F.$$

Rearranging this gets

$$\mathbf{x}^Y = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{x}^F, \tag{4.10}$$

the core equation from Leontief input-output (IO) analysis which tells us how much output is needed based on the demand for final goods.

Following Los, Timmer, and Vries 2015, we multiply both sides by $\hat{\mathbf{W}}$ to get

$$\hat{\mathbf{W}}\mathbf{x}^Y = \hat{\mathbf{W}}(\mathbf{I} - \mathbf{A})^{-1}\mathbf{x}^F \tag{4.11}$$

where $\hat{\mathbf{W}}$ is the matrix with $\mathbf{W}$ along its diagonal and 0s everywhere else. By definition of $\mathbf{W}$, $\hat{\mathbf{W}}\mathbf{x}^Y = \mathbf{x}^V$. Therefore, we have

$$\mathbf{x}^V = \hat{\mathbf{W}}(\mathbf{I} - \mathbf{A})^{-1}\mathbf{x}^F. \tag{4.12}$$

Importantly, this expression holds for any vector of demand for final goods $\mathbf{x}^F$ we plug in on the right. For example, to find where value was added to final goods consumed in a specific country c, we set $\mathbf{x}_c^F$ to a column vectors of all 0s except where c's final demand would be and plug it in to get

$$\mathbf{x}_c^V = \hat{\mathbf{W}}(\mathbf{I} - \mathbf{A})^{-1}\mathbf{x}_c^F \tag{4.13}$$

where $\mathbf{x}_c^V$ tells us where value was added through intermediate production and exports for goods used in c.

We can then turn $\mathbf{x}_c^V$ into a lower bound for the propagation effects of the Suez Canal. If an entry in $\mathbf{x}_c^V$ comes from a country on the other side of the Canal than c, it had to come through the canal at least once. Goods could travel through more than once at different stages in their production, which would cause this method to underestimate the effects of the blockage. This effect is why we're considering our estimation a lower bound instead of prediction for the impact of the blockage.

Since the Leontief setup assumes production is linear, value added can be divided to get any smaller period. For example, we can say half the total value added over the year was added in half the year. This allows us to look at the effects of the six-day blockage specifically rather than looking at how much of the total value used in the entire year the IO table was created for came through the canal, which isn't the effect we're interested in.

4.3 Propagation Effects Limitations

There are a handful of issues with this methodology which affect the reliability of the estimates.

It makes very strong assumptions about when and how often goods travel across the Suez Canal. This effect means the estimate from this paper should be viewed as a lower bound, not an actual estimate, but also means we ignore trade that goes through alternate routes, like around the Horn of Africa or crosses the Pacific and travels across the other side of the world.

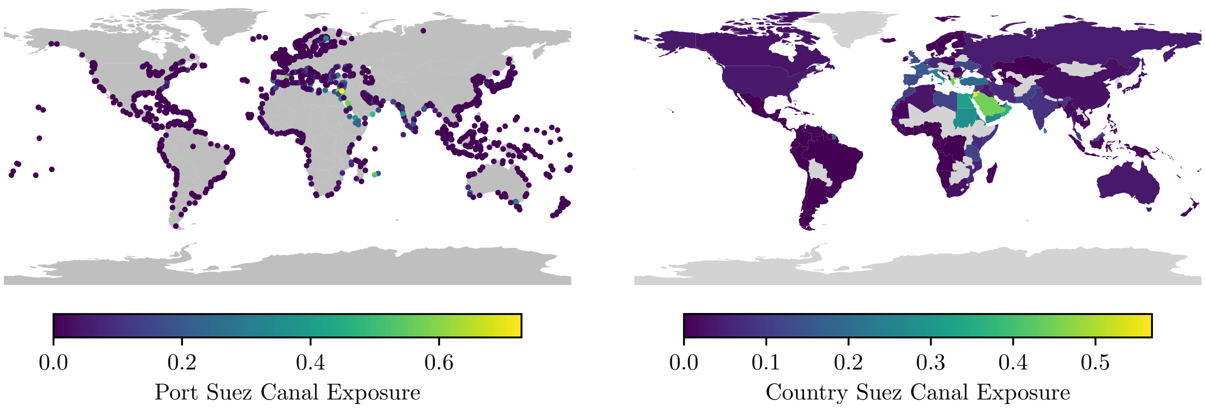
Like the model in Section 4.1, it assumes countries prefer to trade along the most direct maritime route possible when estimating whether the step in the value chain was affected by the canal shutdown. This estimation is known to be an oversimplification of reality (Zissis et al. 2020), but is generally accurate.

It also doesn't allow us to estimate propagation effects for inland countries, even though Colon, Hallegatte, and Rozenberg 2019 suggests they should face some despite not being directly exposed to the shock. In this way, we're only able to examine propagation effects in a limited sample of countries.

Finally, it makes very strong assumptions about the linearity of the production function. We assume that the value and type of goods traveling through the canal to a country is continuous and uniform in order to make our estimate for the 6-day period effects.

Still, this method gives us a strategy to very conservatively estimate the second order effects at a country level.

Figure 5.1: Suez Canal exposure scores.



Countries with no calculated canal score, meaning they have no ports included in the network, are shown in gray.

5 Data

5.1 Network

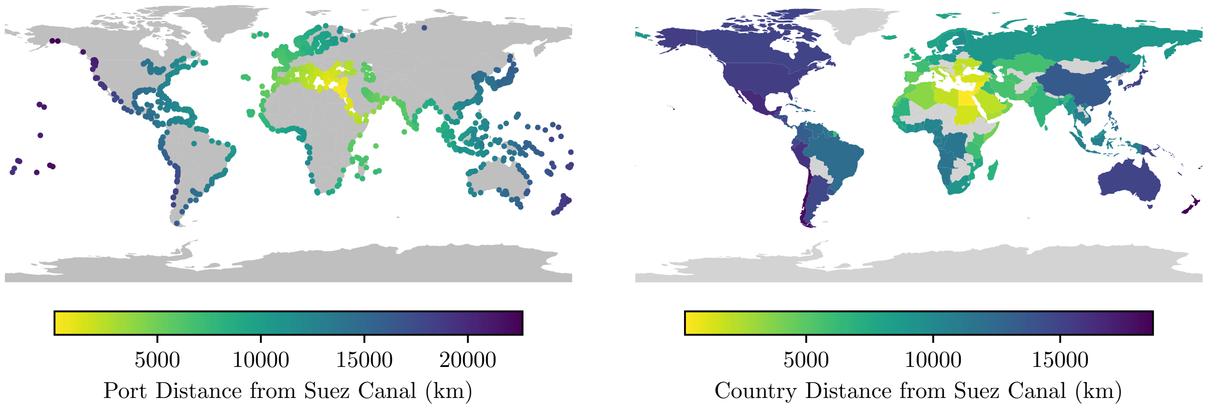
For this paper, we'll use the network outlined in Verschuur, Koks, and Hall 2022. Constructed using a combination of import and AIS data, this network connects 1,357 ports around the world along commonly used maritime routes. Importantly, it also includes 2015 trade volumes along each route in dollar and tonne amounts. The network and dollar amount trade volumes are shown in Figure 2.1.

The Verschuur, Koks, and Hall 2022 network also includes information about trade volumes along each route that have traveled through specific chokepoints, including the Suez Canal. For each route, we can divide dollar-amount flows that have come through the Suez Canal by total dollar-amount flows to get the Suez Canal exposure score we use in the empirical model presented in Section 4.1.

For port-level analysis, we use the score for the route that travels into the port.[3] At a country level, we average the scores for all the ports within a country, weighting them by dollar-amount trade volume to avoid small, unimportant ports being disproportionately represented in the score. The Suez Canal exposure scores are presented in Figure 5.1.

3. This means the score is calculated using both imports and transhipments, where goods are kept on a ship to travel to another port later in a ship's route.

Figure 5.2: Maritime Distances from the Suez Canal.



Countries with no calculated distance, meaning they have no ports included in the network, are shown in gray.

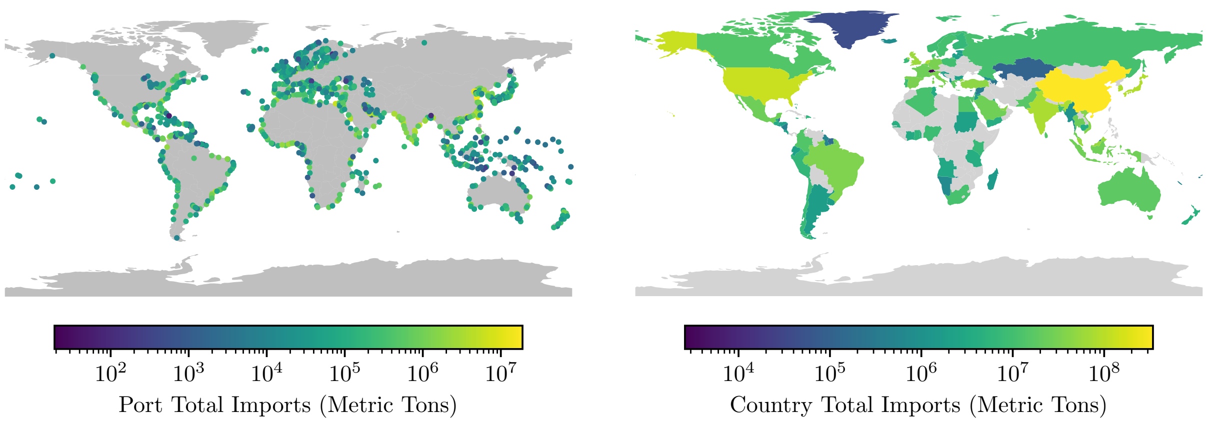
Finally, the network includes data on the length of each route. This means we can calculate a minimum for how far ships need to travel to get from the Suez Canal to the port. This will be used to determine the lags for each port and country in the models presented in Equations 4.8 and 4.9. Especially as ports or countries get farther away from the canal, ships may take less direct routes and deliver goods to other ports on the way, meaning the approximation may underestimate distance traveled and, therefore, overall effects. Therefore, the actual effects will be more spread out and picked up less in the model for some, further ports. Still, our strategy gives us a method for analysis, and this effect will be lessened for the closer ports to the canal, which tend to have higher exposure (Figure 5.1).

Figure 5.2 shows the calculated maritime distances from the canal. For each port, we use a shortest-maritime-path approximation to find the distance. To aggregate at the country level, we, again, average the port level distances weighting by dollar-amount trade volume.

5.2 Imports

The model in Section 4.1 uses the network statistics from Section 5.1 and high frequency import data. Using AIS data, Cerdeiro et al. 2020 outlines a process to estimate country-level daily maritime imports. Arslanalp, Koepke, and Verschuur 2021 expands this process to port-level daily maritime imports. These estimates are both published weekly by the IMF for 113 countries and

Figure 5.3: Total Imports



Imports summed between March 1, 2021 and May 31, 2021. Countries with no data are shown in gray.

1,401 ports. Some of these ports have missing data from 2021, meaning our analysis covers 1,357 ports.

These estimates exhibit large geographic variability, but only random intertemporal variability, especially when aggregated. The geographic variability, shown in Figure 5.3, is to be expected, since there are many ports of different sizes in the world. Figure 5.4 shows what imports look like over time aggregated and for a handful of example ports and countries. The aggregated estimates on the far left stay relatively consistent over time, justifying the lack of time fixed effects in the estimating equation since time effects would only pick up global trends.

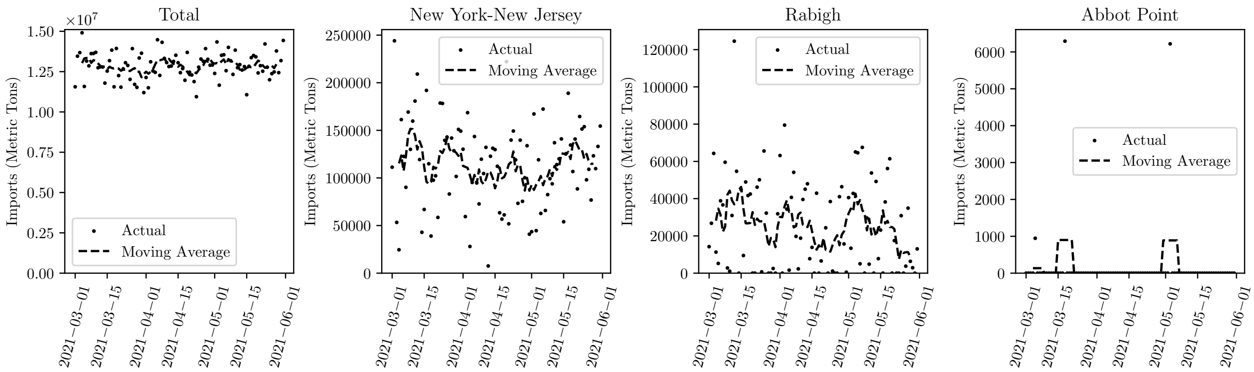
5.3 Input-Output Tables

To estimate the second order effects, we'll use the Inter-Country Input-Output Tables from the OECD. These tables allow us to get an industry level view at how intertwined global value chains are on.

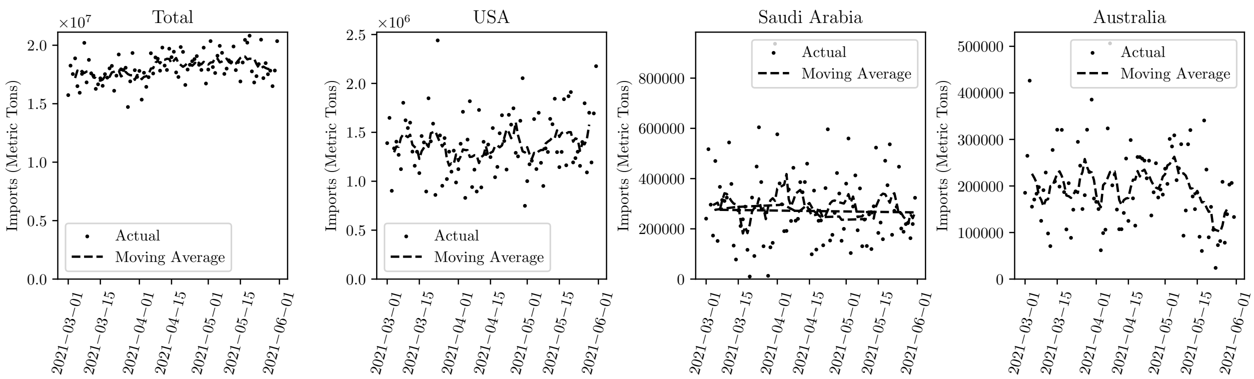
The tables from the OECD include 76 countries plus one entry for the rest of the world, 45 industries, 6 final uses, and 2 areas value can be added. Therefore, $\mathbf{Z}$ is a $3,465 \times 3,465$ square matrix of intermediate good use, $\mathbf{F}$ is a $3,465 \times 462$ matrix of final goods use, $\mathbf{V}$ is a $3,465 \times 2$ matrix of value added, and $\mathbf{x}^Y$ is a $3,465 \times 1$ vector of outputs.

Unfortunately, these tables are only available through 2020. Because of the 2020 COVID shock,

Figure 5.4: Daily Imports For Select Ports



(a) Daily port-level imports summed and at three ports



(b) Daily country-level imports summed and in three countries

Data shown from March 1, 2021 and May 31, 2021. The first graph in each row is the total for all ports or all countries that day, then the next three graphs show different example ports or countries. The first graph in the two rows are different because the country-level data includes small ports that aren't in the port-level dataset.

we'll use the data for 2019 in our analysis, however we'll also make similar estimates using 2016-2020 data to make sure our results stay consistent intertemporally.

6 First Order Effects Estimation

6.1 Estimation

The results for the port model in Equation 4.8 are in Table 6.1. The speed used to lag port data based on how far they are from the canal is chosen based on speed information in Sirimanne et al. 2022. The exact specification in Equation 4.8 is model (2) in the table and our preferred specification. (1) is identical to (2) except is excludes the indicator variable for dates during the

Table 6.1: Port Model Regression Results.

	Total		Cargo		Tanker	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure × Crash	-0.999**	-1.171***	-0.686**	-1.237***	-0.999**	-0.733**
	(0.426)	(0.448)	(0.314)	(0.405)	(0.426)	(0.326)
Crash		0.045		0.011		0.012
		(0.036)		(0.034)		(0.028)
Port FE	Yes	Yes	Yes	Yes	Yes	Yes
Speed (km/h)	40	40	40	40	20	20
Observations	48,744	48,744	48,744	48,744	48,744	48,744
No. of Ports	1,354	1,354	1,354	1,354	1,354	1,354
R^2	0.519	0.519	0.530	0.530	0.408	0.408

Notes: Dependent variable: Log Imports. Standard errors in parentheses. Regression ran across all ports from 3/1/2021 to 4/5/2021. The speed was used to calculate lags based on how far a port is from the Suez Canal.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

blockage and only has the interaction term. (3) and (4) are analogous to (1) and (2) but look only at dry cargo imports. Similarly, (5) and (6) are analogous to (1) and (2) but look only at wet tanker imports.

Across all specifications, the model finds a statistically significant negative α_2 term representing the relationship the interaction term between our canal exposure measure and the crash time period have with log imports. Across all models, the interaction term is significant at the 5% level and in models (2) and (4), the models with an indicator variable for total and cargo imports respectively, it's significant at the 1% level. The coefficient for the indicator variable for the crash is positive but not significant for all three specifications, suggesting there may have been an overall uptick in imports across all ports after the time it takes to get from the canal to the port during the blockage. This may be catching some random daily trends in imports, which is analyzed in a robustness check that adds time fixed effects, or could be caused by some type of diversion effects from the canal blockage that aren't in the theoretical or empirical model.

The results for the country model are outlined in Table 6.2. Each model is the same as their equivalent in Table 6.1, variables are just aggregated to a country-level. For example, model (1) used an interaction term between the country-level Suez Canal exposure and the time the blockage happened adjusted by distance to the country to predict total maritime imports for the country.

The results for overall imports in this model are identical in direction and significance, though much more extreme compared to the port model. The interaction term in both (1) and (2) is significant at the 5% level and negative and the indicator variable is insignificant, although positive.

The cargo and tanker models have no statistical significance at a country-level. The tanker model specifically has all the coefficient values flip direction. The statistical ambiguity suggests that the method of modeling the time a ship affected by the blockage would get to the country may not work as well when aggregated, likely due to the fact that different ports in the country take different amounts of time to get to and from the canal and the idea that rerouting could be more likley within a country. This could also explain why the sign on tanker imports flips — it's picking up a lot of noise since the canal blockage effects are ambiguous.

Using the preferred specification in Model (2), we can map these country and port level estimates to a real world interpretation for the effect of the blockage. Figure 6.1 shows the predicted percent change in imports versus Suez Canal exposure for ports and countries based on our model. The line in the center shows the predicted percent import effect based on exposure. The density plots on the top show the distribution for exposure and the density plots on the right show the distribution for predicted import effect.

Based on the density plots, we can see that most ports and countries are relatively unexposed, so

Table 6.2: Country Model Regression Results.

	Total		**Cargo**		**Tanker**	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure × Crash	-1.821**	-2.438**	-1.210	-1.867	0.312	0.526
	(0.846)	(1.107)	(1.045)	(1.245)	(1.100)	(1.325)
Crash		0.163		0.173		-0.056
		(0.192)		(0.166)		(0.202)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Speed (km/h)	40	40	40	40	20	20
Observations	3,100	3,100	3,100	3,100	3,089	3,089
No. of Countries	90	90	90	90	90	90
R^2	0.515	0.515	0.511	0.511	0.522	0.522

Notes: Dependent variable: Log Imports. Standard errors in parentheses. Regression ran across all countries from 3/1/2021 to 4/5/2021. The speed was used to calculate lags based on how far a country is from the Suez Canal.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

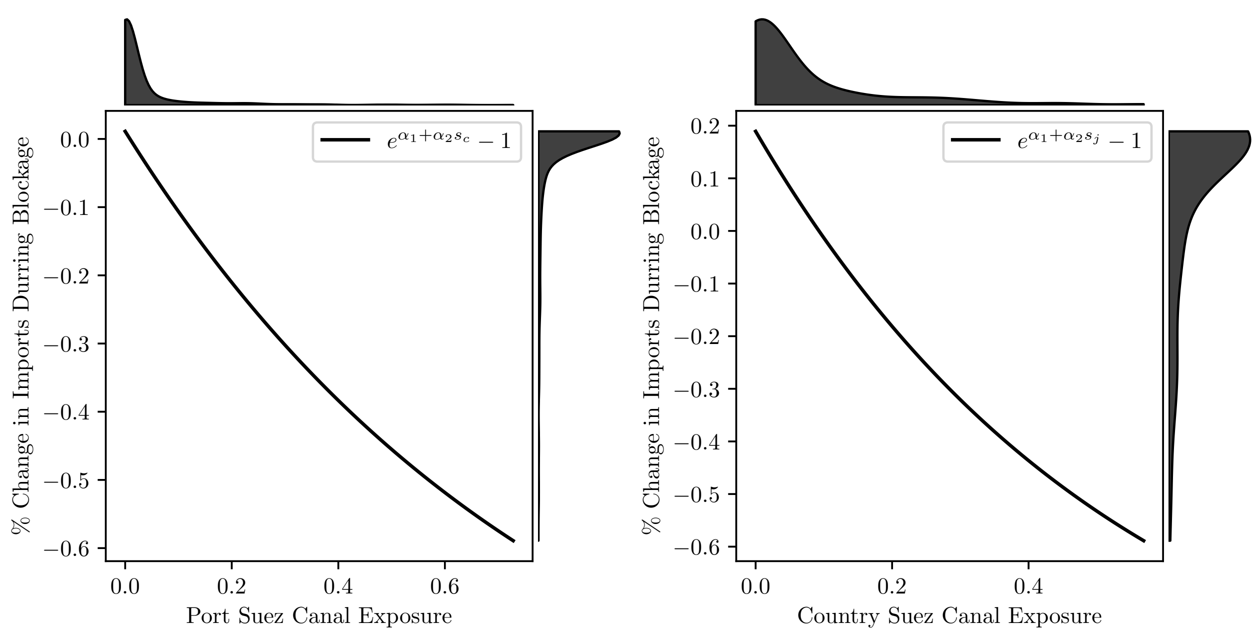
the blockage has limited effects on them. Both distributions have a significant right skew, however, meaning there are a handful of ports and countries that we predict a fairly large effect for. For example, the 47 ports that are at least 10% exposed see a 7.0% decrease in imports during the blockage and the 10 countries that are at least 10% exposed see a 7.7% decrease in imports during the blockage. This highlights the economic significance of the event for the most exposed ports and countries, since, although the effects were insignificant at the peak of the distribution, there are quite a few are as which were meaningfully impacted.

Altogether, these models outline the risks for a single port or country routing most of their trade through a single chokepoint. Doing so makes them vulnerable to significant decreases in trade during events that block shipments going through the chokepoint.

6.2 Robustness

Speed Choice. In the model, we line up imports with the blockage by assuming ships travel at a certain speed. In our results, we've used 20 km/h as the speed tankers move at and 40 km/h as the speed other ships move at. We can test how sensitive our results are to this assumption by

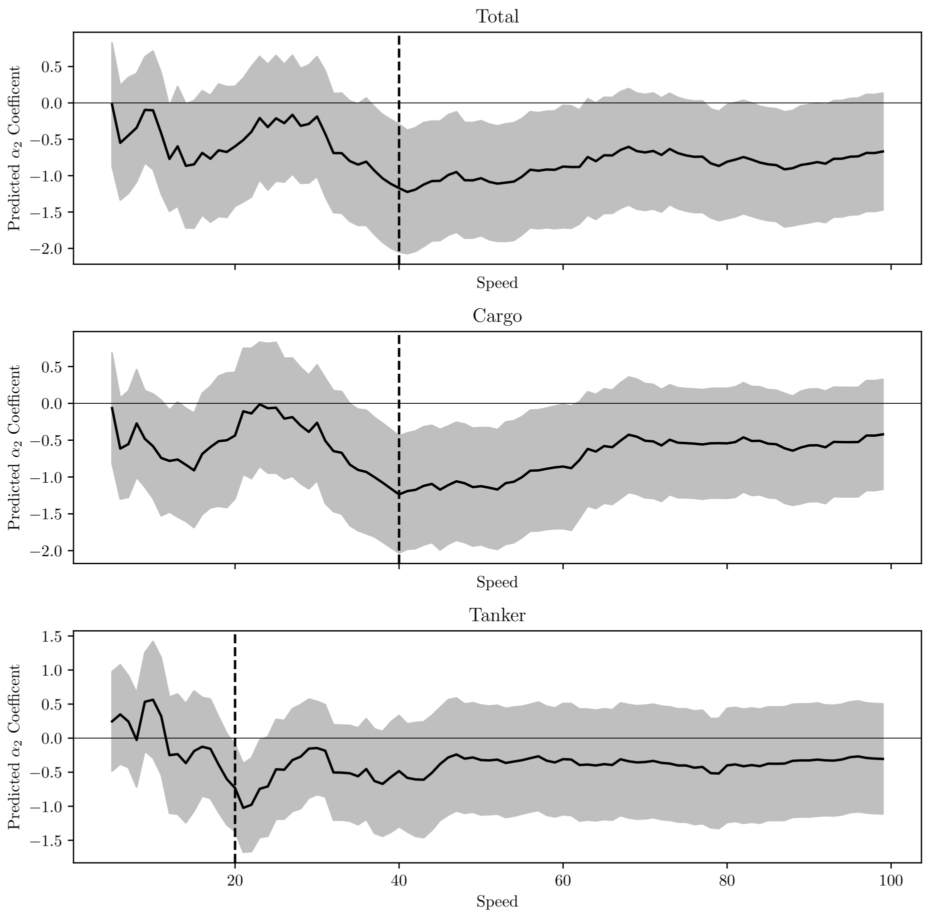
Figure 6.1: Estimated effects of the blockage.



running the model for many assumed speeds and seeing how the results change.

Figure 6.2 shows the results for the regressions on ports and Figure 6.3 shows the results for the regressions on countries for integer speeds between 5 and 100 km/h.

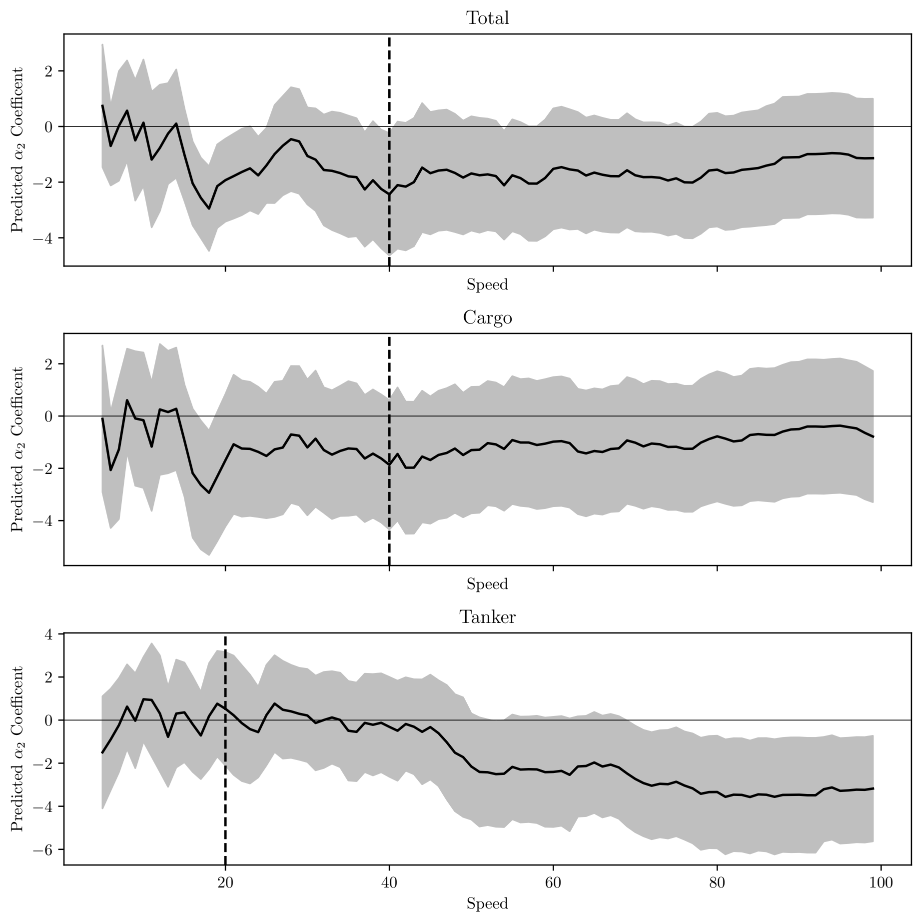
Figure 6.2: Port Regression Estimates by Assumed Speed



Regression estimates for the α_2 coefficient on the interaction term for assumed speeds between 5 and 100 km/h. The first graph corresponds to (2) in Table 6.1, the second to (4), and the third to (6). 95% confidence interval shown shaded in gray and the speed used in Table 6.1 shown by the vertical dashed line.

The port graphs in Figure 6.2 suggest varying levels of robustness to changes in assumed ship speed. The total and cargo regressions get similar results for any assumed speeds within the neighborhood of the 40 km/h value presented. Especially for faster speeds, the coefficient would stay within the same realm and be significant, at least at the 5% level shown on the plot. The tanker regression would get similar results for any assumed speed very near the 20 km/h value used. A slight increase in assumed speed would yield a value that is both more significant and a larger effect on exposed ports. However, increasing or decreasing the assumed speed by a moderate amount in either direction would cause the model to lose significance.

Figure 6.3: Country Regression Estimates by Assumed Speed



Regression estimates for the α_2 coefficient on the interaction term for assumed speeds between 5 and 100 km/h. The first graph corresponds to (2) in Table 6.2, the second to (4), and the third to (6). 95% confidence interval shown shaded in gray and the speed used in Table 6.2 shown by the vertical dashed line.

The country graphs in Figure 6.3 suggest the current results are also robust to changes in assumed speed. Estimations near the dashed line have very similar significance and coefficient values, but that doesn't mean as much given the Table 6.2 regressions for cargo and tanker imports aren't significant. Interestingly, using a much slower speed just under 20 km/h would yield much more significant results, both statistically and economically. This might suggest that the spread of a country causes the impact of the canal blockage on a country's total imports to be more delayed than for a single port in a specific place. It could also suggest that ships are spending large amounts of time idle, since the average speed estimates in Sirimanne et al. 2022 only include ships going faster than 6 knots (∼11 km/h), but if this was the primary cause, we'd expect it to be more visible in Figure 6.3 since it would have the same impact on ports as countries.

Overall, the results are fairly robust to changes in assumed speed within the neighborhood of what was used previously in the paper with estimation results changing significantly only with moderate or large changes in assumed speed.

Distance Effects. Dispersion effects caused by ships not traveling at exactly the assumed speed would have a larger effect farther away. Furthermore, to get to locations farther away, taking an alternate routes that doesn't go through the Suez Canal has less of a trade-off. The shortest route from Mumbai to both New York and Naples is through the Suez Canal, but taking a route around the Horn of Africa is closer in length to the initial path going to New York than that to Naples. Therefore, the effects of the shutdown might be different at different distances from the canal.

To test for this, we split the ports into three bands based on their distance to the Suez Canal. The first band contains the closest ports, the second band contains the next-closest ports, and the third band contains the farthest ones. We then run the regression separately for each of these three bands to compare whether the effects are different.

Table 6.3 shows the results for this estimation on ports. For each band, we use one model with just the interaction term and one other model with the interaction term and indicator variable on total log Imports. The first band includes ports within 2,500 km of the canal, second includes ports between 2,500 and 10,000 km of the canal, and the third includes ports more than 10,000 km from the canal. We choose these bounds to separate ports that are very close to the canal, ports that are a moderate distance from the canal, and ports that are far from the canal.

The results for the first band are identical in direction and significance than the results in Table 6.1. This makes sense, since based on Figure 5.1, the most exposed ports which drive the relationship in Table 6.1 are in this first band. This suggests the closure may have had a larger than predicted effect on the most exposed ports, especially closer to the Canal.

Table 6.3: Banded Port Regression Results.

	Under 2,500 km		**2,500-10,000 km**		**Over 10,000 km**	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure × Crash	-1.582**	-1.744***	-0.405	0.022	-0.290	-1.335
	(0.587)	(0.775)	(0.632)	(0.662)	(1.299)	(1.372)
Crash		0.055		-0.104*		0.130***
		(0.180)		(0.062)		(0.047)
Port FE	Yes	Yes	Yes	Yes	Yes	Yes
Speed (km/h)	40	40	40	40	40	40
Observations	3,924	3,924	16,308	16,308	16,200	16,200
No. of Ports	109	109	453	453	450	450
R^2	0.471	0.471	0.481	0.481	0.545	0.545

Notes: Dependent variable: Log Imports. Standard errors in parentheses. Regression ran across all ports within each band from 3/1/2021 to 4/5/2021. The speed was used to calculate lags based on how far a port is from the Suez Canal.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In the second band, the results become very indeterminate. The interaction term is small and insignificant in both (2) and (3). There is a slight across-the-board decrease in imports in the indicator variable, but this is only significant at the 10% level. The third band has a larger and more economically meaningful interaction term coefficient in model (6) with a value that lines up with what is found in Table 6.1, but it is statistically insignificant. The indicator variable is positive and significant, suggesting ports farther from the canal might have had more trade divert to them during the blockage when closer ones were harder to get to. These ambiguous predictions might be driven by the fact that second and third bands have very few ports that are exposed.

Table 6.4 shows these estimates for countries using these same bands. The weighted average distance for ports used to calculate lags is used to separate countries into their bands.

The closest band loses statistical significance, but the coefficient estimates are in line with our earlier predictions. The second band has a much larger predicted effect, but also has a much larger positive coefficient, possibly suggesting there was a lot of trade redirected a moderate distance from the canal. The final band coefficients flip in direction, but have massive standard error bars and are likely affected by the same lack of variability in canal exposure as the farther away ports that would skew the results and make them less accurate.

These results for the most exposed, closer ports and countries suggest the initial estimates

Table 6.4: Banded Country Regression Results.

	Under 2,500 km		**2,500-10,000 km**		**Over 10,000 km**	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure × Crash	-2.227*	-0.964	-0.523	-4.615***	1.037	3.218
	(1.077)	(0.969)	(1.049)	(1.534)	(2.045)	(11.064)
Crash		0.400		0.607***		-0.070
		(2.641)		(0.197)		(0.369)
Port FE	Yes	Yes	Yes	Yes	Yes	Yes
Speed (km/h)	40	40	40	40	40	40
Observations	448	448	1,382	1,382	1,270	1,270
No. of Countries	14	14	39	39	36	36
R^2	0.352	0.354	0.502	0.504	0.541	0.545

Notes: Dependent variable: Log Imports. Standard errors in parentheses. Regression ran across all ports within each band from 3/1/2021 to 4/5/2021. The speed was used to calculate lags based on how far a port is from the Suez Canal.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

are correct in their predictions, but may be underestimating effects in their coefficients. It also suggests that the slight across the board predicted increases in imports during the blockage, shown by the positive indicator coefficient in model (2) of Table 6.1 and 6.2, could be driven by farther and moderate distance ports and countries getting trade diverted to them, and not trends in more exposed ports closer to the event.

Other Checks. We find the results are robust to other changes in our model and predictors.

Using the same network, we can create an exposure score that looks on the quantity of trade that goes into the port through the Suez Canal, not value. These measures are correlated, since they measure the same thing, but not identical (Figure A.1). Using this alternate measure, we find similar, even more significant effects of the blockage across all models except the country-level tanker one, which also had some weird behavior in our value-based model (Table A.1 and A.2).

To make sure the trends we're seeing are consistent through the whole period and don't overflow past when the blockage was cleared, we estimate the dynamic model

$$\log M_{j,t+\hat{t}_{sj}} = \alpha_t s_j + \beta_j + \varepsilon_{j,t} \tag{6.1}$$

and

$$\log M_{c,t+\hat{t}_{cj}} = \alpha_t s_c + \beta_c + \varepsilon_{j,t} \tag{6.2}$$

where each period t has it's own coefficient for how it was affected by the blockage. The results to this are shown in Figure A.2. In general, the effects lose statistical significance, likely because we're losing a lot of power by adding this many new variables, but do persist for the whole period and go away when the blockage is cleared like our model predicts.

In our model, we exclude time fixed effects since all of our data comes from a short period, which limits the general trends we'd need time effects to control for. We can, however, estimate the model

$$\log M_{j,t+\hat{t}_{sj}} = \alpha_2 \left(c_t \times s_j\right) + \beta_j + \gamma_t + \delta_{t+\hat{t}_{sj}} \tag{6.3}$$

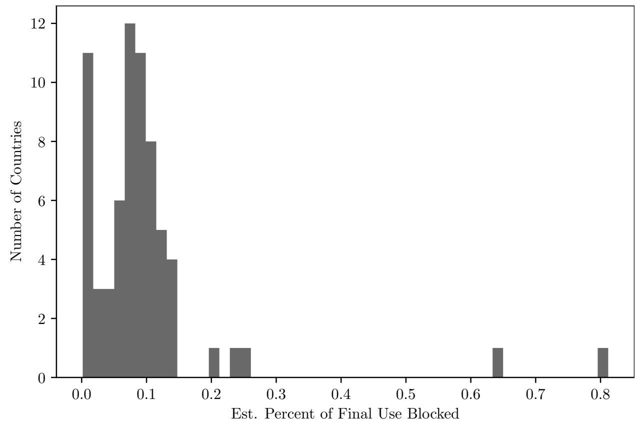
for ports and

$$\log M_{c,t+\hat{t}_{sc}} = \alpha_2 \left(c_t \times s_c\right) + \beta_c + \gamma_t + \delta_{t+\hat{t}_{sc}} \tag{6.4}$$

for countries where γ_t is the reference time fixed effects, since the times for the actual imports have been adjusted to line up with time t, and $\delta_{t+\hat{t}_{sj}}$ and $\delta_{t+\hat{t}_{sc}}$ are the time fixed effects to see if the addition of these would impact our results. Table A.3 shows the results to this estimate. We find the results are comparable to our estimates, suggesting the exclusion of these effects isn't driving our results.

Finally, we'll use placebo regression to test that the model isn't picking some structural characteristics of canal exposure and is picking up the effects of the blockage. Table A.4 shows the estimated results using Panama Canal exposure during the time period, which shouldn't be related to the blockage, and Table A.5 shows the estimated results looking at the same period in 2019. Both tables show results that aren't significant, both economically and statistically, suggesting the results from the paper are related to the blockage and not some bigger pattern.

Figure 7.1: Estimated Propagation Effects, Histogram



Estimated lower bound propagation effects of a 6-day stop to value-added that goes through the Suez Canal as a percentage of final use by country. Note that 100% is the maximum possible, not 1.

7 Propagation Effects Estimation

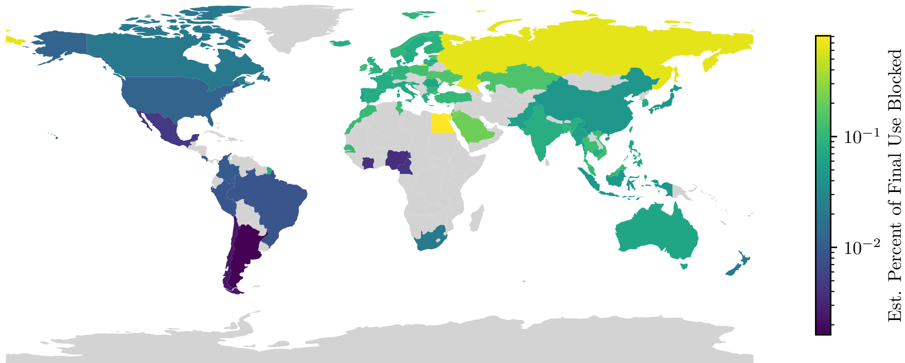
7.1 Estimates

Using the IO tables and the process outlined in Los, Timmer, and Vries 2015, we calculate the value added by each country to each other country. Then, by calculating the fastest routes between ports in pairs of countries and weighting by their share of trade between both countries, we can estimate the percentage of trade between the two countries that goes through the Suez Canal. This technically creates a continuous variable in $[0, 1]$, but in reality more than 80% of the values are either 0 or 1.

As discussed in Section 4.2, this only creates a lower bound since it assumes no goods cross the canal more than once between production processes. It also assumes trade is going by sea when possible, a reasonable assumption since more 80% of global trade happens by sea (Sirimanne et al. 2023), and this number is likely deflated by landlocked countries, which are excluded from our analysis since we use ports to estimate whether goods travel through the canal. It also assumes ships travel along the shortest route, an assumption that is discussed more in Section 4.1.

Using the linearity assumption with Leontief IO analysis, we then estimate how much of this value would have passed through the canal during the six-day blockage. The results for this estimation are shown in Figure 7.1 and Table 7.1.

Figure 7.2: Estimated Propagation Effects, Locations.



The histogram in Figure 7.1 has a significant right-skew. Our estimated lower bound on the effect of the blockage on final use was less than 0.1% in most countries, but some countries were affected substantially more. The largest effect predicted was just above 0.8%. On their own, a 0.1%, or even 0.8% decrease in expenditure is economically meaningless, but in the context of an accident caused by only a single cargo ship, demonstrates a significantly higher than ideal effect and illustrates the fragility of global value chains.

Colon, Hallegatte, and Rozenberg 2019 finds that transport shocks have propagating effects on areas that wouldn't normally be impacted. To test this idea, we observe where our lower-bound propagation effects are located geographically. A map of the estimated effects is shown in Figure 7.2

On the map, the country where the canal is located, Egypt, is very affected. Russia, the other most impacted country, is near the canal, though the impacts for both of these may be a result of the assumptions made about how trade routes are connected and overestimated since they have ports on both sides of the canal. All the countries near the canal, especially in Europe and the Middle East, are very affected, but some countries farther away, like Australia, Vietnam, and Thailand,

Table 7.1: Estimated Propagation Effects, Summary Statistics

	Count	**Mean**	**St. Dev**	**Min**	**25%**	**50%**	**75%**	**Max**
Total Effects	68	0.098	0.122	0.002	0.053	0.081	0.110	0.812

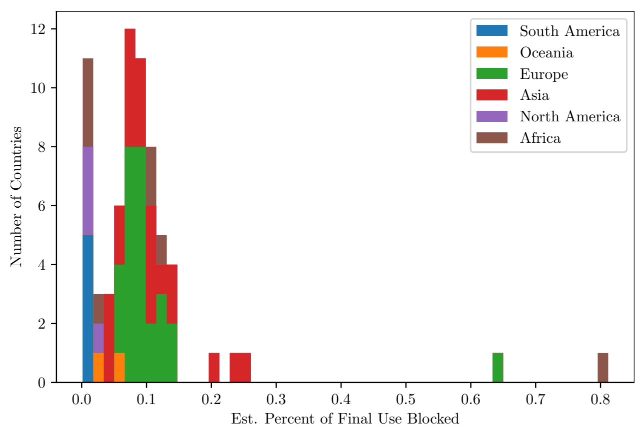
Notes: Note that 100% is the maximum possible, not 1.

are also very affected, so the blockages effects aren't entirely concentrated in the geographic area near the blockage.

Separating the histogram and summary statistics from Figure 7.1 and Table 7.1 by continent gets Figure 7.3 and Table 7.2.

There is quite a bit of variation between continents. Europe, Asia, and Africa have very similar estimated effects, especially between percentiles. The 75th percentile estimated effect for all three is within 0.01 percentage points of each other. The means display variation, likely because the two most affected countries, Egypt and Russia, pull the mean up. North and South America also follow similar patterns between them. The median estimated lower bound for counties in North and South America, however, is 4 times lower than the median for a country in Oceania and 6-8 times

Figure 7.3: Estimated Propagation Effects by Continent, Histogram



Note that 100% is the maximum possible, not 1. Russia treated as part of Europe and Türkiye as part of Asia.

Table 7.2: Estimated Propagation Effects by Continent, Summary Statistics

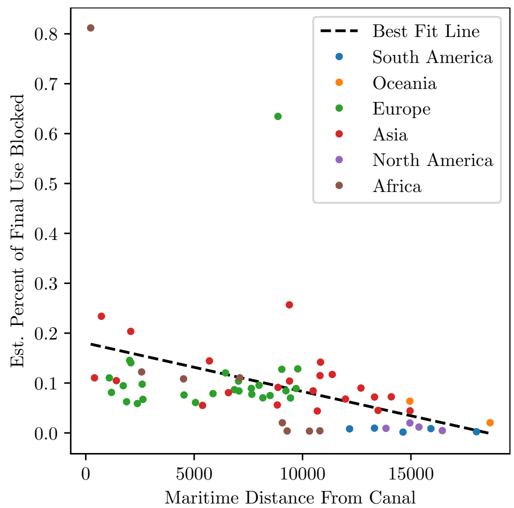
	Count	Mean	St. Dev	Min	25%	50%	75%	Max
Africa	8	0.148	0.273	0.004	0.004	0.064	0.113	0.812
Asia	23	0.106	0.059	0.044	0.069	0.091	0.117	0.257
Europe	27	0.112	0.107	0.059	0.076	0.087	0.107	0.635
North America	4	0.011	0.005	0.008	0.008	0.010	0.014	0.020
Oceania	2	0.042	0.031	0.020	0.031	0.042	0.053	0.064
South America	5	0.006	0.004	0.002	0.002	0.008	0.009	0.010
Total	68	0.098	0.122	0.002	0.053	0.081	0.110	0.812

Notes: Note that 100% is the maximum possible, not 1. Russia treated as part of Europe and Türkiye as part of Asia.

lower than for countries in Africa, Asia, or Europe. This suggests there could be some relationship between geography and propagation effects.

To test this, we examine how the lower bound effect estimate is related to maritime distance from the Suez Canal. A plot of this is shown in Figure 7.4. Estimated distance from the Suez Canal is found using the shortest route approximation in Section 4.1.

Figure 7.4: Estimated Propagation Effects by Distance



Note that 100% is the maximum possible along the y-axis, not 1. Russia treated as part of Europe and Türkiye as part of Asia. Best fit line calculated using OLS (Results not shown).

The trendline on the graph is negative, but around it there is significant variation. Especially within Asia, there are quite a few countries with the higher than expected effect. North and South American countries are clustered in the bottom right with lower than expected effects, which makes sense given the size of the effects in those continents were extremely low (Table 7.2).

We can also analyze the propagation effects compared to the exposure score used in Section 6. From Section 6, we know these exposure scores are predictive of the direct effects of the blockage. Finding a strong correlation between propagation effects and exposure scores would contradict the idea that propagation effects spread and impact would-be-unaffected groups (Colon, Hallegatte, and Rozenberg 2019). This comparison is shown in Figure 7.5

Like in the distance comparison, the results are correlated, but there is significant, unpredicted variation, especially in the bottom-left cluster with low exposure and low propagation effects. This suggests that in general, more exposed ports are affected more by propagation effects, but also that there are many exceptions to this rule.

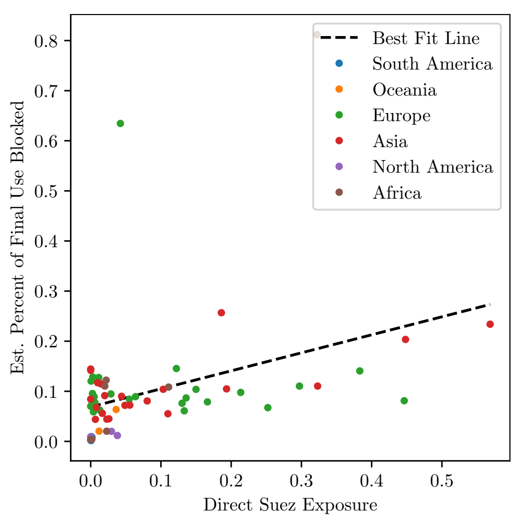
Therefore, our lower bound estimation is consistent with Colon, Hallegatte, and Rozenberg 2019 in that effects are distributed across groups that wouldn't be affected directly. We don't find these effects are distributed evenly, however, just that they exist in certain cases. There are quite a few countries that face higher propagation effects than would be suggested by their distance or canal exposure, but there are just as many countries that face very limited propagation effects.

7.2 Robustness

Time of Estimation. Because 2021 data during the event was unavaliable, the previous estimations were made using 2019 data. The accuracy of these estimates depends on the value-added across the canal in IO tables to be relatively consistent over time so we can extrapolate them to 2021. Therefore, we reestimate the model using IO tables from different years between 2016 and 2020.

The results of this estimation are shown in Figure 7.6. The same process used to estimate the

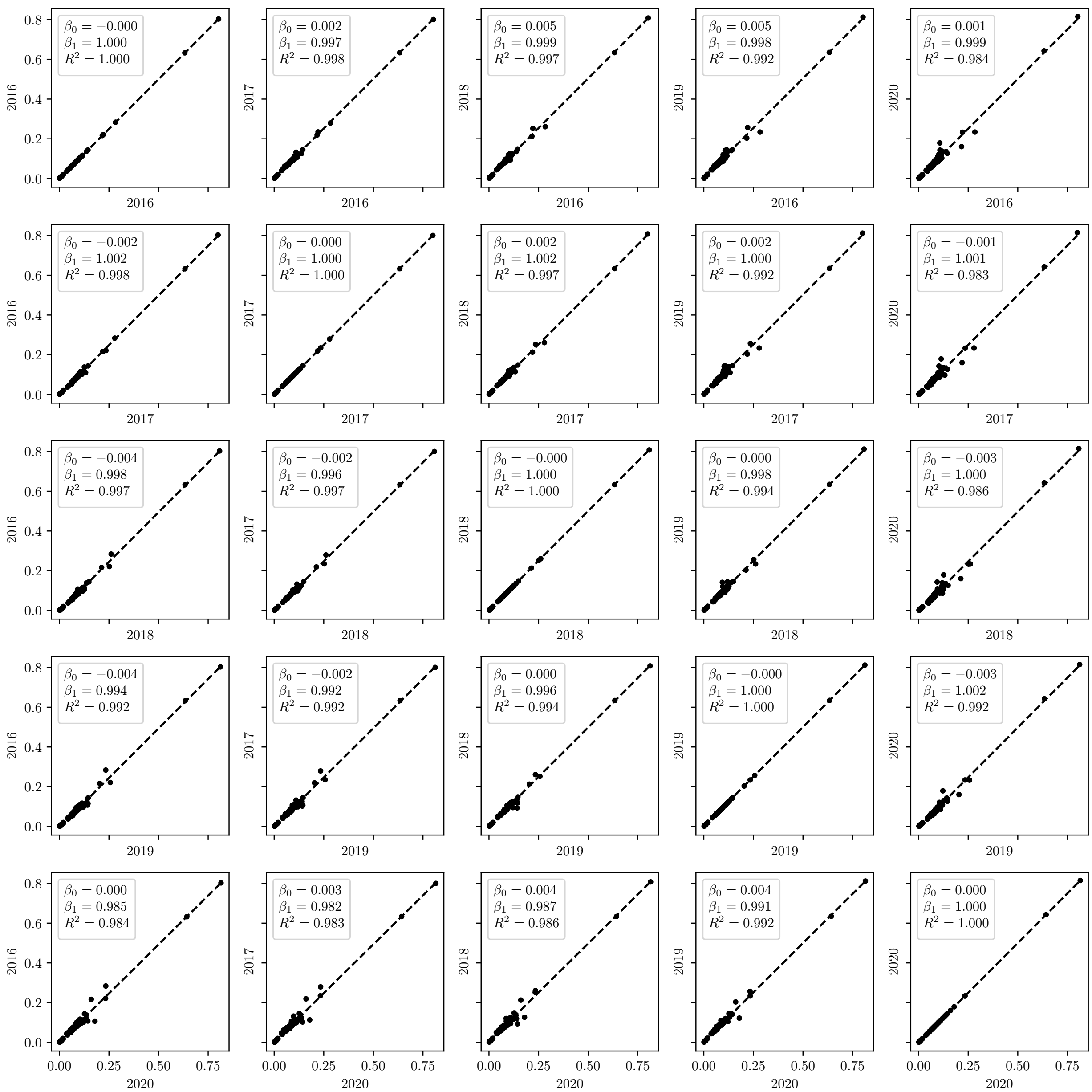
Figure 7.5: Estimated Propagation Effects by Exposure



Estimated lower bound propagation effects of a 6-day stop to value-added that goes through the Suez Canal as a percentage of final use by country versus Suez Canal exposure. Colored by continent. Note that 100% is the maximum possible along the y-axis, not 1. Russia treated as part of Europe and Türkiye as part of Asia. Best fit line calculated using OLS (Results not shown).

initial model was repeated for years between 2016 and 2020. The results are plotted against each other, with a best fit line and basic OLS statistics also shown.

Figure 7.6: Estimated Propagation Effects in Different Years



Y and x-axis are the propagation effect estimates using data from that year. Note that 100% is the maximum possible along the y-axis, not 1. Best fit line calculated using OLS.

In every model, the R^2 for the best fit line is very close to 1, meaning the two estimations are almost 100% predictive of each other. The β_0 intercept is almost 0 and the β_1 coefficient is almost

1, which suggests the models get mostly identical results.

Therefore, we can conclude that there is little intertemporal variation and our 2019 estimation is applicable during the time of the blockage in 2021.

Other Checks. When we created our lower bound estimate, we completely excluded the effects of the "Rest of World" category in the data and assumed it didn't cross the canal. Figure B.1 shows what happens when we flip that assumption and assume all ROW trade goes through the canal. We see limited effects, suggesting out results are robust to the effects of trade from other, excluded countries and that the included countries trade the most with other included countries.

8 Conclusion

Overall, we have found the Suez Canal blockage had significant impacts on global trade, primarily in countries more exposed to the canal.

The estimates in Section 6 suggest that an exposed port could see up to a 70% decrease in imports and an exposed country could see up to a 90% decrease in imports compared to normal canal operation. These results are all robust to changes in our measures and assumptions and aren't a result of general trends. The effects are also found to be stronger at the start of the blockage and focused nearer to the blockage, though these may just be an artifact of our estimation method and data.

The lower bound in Section 7 suggests that most countries had approximately 0.1% of their annual final goods use affected by the blockage, a result that holds economic significance due to the fact that the shock that caused this was a single ship stranded in a single canal for only six days. These impacts are concentrated around countries closer to the canal and more exposed to the canal, but a handful of countries that fit neither of these criteria were also significantly affected, illustrating the propagative nature of these second order effects.

These results are exceptionally important given current events surrounding maritime chokepoints. As of March 2024, Houthi Rebels have attacked more than 60 ships in the Red Sea, a chokepoint that leads into the Suez Canal (CRS 2024; Bigg, Shankar, and Fuller 2024). The effects of climate change in Central America are causing lower water levels in the Panama Canal, making trade through it slow down (Arslanalp et al. 2023). Our results suggest countries should insure themselves against these canal shocks by reducing exposure to chokepoints.

8.1 Limitations

This research has a number of limitations. The theoretical model ignored congestion, trade costs, and non-maritime trade. Much of the empirical work was done based on assumptions for how ships travel, the speed they travel at, what domestic production functions look like, and so on. These assumptions were primarily made due to limitations in the datasets that made a more robust analysis impossible.

There also are possibilities that there are confounding factors that aren't accounted for in our models. The results appear reasonably robust to different types of trend analysis that should capture many of these effects, but this possibility can never be entirely eliminated.

8.2 Farther Work

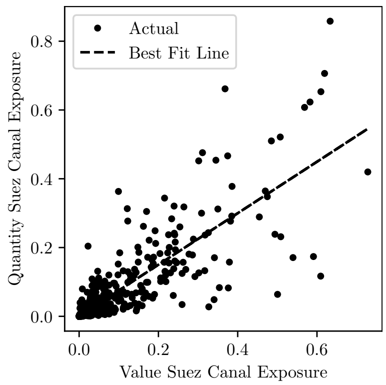
Farther research into this topic should attempt to address many of these limitations. Using AIS data could alleviate many of the issues with data that have plagued us throughout the paper. It would allow us to get a better view at exactly what happened to ships impacted by the blockage and perform a more robust analysis, especially of the first-order effects.

New research could also look into the events going on today. The slowdown of trade through the Panama and Suez Canal is very different from the sudden blockage in the Ever Given incident. These events are fairly recent, so a comprehensive analysis may be impossible for the next year or two, but they have been going on for long enough to get preliminary results about how those slower shocks with more longevity affect trade differently than sudden blockages that gets addressed within a week.

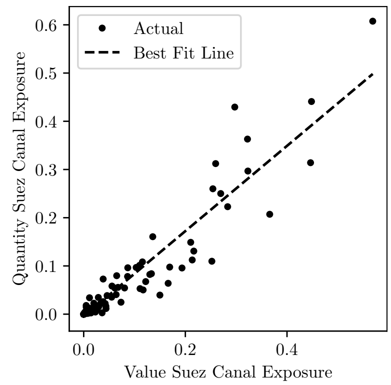
Appendices

A First Order Effects

Figure A.1: Value Suez Canal Exposure Versus Quantity Suez Canal Exposure.



(a) Port-Level Exposure. $R^2 = 0.733$.



(b) Country-Level Exposure. $R^2 = 0.891$.

Best fit lines calculated using OLS (Results not shown).

Table A.1: Port Model Regression Results Using Quantity Exposure.

	Total		**Cargo**		**Tanker**	
	(1)	(2)	(3)	(4)	(5)	(6)
Q Exposure × Crash	-1.467***	-1.655***	-1.711***	-1.768***	-0.795**	-0.830**
	(0.494)	(0.508)	(0.437)	(0.447)	(0.362)	(0.373)
Crash		0.048		0.015		0.009
		(0.036)		(0.033)		(0.027)
Port FE	Yes	Yes	Yes	Yes	Yes	Yes
Speed (km/h)	40	40	40	40	20	20
Observations	48,744	48,744	48,744	48,744	48,744	48,744
No. of Ports	1,354	1,354	1,354	1,354	1,354	1,354
R^2	0.519	0.519	0.530	0.530	0.408	0.408

Notes: Dependent variable: Log Imports. Standard errors in parentheses. Regression ran across all ports from 3/1/2021 to 4/5/2021. The speed was used to calculate lags based on how far a port is from the Suez Canal.

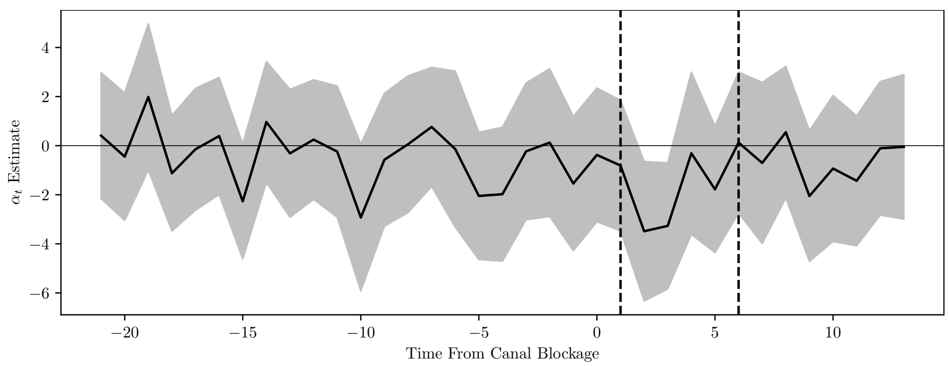
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Country Model Regression Results Using Quantity Exposure.

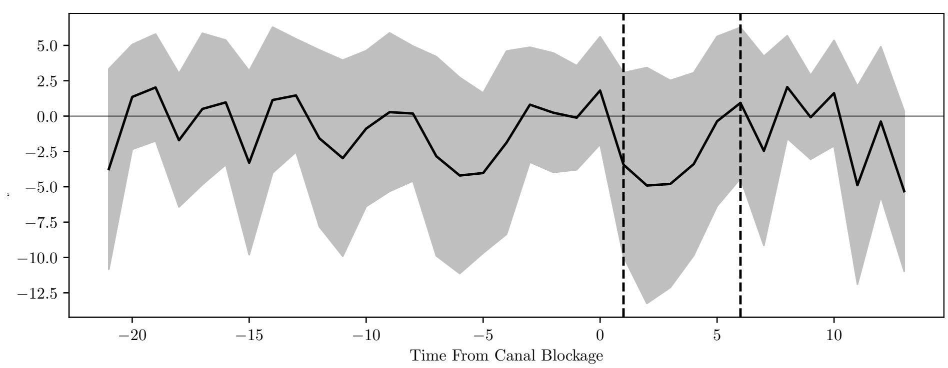
	Total		**Cargo**		**Tanker**	
	(1)	(2)	(3)	(4)	(5)	(6)
Q Exposure × Crash	-2.070**	-2.582**	-1.463	-2.045*	1.235	1.667
	(0.832)	(1.013)	(1.090)	(1.211)	(1.135)	(1.305)
Crash		0.142		0.162		-0.120
		(0.179)		(0.154)		(0.191)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Speed (km/h)	40	40	40	40	20	20
Observations	3,100	3,100	3,100	3,100	3,089	3,089
No. of Countries	90	90	90	90	90	90
R^2	0.515	0.515	0.511	0.511	0.522	0.522

Notes: Dependent variable: Log Imports. Standard errors in parentheses. Regression ran across all countries from 3/1/2021 to 4/5/2021. The speed was used to calculate lags based on how far a country is from the Suez Canal.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure A.2: Dynamic model estimations.



(a) Port-Level Estimation



(b) Country-Level Estimation

Model ran from March 1, 2021 (-22 on the x-axis) to April 5, 2021 (12 on the x-axis). Gray region denotes the 95% confidence interval. Vertical bars denote the start and end of the blockage.

Table A.3: Time Fixed Effects Regression Results.

	Port			Country		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure × Crash	-0.921**	-1.171***	-1.067**	-2.042**	-2.435**	-3.690***
	(0.435)	(0.448)	(0.459)	(0.982)	(1.108)	(1.321)
Port FE	Yes	Yes	Yes			
Country FE				Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	No	Yes
Ref. Time FE	No	Yes	Yes	No	Yes	Yes
Speed (km/h)	40	40	40	40	40	40
Observations	48,744	48,744	48,744	3,100	3,100	3,100
No. of Geo Effects	1,354	1,354	1,354	90	90	90
R^2	0.520	0.519	0.521	0.524	0.519	0.529

Notes: Dependent variable: Log Imports. Standard errors in parentheses. Regression ran across all ports and countries from 3/1/2021 to 4/5/2021. The speed was used to calculate lags based on how far a port is from the Suez Canal. Ref. time represents time lagged based on how far a port or country is from the canal. Blank effects mean they wouldn't fit in the model.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Regression Results Using Panama Exposure.

	Port		Country	
	(1)	(2)	(3)	(4)
Panama Exposure × Crash	0.123	0.226	-0.242	-0.217
	(0.361)	(0.374)	(0.840)	(0.979)
Crash		-0.041		-0.008
		(0.035)		(0.162)
Port FE	Yes	Yes		
Country FE			Yes	Yes
Speed (km/h)	40	40	40	40
Observations	48,744	48,744	3,085	3,085
No. of Geo Effects	1,354	1,354	90	90
R^2	0.518	0.518	0.513	0.513

Notes: Dependent variable: Log Imports. Standard errors in parentheses. Regression ran across all ports and countries from 3/1/2021 to 4/5/2021. The speed was used to calculate lags based on how far a port is from the Panama Canal. Blank effects mean they wouldn't fit in the model.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Regression Results in 2019.

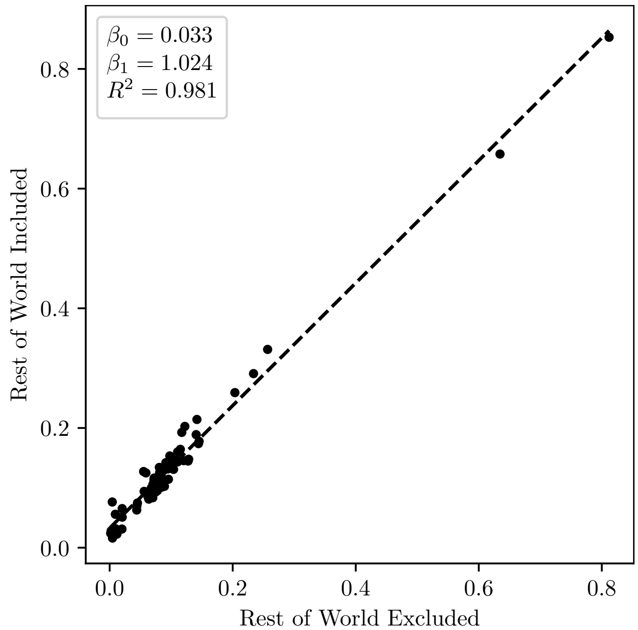
	Port		**Country**	
	(1)	(2)	(3)	(4)
Exposure × Crash	0.179	0.024	0.157	-0.397
	(0.373)	(0.396)	(0.913)	(0.991)
Crash		0.041		0.146
		(0.036)		(0.097)
Port FE	Yes	Yes		
Country FE			Yes	Yes
Speed (km/h)	40	40	40	40
Observations	48,780	48,780	3,113	3,113
No. of Geo Effects	1,355	1,355	90	90
R^2	0.509	0.509	0.510	0.510

Notes: Dependent variable: Log Imports. Standard errors in parentheses. Regression ran across all ports and countries from 3/4/2019 to 4/8/2019. The speed was used to calculate lags based on how far a port is from the Suez Canal. Blank effects mean they wouldn't fit in the model.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B Propagation Effects

Figure B.1: Estimated Propagation Effects in Including vs Excluding the ROW



Estimated lower bound propagation effects of a 6-day stop to value-added that goes through the Suez Canal as a percentage of final use by country including and excluding the rest of the world. Including the rest of the world means assuming trade from them travels through the Suez Canal and excluding them means assuming it doesn't. Note that 100% is the maximum possible along the y-axis, not 1. Best fit line calculated using OLS.

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