Trade From Space: Shipping Networks and The Global Implications of Local Shocks*

Inga Heiland[†] Andreas Moxnes[‡]
Karen Helene Ulltveit-Moe[§] Yuan Zi[¶]

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Abstract

This paper examines the structure of the shipping network and its implications on global trade and welfare. Using novel data on the movements of container ships, we calculate optimal travel routes. We then estimate the impact of a shock to the network on global trade by means of a natural experiment: the 2016 Panama Canal expansion. Trade between country pairs using the canal increased by 9-10% after the expansion. While the building costs were borne by Panama alone, a model-based quantification shows that the welfare gains were shared by many countries, due to the network structure of shipping.

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[†]University of Oslo & CESifo, inga.heiland@econ.uio.no
[‡]Princeton University, University of Oslo & CEPR, andreas.moxnes@econ.uio.no
[§]University of Oslo & CEPR, k.h.ulltveit-moe@econ.uio.no
[¶]University of Oslo, yuan.zi@econ.uio.no

1 Introduction

Container ships are the engines of global trade. Levinson (2010) and Bernhofen et al. (2016) detail the seismic changes that the worldwide adoption of container shipping technology has brought about in international trade. As documented by Rua (2014), by now nearly all countries have container ports, constituting the nodes of the global container shipping network. However, there is scarce empirical evidence on the structure of the shipping network, e.g. which route a container might travel from the dock of port i to port j. At the same time, the structure of the shipping network is an essential determinant of the costs of trade, and there is increasing evidence suggesting that connectivity is at least as important as geographical distance in determining freight costs.[1] The networked environment also implies that a shock to a port, or a link, in the network, such as improvements in shipping infrastructure, can affect shipping costs and trade flows for many countries. In this paper, we use satellite data on the movement of container ships to establish novel evidence on the routes that form the global shipping network. This in turn allows us to analyze how local shocks to the shipping network affect trade costs, global trade flows and real incomes.

Our contribution is threefold. First, we document salient features of the container shipping network based on unique novel data covering the worldwide movements of all container ships in 2016. Second, we demonstrate how information about shipping routes can be used to investigate the impact of a local shock on global trade. We do so by using the Panama Canal expansion in 2016 as natural experiment, which allows us to identify the impact of the improvement of one link of the shipping network on worldwide trade. Exploiting route information inferred from the satellite data, we provide reduced-form estimates of the Panama Canal expansion on global trade. Third, we quantify the trade and welfare effects of the shock using a canonical Ricardian model of trade along with the route information and reduced-form estimates.

[1] See Limao and Venables (2001) on the weak relationship between geographical distance and shipping costs, Wilmsmeier and Hoffmann (2008) on the importance of connectivity, and UNCTAD (2015) for a review of the role of distance and connectivity.

Our empirical analysis of global container ship movements has become possible due to the rapid advent of the global Automated Identification System (AIS) over the last years. AIS reporting of vessel positions offers a degree of automation in data processing and aggregation that was not previously possible. Vessels send out AIS signals identifying themselves to other vessels or coastal authorities, and the International Maritime Organization (IMO) requires all international voyaging vessels with above 300 Gross Tonnage and all passenger vessels to be equipped with an AIS transmitter. This implies that all container ships carrying any significant amount of cargo are parts of our data universe. AIS messages include information regarding vessel identity, physical appearance, voyage-related information such as draught and destination. Simply put, AIS data offers real-time information on the whereabouts of all ocean-going vessels.

Using an exhaustive data set of all port calls made by container ships in 2016, we document novel facts about the container shipping network. First, container ships typically operate on fixed routes, i.e. they serve a stable set of ports, akin to buses serving a fixed number of stops in a city. Second, shipping activity is highly concentrated across ports, with some nodes (ports) in the network handling almost two orders of magnitude more ships than the median port. Third, the network is very sparse in the sense that only few countries have direct shipping routes to their trade partners. Less than 6% of all 22,650 pairs of countries with container ports are directly connected.

While the AIS data provides unprecedented detail about the movement of ships, one cannot observe the movement of the cargo itself, i.e. the actual route of a shipment from country i to country j. To make progress, we use the observed shipping network along with actual travel times between all direct port-pair links and apply standard graph theory to calculate the fastest route between any potential port pair. Consider, for example, a shipping network with direct links between New York-London, New York-Hamburg, London-Oslo and Hamburg-Oslo. The fastest route between New York and Oslo might then be New York-London-Oslo if this route minimizes the sum of travel times of each leg of the journey. Of course, the actual route chosen might be deter-

mined by other factors than speed, such as port costs. However, it is widely recognized that the overall cost efficiency of a ship depends on the total time it takes the ship to complete a voyage, see e.g. Cullinane and Khanna (2000). As such, the calculated fastest route is an approximation to the actual unobserved route. The fastest path calculations reveal that 52% of all country-to-country connections involve stops in more than two other countries in between.

Besides adding to the distance traveled by a container, indirect routes expose bilateral flows to the shipping infrastructure of other countries. To demonstrate the importance of exposure to third-country infrastructure, we analyze the global trade effects of a large improvement in local shipping infrastructure in 2016: the expansion of the Panama Canal. After 10 years of construction, the extended Panama Canal opened on June 26th of 2016. The $5.25 billion massive construction project was a modern engineering marvel: it nearly doubled the capacity of the canal by adding a wider and deeper third lane.[2] We present an event study from the AIS data showing that ships carried significantly more cargo after the expansion date, as the expanded canal allowed for ships that could hold more than twice the amount of cargo (so-called New Panamax ships). While our data do not include information about shipping costs, it is well established that larger ships are associated with lower unit costs of shipping because operating costs per container are lower, see e.g. Cullinane and Khanna (2000). Moreover, we employ our information on shipping routes to explore how exporters and importers worldwide were differentially affected by this local change in the shipping infrastructure. Using a difference-in-difference approach, we find that country pairs whose fastest connection passed through the Panama Canal prior to the expansion traded 9-10% more after the expansion compared to other country pairs.

Finally, we use a canonical model of trade to quantify the general equilibrium effect of the Panama Canal expansion. The model is calibrated by using information on the changes in trade costs according to the reduced form estimates along with the fastest route information described above. The ex-

[2]The project required 5 million cubic meters of high-strength concrete - enough to build a highway from New York to St. Louis (Business Insider, 2016).

pansion increased world real income by 0.02% or USD 20 billion. While the building costs were borne by Panama alone, the gains per capita were shared by many countries, due to the network structure of shipping.

Our paper is closely related to the growing number of studies using satellite data for economic analysis. Donaldson and Storeygard (2016) provide an overview of applications which so far has focused on environmental, development and spatial issues. This paper explores how shipping satellite data can be used within the field of international trade. There are only a few recent papers that have used shipping satellite data to explore issues related to trade. Brancaccio et al. (2017) study the role of the transportation sector in world trade focusing on search frictions and the endogeneity of trade costs. They use AIS data for dry bulk ships, which typically carry commodities such as iron ore, coal, grain and sugar. Our focus is instead on container ships, which typically carry manufactured goods and account for around two-thirds of world trade based on values.

Our paper also aims to contribute to the literature on the effects of containerization. Besides having spurred global trade as documented by Bernhofen et al. (2016), new port technology has been shown to have significantly altered countries' economic geography (Brooks et al., 2018 and Ducruet et al., 2019). Finally, this paper is related to the literature that studies the impact of canal openings or closings. Maurer and Rauch (2019) analyze how the Panama Canal changed U.S. population patterns, whereas Feyrer (2009) studies the relationship between trade and the closing and opening of the Suez Canal.

The rest of the paper is structured as follow. Section 2 documents the satellite data and the construction of the shipping network and presents salient features of the network. In Section 3 analyzes the global impact of the Panama Canal expansion on trade, while Section 4 presents general equilibrium effects of the canal expansion based on a model of international trade. Section 5 concludes.

2 Data and Descriptives

2.1 Data

AIS data. We build a comprehensive and global data set for the container shipping network based on satellite data for ships. Our data set is based on AIS (Automatic identification System) data provided by Marine Traffic. AIS is an automatic tracking system used on ships and by vessel traffic services (VTS). AIS is intended to assist a vessel's watch-standing officers and allow maritime authorities to track and monitor vessel movements. AIS information supplements marine radar. The International Maritime Organization's International Convention for the Safety of Life at Sea requires AIS to be fitted aboard international voyaging ships with 300 or more gross tonnage (GT), and all passenger ships regardless of size. The coverage of AIS globally has increased rapidly over the last decade, and does now allow for a global coverage of all vessels and ports of significance.

Our data set is based on port calls. Every time a ship arrives or departs a port a signal is sent. This is referred to as a port call. We use data on all port calls made tracked by the AIS satellite system during the calendar year 2016. Every observation of a port call has a time stamp, which tells us when and where the call was made and by which ship. The observation contains information on the name of the port, country and geographical location (latitude and longitude). In addition, we get information on whether the ship is arriving or departing, whether it is in transit or not, as well as the draught of the ship at the time the port call is made. We merge the AIS data to the World Fleet register data base constructed by Clarksons, which has vessel specific information on a range of ship characteristics (see Appendix A).

Our point of departure is containerized trade.[3] Containerized seaborne trade captures the majority of merchandise world trade. Seaborne trade volumes accounted for over 80% of world merchandise trade in 2015 (UNCTAD,

[3]Based on the ship categories used by data supplier, Marine Traffic, we use the ships categorized as "container ship" and "Cargo/container ship".

2016).[4] Appendix Section A describes how we clean and process the port calls data. The final data set includes 4,908 container ships and 515 ports for the year 2016.

Other data sets. The analysis in Section 3 requires data on trade flows, which we obtain from COMTRADE.[5] We aggregate monthly bilateral trade data to the quarterly level for the years 2015-2017. The analysis also requires variables such as distance and contiguity, which we obtain from the gravity database of CEPII. Data on free trade agreements come from the WTO's RTA databases. The analysis in Section 4 requires additional information about domestic absorption along with a few other variables, which we obtain from the Eora MRIO global supply chain database; we gather data for 189 countries for the 2015 cross-section.

2.2 Stylized Facts: The Shipping Network

This section documents three key facts about the shipping network that will guide the subsequent analysis.

Fact 1: Container ships typically operate on fixed routes. Table 1 provides descriptive statistics on the number of ports passed per ship as well the number of ships that arrive and depart per port. A key feature of container ships is that they typically visit the same port many times. The table shows that the average number of distinct ports passed per ship is roughly one sixth of the total number of ports passed per ship (12 versus 68).

Fact 2: Shipping activity is highly concentrated in space. A few ports act as major hubs in the shipping network. While the median port only serves around 200 ships per year, the top ports serve close to 15,000 ships per year. The same pattern is observed at the port-pair level, i.e. there are a few links in the network that account for a large share of total shipping activity.

Fact 3: Only 6 percent of all country pairs have a direct shipping connec-

[4] Global seaborne container trade accounted for approximately 60 percent of the value of all seaborne trade in 2016 (Rajkovic et al., 2014).

[5] Downloaded from https://comtrade.un.org/api/get/bulk/C/M/201801/ALL/HS on March 15th, 2019.

Table 1: Ships and Ports

Variable:	Obs	Median	Mean	Sd	Min	Max
Ships:						
# ports passed	4,908	64	68	40	1	312
# distinct ports passed	4,908	11	12	7	1	46
Ports:						
# incoming ships	515	203	647	1,451	5	14,473
# outgoing ships	515	199	647	1,447	5	14,407
Port pairs:						
# ships	4160	38	80	168	5	2775
deadweight tonnes (in mio)	4160	1	4	9	.1	210

Note: Summary statistics are based on the port calls made by container ships in 2016. Only ships with non-zero duration are used. Summary statistics include only routes taken by at least 5 ships and only routes between ports that appear both as arrival and departure ports.

tion. We calculate the in-degree as the number of ports to which a port is directly connected based on incoming ships, and the out-degree as the number of ports to which a port is directly connected based on outgoing ships. Table 2 shows that on average most ports are connected to rather few other ports. However, there is great variation between ports in how well connected they are. Nevertheless, even the best connected ports are only directly connected to around one sixth of the total number of ports. The 515 ports in our data are allocated across 151 countries. Only 6 percent of all country pairs have a direct shipping connection. Trade between these countries accounts for only 54 percent of world trade. Therefore, a large share of global trade does not travel on direct routes, but on routes with multiple hops.

Table 2: Port Networks

Variable:	Obs	Mean	Sd	Min	Max
All ports:					
Indegree	515	8.08	10.26	1	84
Outdegree	515	8.08	9.84	1	82
Top 10 ports:					
Indegree	10	54.10	12.03	42	84
Outdegree	10	50.10	13.88	37	82

Note: Summary statistics are based on the port calls made by container ships in 2016. Only ships with deadweight tonnes>15,800 and trips with non-zero duration are used. Summary statistics include only routes taken by at least 5 ships and only routes between ports that appear both as arrival and departure ports.

2.3 Calculation of Fastest Routes

While the AIS data provides unprecedented detail about the movement of ships, one cannot observe the movement of the cargo itself, i.e. the actual route of a shipment from country i to country j. This section documents our methodology to calculate routes and shows descriptive statistics on those routes. The route information will be an important part of the methodology in Section 3.

We calculate the routes as follows. First, based on the time stamps provided in our port-to-port data set, we observe *direct travel time* between two ports. The direct travel time between two ports is computed as the median over all ships' trip duration (see Appendix A). Note that these travel times are *directed*, i.e. the travel time from D to A need not equal the travel time from A to D.[6] Second, for all port pairs, including the ones that are not directly con-

[6]Note, that as we calculate travel time, we exclude trips which involve crossings of anchorages where the ship is sailing in ballast and does not indicate that it is *in transit*. Moreover, we exclude port-to-port connections where less than 5 ships were observed over the whole year. Note also that the travel time reflects the time it takes to get from port

nected, we calculate the *indirect minimum travel time* over all possible multi hop routes. Using the port-to-port data and Dijkstra's algorithm, we compute the minimum travel time as the shortest path in a weighted directed network where edges reflect direct connections and weights are the direct travel times described above.

Figure 1 shows a subset of the fastest routes calculated by our algorithm. Focusing on the U.S., the graph plots the fastest routes for U.S. exports to all other countries. The fastest routes typically go through hubs. E.g., U.S. shipping to Europe tends to pass through Germany and the Netherlands, whereas U.S. shipping to Africa goes through a hub in Spain.

Figure 2 plots the fastest travel times between all port pairs against geodetic distance. Distance is strongly correlated with direct travel time, represented by the light blue dots in the figure. However, we observe that for indirect routes, represented by the dark blue dots, geodetic distance is much less informative for travel times.

To understand further the role of shipping hubs, we examine the number of hops on the fastest shipping routes between all ports in the network. Figure 3 shows the frequency of hops after aggregating ports by country.[7] Most country pairs are connected by routes involving one to four hops.[8]

3 The Panama Canal Expansion

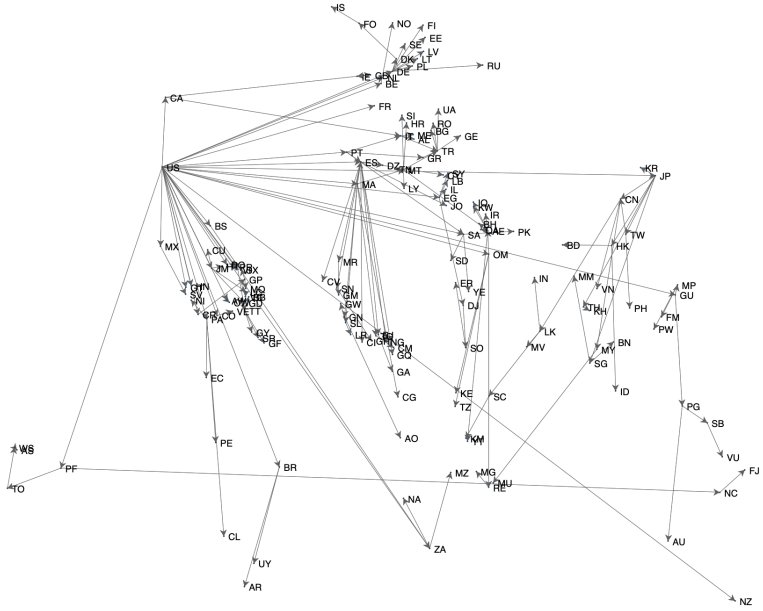
Guided by the stylized facts on shipping networks presented in Section 2, we investigate how a shock to a particular link in the network not only affects trade between ports/countries on either side of the link, but also trade between any

D's geofence to port A's geofence plus the time spent traveling, waiting or lading/unloading within the port area. Since we do not observe the time when ships arrive at the dock, we account for the latter by adding one half of the median time that ships spent within the geofence of port D and port A, respectively to the travel time between the geofences.

[7]For countries with multiple ports, we use the minimum number of hops across multiple connections to the partner country.

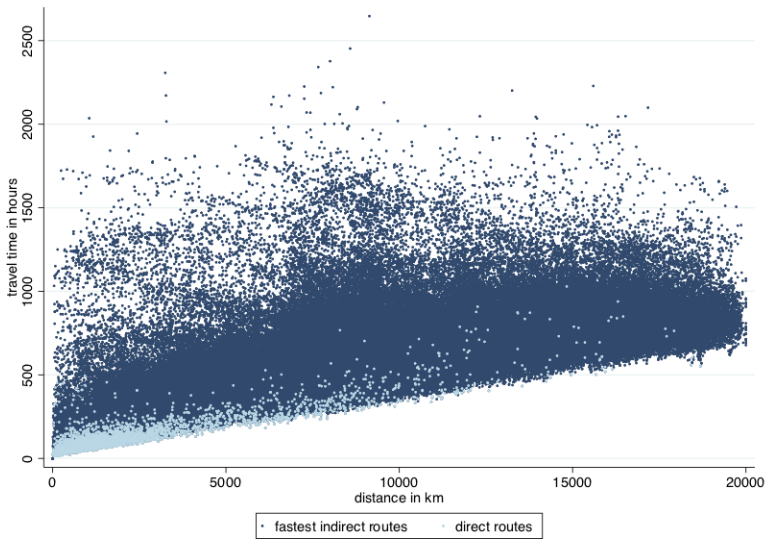
[8]Figure 3 shows that for roughly 5% of country pairs the direct route is also the fastest. This is slightly lower than the 6% percent of directly connected country pairs reported above, due to the fact that for a small number of pairs there exists an indirect connection that is faster than the direct route.

Figure 1: Fastest Travel Times.



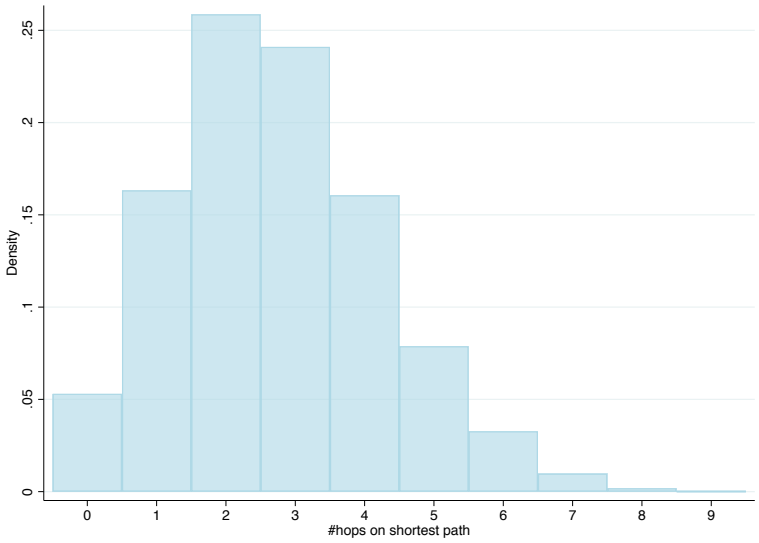
Note: The figure plots the fastest routes from the U.S. to other countries. All computations are based on observed travel times between all regular (non-anchorage) ports in the AIS. Routes with less than 5 ships are dropped. Indirect travel time computed as shortest path in port network where edges, reflecting direct connections, are weighted by direct travel times.

Figure 2: Travel time and distance across port-pairs.



Note: The figure plots travel times between two ports against their geodetic distance. All computations are based on observed travel times between all regular (non-anchorage) ports in the AIS data. Routes with less than 5 ships are dropped. Indirect travel time is computed as the shortest path in port network where edges, reflecting direct connections, are weighted by direct travel times.

Figure 3: The distribution of the number of hops across country-pairs.



Note: The figure shows the distribution of the number of hops along the fastest route between all country pairs in the sample. The average (median) is 2.7 (3). Computations are based on port-to-port shipments from the AIS data and a shortest-path algorithm using travel-time-weighted edges. For countries with multiple ports, the number of hops refers to the connection with lowest number of hops.

port/country that is using that link indirectly.

We use the recent Panama Canal expansion as a natural experiment. The Panama canal opened in 1914 and is one of the important links of worldwide maritime trade. Since the end of the second World War, transits through the canal have steadily increased in response to the rise of global trade. The majority of all cargo that passes through the canal originates in, or is destined to, the Americas and East Asia. The Panama Canal Authority approved the expansion in April 2006, and the construction began in 2007 with an estimated total cost of US$5.25 billion.[9] The motivation for the expansion was twofold. First, the canal was approaching a capacity constraint with the rapid increase of world trade. Second, ship sizes were increasing. According to forecasts, only 41 percent of container ships and 52 percent of dry bulk ships would be able to pass through the original canal, while the planned expansion would allow for 92 and 86 percent respectively to pass.[10] The Panama Canal Authority initially announced that the Canal expansion would be completed by August 2014 to coincide with the 100th anniversary of the opening of the Panama Canal. But various setbacks, including strikes and disputes with the construction consortium over cost overruns, pushed the completion date back several times. There was, therefore, substantial uncertainty about exactly when the expanded canal would open. The expanded canal began commercial operation on 26 June 2016. The enlarged canal is a formidable feat of modern engineering: it doubled capacity by adding a new, wider and deeper lane of traffic, allowing for more and larger ships to pass. In particular, the expanded canal allowed for the passage of so-called New Panamax ships, which carries more than twice as much cargo compared to the older Panamax ships.[11] As the new third lane opened, a new toll structure was introduced that differentiated across ship size. It implied higher rates for bigger ships on a per-ship basis,

[9] https://web.archive.org/web/20110721055325/http://www.acp.gob.pa/eng/plan/documentos/propuesta/acp-expansion-proposal.pdf

[10] See Wilson and Ho (2018) for a comprehensive case study of the Panama Canal.

[11] For a detailed description of the expansion project, see e.g. https://www.nationalgeographic.com/news/2014/8/140815-panama-canal-culebra-cut-lake-gatun-focus/

but lower rates for bigger ships on a per-container basis (see Wilson and Ho, 2018). From June to December 2016 the share of New Panamax ships passing through the canal increased from 0 to 15 percent. In 2017, the canal container tonnage increased by 22%.[12] The old canal continued to operate both during and after the construction period, facilitating clean identification of the impact of the expansion on global trade and container traffic.

We perform two complementary empirical analyses. First, we use the route information calculated above to estimate the effect on trade between country-pairs using the Panama Canal versus countries not using the Panama Canal. Second, we perform an event study estimating the effect of the expansion on various margins of container traffic on the canal.

3.1 The Effect of the Panama Canal Expansion on Global Trade

Combining the AIS based network data with COMTRADE data on bilateral world trade, we investigate how the Panama Canal expansion affected global trade. We do so by employing a simple differences-in-differences analysis:

$$y_{ikt} = \beta Post_t \times PanExposure_{ik} + \delta \cdot Z_{ikt} + \delta_{ik} + \delta_{it} + \delta_{kt} + \varepsilon_{ikt}, \qquad (1)$$

where y_{ikt} is log quarterly exports (from COMTRADE, see Section 2) from country i to country k at time t. The variable $Post_t$ is a dummy that takes on the value one if the date is after June 2016, and zero otherwise. Exposure to the Panama Canal expansion is captured by the variable $PanExposure_{ik}$, which takes on the value one if the fastest route between countries i and k passes the Panama canal and zero otherwise.[13] Z_{ikt} refers to a set of bilateral controls: a dummy for joint membership in a free trade agreement, as well as

[12] http://www.pancanal.com/common/maritime/advisories/2017/a-02-2017.pdf and https://www.moodys.com/research/Moodys-Upgrades-Panama-Canal-Authority-to-A1-Outlook-stable--PR_396338

[13] For country pairs with multiple ports we average over the binary indicator across all port-to-port connections using the source and destination port size as weights.

Table 3: Panama Canal Exposure: Summary Statistics for 2016.

Country pairs with exposure		Global trade exposed		Importers with exposure	
(1)	(2)	(3)	(4)	(5)	(6)
# pairs	% of total	value in trn $	% of total	# importers	% of total
3,085	12 %	1.8	12 %	141	65 %

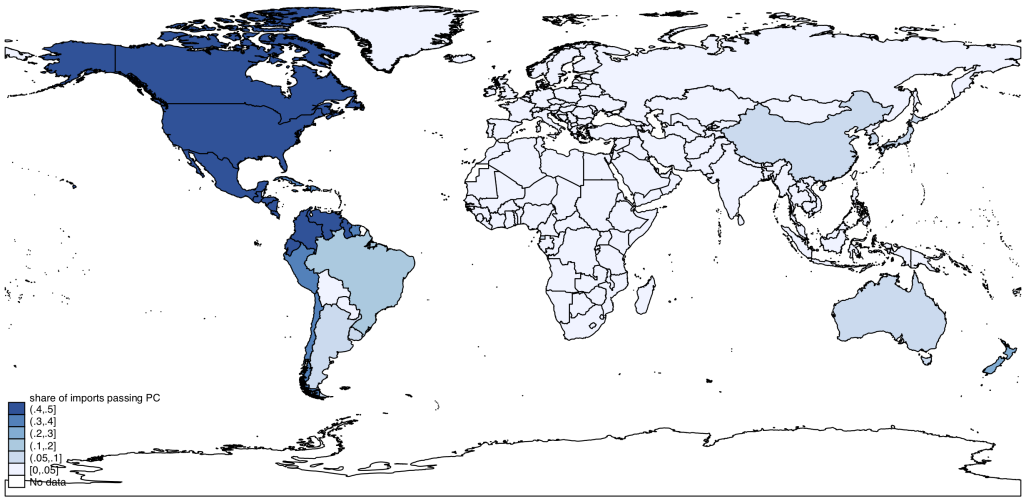
Note: The table shows in column 1 (2) the number (share) of country pairs with a fastest connection passing the Panama Canal; in column 3 (4) the value of (share of global) trade between country pairs whose fastest connection passes the Panama Canal; in column 5 and 6, respectively, the number of importers with at least one fastest connection passing the Panama Canal and their share in the total number of importers.

bilateral geographical variables (distance, contiguity and common language) interacted with the $Post_t$ dummy. Hence, we allow for trends in trade that may differ according to observed geographical characteristics. We also include a large set of fixed effects: source country-time δ_{it} and destination country-time δ_{kt} fixed effects will control for trends in overall exporting and importing for each country, while source-destination country fixed effects δ_{ik} control for time-invariant country pair characteristics.

Panama Canal exposure. Table 3 presents summary statistics for the Panama Canal exposure measure in 2016. There are 3,085 country pairs (12% of 25,025 pairs with positive trade flows) which are connected by a fastest route passing the Panama Canal. The value shipped between these countries accounts for 12% of global trade. The table also shows that the majority of countries are in some way exposed to the Panama Canal: 65% of all importers have at least one fastest connection to a trade partner that passes through the canal. Across all importers, the average share of imports exposed to the Panama Canal is 7%. Figure 4 shows the share of imports passing through the Panama Canal by country, and illustrates the importance of the Panama Canal as a shipping route for the Americas.

Our identification strategy relies on the differential exposure of country pairs to the Panama Canal *prior* to the opening of the expanded canal and

Figure 4: Panama Canal Exposure by Country.



Note: The figure shows the share of imports passing through the Panama Canal in total imports by country.

presumes that the exposure is stable over time. To test this conjecture, we compute the Panama Canal exposure measure also for the post period. The correlation with the pre period exposure measure is 0.92, indicating that our estimates are not significantly affected by changes in the route network. Moreover, if country pairs in the control group started using the canal after the expansion, our estimates would be biased towards zero.

Empirical Results. We estimate the empirical specification in equation (1) using quarterly COMTRADE trade data as the dependent variable. Our preferred time period is one year before and one year after the expansion of the canal (2015Q3 to 2017Q2). Appendix Table 9 summarizes the estimation sample.[14] Estimation results are reported in Table 4. Across specifications, we find that bilateral trade between country pairs whose fastest route passes the Panama Canal increased by 8-9 percent after the expansion. Columns (1)-(3)

[14]Our estimation sample covers about 82% of global imports reported to COMTRADE. The missing 18% are due to countries not reporting trade data to Comtrade on a monthly basis (which are aggregated to the quarterly level).

report results for the full sample of country pairs and quarters, while columns (4)-(6) show results using a balanced panel where all country-pairs are observed in every quarter. The inclusion of the vector of controls in columns (2) and (5) does not change the results significantly, underscoring the robustness of the results.

Heterogeneity. We also explore whether the treatment effect is heterogeneous across country pairs. One hypothesis is that country pairs with fewer hops along the route will have a greater treatment effect than country pairs with many hops. For example, if the expansion reduces shipping costs due to the adoption of larger ships, then the cost savings in percent will be higher on routes with fewer hops. Columns (3) and (6) in Table 4 interact the main regressor with an indicator variable for whether the number of hops between i and j is below or above the median number of hops. The results strongly support the hypothesis; the treatment effect is roughly twice as high for country pairs with below median number of hops compared to the average treatment effect.

Placebo. To check the robustness of our results, we also re-estimate the specification from column two of Table 4 with placebo treatments in June 2015 or 2017, using four quarters of 2015 and 2017, respectively. The results are reported in Table 5. The estimated coefficients are not significant, suggesting that there are no pre-trends driving our results.

Table 4: The impact of the Panama Canal expansion on trade.

Sample:	Unbalanced			Balanced		
	(1)	(2)	(3)	(4)	(5)	(6)
$Post_t \times PanExposure_{ik}$	0.089**	0.090**		0.084**	0.090**	
	(0.042)	(0.043)		(0.037)	(0.038)	
$\times 1[\#hops \leq med]$			0.216**			0.237**
			(0.087)			(0.092)
$\times 1[\#hops > med]$			0.042*			0.074*
			(0.087)			(0.038)
Controls	No	Yes	Yes	No	Yes	Yes
Fixed effects: ik, it, kt	Yes	Yes	Yes	Yes	Yes	Yes
Observations	68,112	68,112	68,112	49,978	49,978	49,978
Exporters/Importers	209/90	209/90	209/90	200/61	200/61	200/61
R^2	0.964	0.964	0.964	0.968	0.968	0.968

Note: The time period is 2015Q3 to 2017Q2. $Post_t = 1$ if $t > 2016Q2$. The control variables are: an FTA indicator and geographical variables (distance, contiguity and common language) interacted with $Post_t$.S.e. in parentheses clustered by exporter and importer. The three first columns include all country-pairs, while the three last columns only include country-pairs with positive trade in all quarters. The triple interaction term in columns (3) and (6) is an indicator variable for whether the number of hops between i and j is below of above the median number of hops. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Placebo treatments in 2015 and 2017.

Time period:	2015Q1-2015Q4	2017Q1-2017Q4
$Post_t \times PanExposure_{ik}$	-0.035	0.010
	(0.045)	(0.044)
Controls	Yes	Yes
Fixed effects: ik, it, kt	Yes	Yes
Observations	39,449	39,748
Exporters/Importers	208/90	209/88
R^2	0.971	0.971

Note: Column 1 (2): Placebo treatment is $Post_t = 1$ if $t > 2015Q2$ ($Post_t = 1$ if $t > 2017Q2$).The control variables are: an FTA indicator and geographical variables (distance, contiguity and common language) interacted with $Post_t$. S.e. in parentheses clustered by exporter and importer. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

3.2 The Effect of the Panama Canal Expansion on Container Traffic: An Event Study

We supplement the analysis above with an event study design to assess the impact of the Panama Canal expansion on container traffic going through the canal. To do so, we exploit the AIS data further, and use them to construct a set of measures of container traffic, which we use as dependent variables. The AIS data allows us to identify the ships and cargo that pass through the canal. Additionally, it provides a substantially higher degree of temporal resolution, which enables us to zoom in on role of the canal expansion.

Global Container Traffic. We measure container traffic by (i) average shipments per ship (in tonnes), (ii) the number of ships and (iii) total shipments (in tonnes). To compute container shipments in tonnes, we follow the recent maritime literature and construct a draught-based estimate of a ship's cargo (see e.g., Adland et al., 2017). The draught of a ship refers to the vertical distance between the surface of the water and the lowest point of a vessel.

The Appendix A and B provide details on the data and the construction of the draught based measure of shipments.

Empirical Model and Identification. We split voyages into two groups: voyages leaving country i that pass through the Panama Canal ($p = 1$) in week t and voyages leaving country i that do not pass through the Panama Canal ($p = 0$). We then sum across voyages according to exposure (p) and take logs of the relevant variable. The event study compares all container traffic passing through the Panama Canal before and after the Panama Canal expansion, with all global container traffic that do not pass through the canal. The key identifying assumption is that in the absence of the canal expansion, the cargo flows that pass through the Panama Canal and those that do not, would have followed the same trend.

We proceed by estimating a set of differences-in-differences regressions:

$$x_{ipt} = \sum_t \gamma_t I_t \times I_{ip} + I_p + I_i + I_t + \epsilon_{ipt}, \tag{2}$$

where x_{ipt} refers to one of the three different margins of container traffic, I_t is a week fixed effect, I_i is a country fixed effect and I_{ip} equals one if the flow refers to a Panama Canal crossing and zero otherwise. The vector of coefficients for the interaction terms $I_t \times I_{ip}$ then measures the growth in Panama Canal flows compared to non-Panama Canal flows in week t relative to a base week. We choose the base level week 25, which was the week prior to the expansion (June 20 to June 26, 2016). The battery of fixed effects will control for seasonality (I_t) and average levels of shipping cross countries and mode (I_i and I_p).[15] The time period is week 5 to 48 in 2016.[16]

Empirical Results. The event study is presented graphically in Figures 5 and 6. Figure 5 shows the point estimates and standard errors of γ_t when using

[15] In practice, we classify all shipments passing through the Panama canal as originating from Panama, i.e. we set $i = Panama$ for all $p = 1$. The reason is that voyages using the canal are more likely to stop at a Panama port after the expansion. In the raw data, this would appear as a drop in shipments from country i for $p = 1$.

[16] The four first and last weeks of 2016 are omitted because we do not observe the complete trip for many of these observations (e.g., a ship departing December 31 2015 and arriving January 5 2016 will be incomplete in our data).

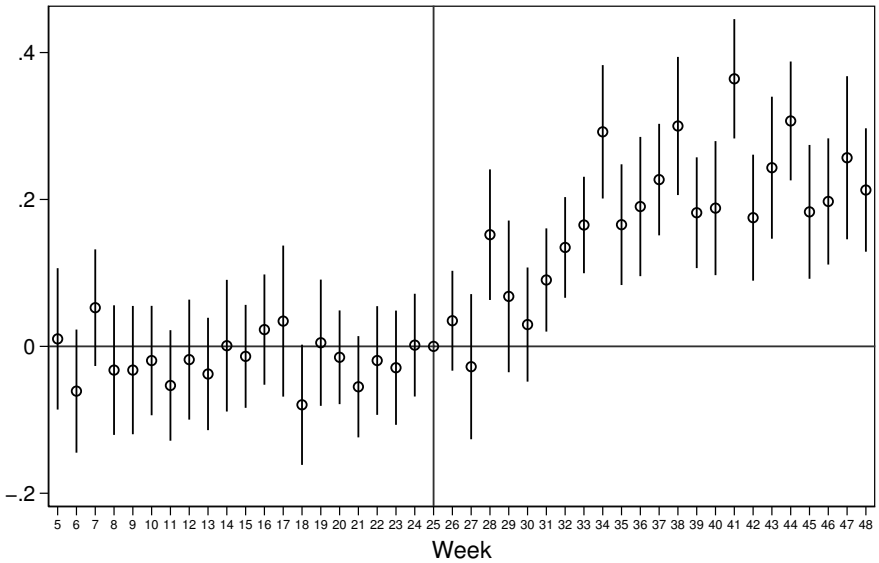
log shipments per ship as the dependent variable. In the figure, the vertical line represents the week before the expansion. Average shipments increased substantially after the expansion, with point estimates relatively stable at 0.2 log points, suggesting that ships carried more than 20 percent more cargo (in tonnes) after the expansion. Importantly, the pre-trends are all centered around zero before the expansion, supporting the identifying assumption that there are no pre-trends that are driving our results. Our results are in line with the Panama Canal Authority's reports stating that the expansion doubled the canal's capacity and significantly shifted traffic towards bigger containerships.[17] Our findings suggest that the canal expansion reduced transport costs by allowing for the passage of more cost effective bigger containerships, with lower operating costs per container (see e.g. Cullinane and Khanna, 2000) and lower Canal tolls per container.

Figure 6 shows a similar plot for the number of ships and total shipments. Here the results are less clear cut: The number of ships appears to decline somewhat, and total shipments appear to increase, however the point estimates fluctuate substantially from week to week.

[17] https://micanaldepanama.com/ampliacion/2018/03/canal-ampliado-alcanza-tres-mil-transitos-neopanamax-en-20-meses-de-operacion/

According to the report, 3,000 New Panamax ships, whose dwt is around twice as large as Panamax ships (the biggest containerships allowed to pass before the expansion), had crossed the canal expansion during its first 20 months of operation.

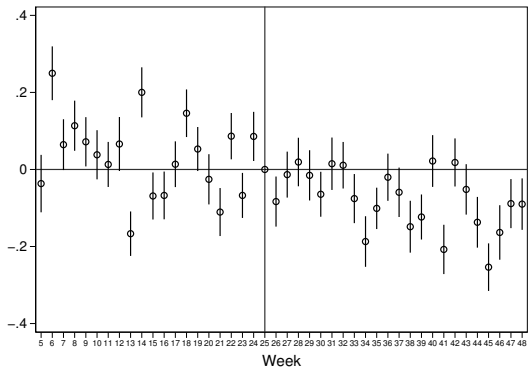
Figure 5: Shipments per ship - Pre and Post Expansion



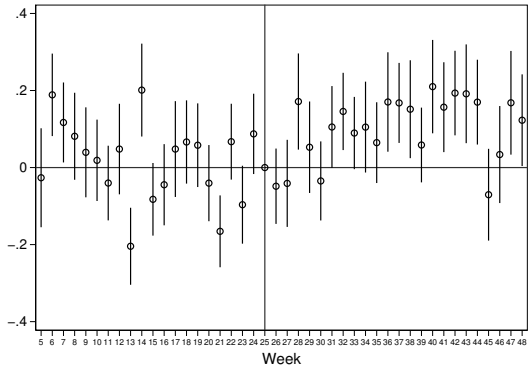
Note: The figure reports the coefficient estimate and standard error of γ_t from the estimating equation (2). The dependent variable is log shipments (in tonnes) per ship. Standard errors are clustered by country.

Figure 6: Number of Ships and Total Shipments - Pre and Post Expansion

(a) Number of Ships



(b) Total Shipments



Note: The figure reports the coefficient estimate and standard error of γ_t from the estimating equation (2). The dependent variable is the number of ships and total shipments (in tonnes), both in logs. Standard errors are clustered by country.

4 The General Equilibrium Effect of the Panama Canal Expansion

So far the empirical analyses have provided evidence on the impact of the Panama Canal expansion for global trade and container traffic. This section introduces a canonical model of world trade to quantify the general equilibrium

– and thus welfare – effects of the Panama Canal expansion. After presenting the economic framework, we will quantify the effect of the expansion by feeding in (i) changes in bilateral trade costs based on the reduced form estimates from Section 3.1 along with (ii) the fastest route information from Section 2.3, while holding all other parameters constant. We then calculate the resulting changes in all equilibrium outcomes according to the model.

In the model, the shipping network is pre-determined, i.e. we take the observed shipping network and optimal routes as given, and do not allow for re-optimization of routes after the expansion of the canal. This is motivated by the empirical evidence presented in Section 3.1 that the optimal routes did not change much from the first to second half of 2016 (the correlation between the pre- and post period Panama canal exposure measure is 0.92). As such, our results on welfare can be viewed as a lower bound, as allowing for re-optimization of routes would presumably yield slightly larger effects.

4.1 World Equilibrium

Consider a global economy of N countries, a continuum of differentiated goods, and a constant elasticity of substitution (CES) aggregator. Several theories of international trade then support a gravity equation of the form

$$\chi_{ij} = \frac{T_i w_i^{-\theta} d_{ij}^{-\theta}}{\Phi_j}, \tag{3}$$

where χ_{ij} is country i's share in country j's manufacturing spending and $\Phi_j = \sum_{i' \in N} T_{i'} w_{i'}^{-\theta} d_{i'j}^{-\theta}$. In the Eaton-Kortum (2002) model, T_i denotes country i's average efficiency (absolute advantage), θ is the dispersion in efficiency across goods (comparative advantage), $d_{ij} \geq 1$ is the iceberg trade cost between i and j and w_i is the nominal wage.

There are two sectors, manufacturing (M) and non-manufacturing (N). Only manufacturing goods are traded. Gross production of manufactures in a country, Y_i^M, equals total worldwide spending on goods from country i. This

gives the goods market clearing condition

$$Y_i^M = \sum_{j=1}^{N} \chi_{ij} X_j^M,$$

where X_i^M is manufacturing spending in country i.

We allow for the possibility of unbalanced trade, and denote the trade deficit as $D_i^M = X_i^M - Y_i^M$. The trade deficit relative to GDP, D_i^M/Y_i, is assumed to be constant. A constant share α of income is spent on manufacturing goods, so $X_i^M = \alpha X_i$, where total spending is $X_i = Y_i + D_i^M$ and Y_i is total income. Under perfect competition, aggregate income equals labor income, $Y_i = w_i L_i$. We can then manipulate the goods market clearing condition to (see Appendix D):

$$w_i L_i \left(1 - \frac{1-\alpha}{\alpha} \frac{D_i^M}{Y_i}\right) = \sum_j \chi_{ij} w_j L_j \left(1 + \frac{D_j^M}{Y_j}\right). \tag{4}$$

An equilibrium is then a vector of wages w_i that satisfies equations (3) and (4).

4.2 Quantification

Consider relative changes from an initial to a counterfactual equilibrium and denote the relative change by $\hat{x} = x'/x$, where x' and x are the new and initial equilibria. The change in trade shares are then

$$\hat{\chi}_{ij} = \frac{\hat{w}_i^{-\theta} \hat{d}_{ij}^{-\theta}}{\hat{\Phi}_j}, \tag{5}$$

where $\hat{\Phi}_j = \sum_{i \in N} \chi_{ij} \hat{w}_i^{-\theta} \hat{d}_{ij}^{-\theta}$ (see Appendix D). The goods market clearing conditions can be written as

$$\hat{w}_i = \sum_j \frac{\chi_{ij} X_j^M}{Y_i^M} \hat{w}_j \hat{\chi}_{ij}. \tag{6}$$

As is well known (e.g., Caliendo and Parro, 2015), in this class of models the change in real income is simply

$$\frac{\hat{w}_i}{\hat{P}_i} = \hat{\chi}_{ii}^{-\alpha/\theta},$$

where $\hat{P}_i$ is the relative change in consumption prices.

We now ask what would happen to the world equilibrium if we change trade costs d_{ij} for the country pairs affected by the Panama Canal expansion. The data requirements for this exercise are relatively modest: First, it requires data on X_i^M, Y_i^M, χ_{ij} and α in the initial equilibrium. All these variables are available from Eora MRIO global supply chain database; we gather data for 189 countries for the 2015 cross-section.[18] Second, it requires data on the trade elasticity θ. Since our analysis does not identify the trade elasticity, we rely on estimates from the previous literature, and choose the value $\theta = 5$, close to the aggregate elasticity estimated in Caliendo and Parro (2015).

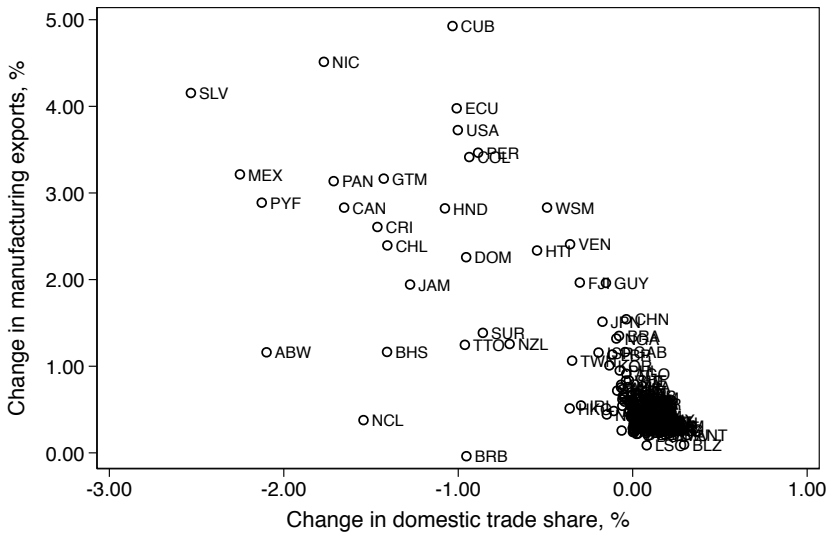
Finally, it requires data on the change in trade costs $\hat{d}_{ij}$. Recall that we know from Section 2.3 which country pairs are exposed to the canal, i.e. that the fastest route from i to j is using the canal. Country-pairs not trading through the canal therefore have $\hat{d}_{ij} = 1$. For country pairs using the canal, the reduced from results from Section 3 gave us an estimate β of the impact on trade caused by the expansion. We assume the following functional form for trade costs: $\hat{d}_{ij} = \alpha^{-Panama_{ij}}$, where $Panama_{ij} = 1$ if i and j are connected by the Panama Canal, and 0 otherwise. For canal-connected countries, the relative change in trade costs d_{ij} is then $1/\alpha$. The structural interpretation of the coefficient estimate β from equation (1) is then simply $\theta \ln \alpha$. Given the estimate $\beta = 0.09$ and $\theta = 5$, we get $\alpha = exp\,(0.09/5) \approx 1.02$, or $\hat{d}_{ij} = 0.98$, i.e. the expansion caused a 2 percent decline in trade costs for canal-connected countries.

[18] α (the share of spending on manufacturing goods) is only required for the calculation of the change in the consumer price index. We choose a value of 0.35, which is the average share across countries in Eora MRIO.

4.3 Welfare Effects

Figure 7 shows the change in the domestic trade share, $\hat{\chi}_{ii}$, plotted against the change in manufacturing exports for all the countries in our sample (both in percent). As expected, countries close to the Panama Canal increase their share of imports in total spending (i.e., the percent change in χ_{ii} is negative). This includes the U.S, Canada, Mexico and Panama itself. These countries also increase their total exports, as their market access to other countries improves. For the world as a whole, global trade increases by roughly 1 percent.

Figure 7: Counterfactual: The Impact of the Panama Canal Expansion.



Note: The figure shows the counterfactual change in the domestic trade share on the horizontal axis plotted against the change in manufacturing exports on the vertical axis (both in percent).

Table 6 reports the changes to manufacturing exports, imports, the domestic trade share and the real wage for the top 5 countries with the largest real wage gains. Countries close to the canal emerge as the top winners from the expansion, with increases in real wages of around 0.20 percent. For the large majority of countries, the real wage gains are close to zero. A few countries, including Austria, Hungary and Zimbabwe, experience a (small) real wage loss

due to the expansion. These are landlocked countries that do not themselves get improved market access, but might compete with exporters that do get better market access. The weighted average of the real wage change across all countries is 0.02%, or roughly 20 billion USD.[19]

Table 6: Counterfactual: The Impact of the Panama Canal Expansion.

	Exports	Imports	$\hat{\chi}_{ii}$	Real wages
El Salvador	4.15	4.31	-2.53	0.18
Mexico	3.21	4.55	-2.25	0.16
Nicaragua	4.51	4.32	-1.77	0.13
Panama	3.14	3.55	-1.71	0.12
Canada	2.83	3.83	-1.65	0.12

Note: The table shows the change in outcomes for the countries with the largest increase in real wages from the Panama Canal Expansion. Small island states are excluded. All values in percent.

5 Concluding remarks

We exploit novel satellite data on all global port calls made by container ships in 2016. This allows for the construction of a new comprehensive dataset on the shipping network and optimal shipping routes. We apply this dataset to analyze how shocks hitting a segment of the shipping network affect all trading partners worldwide to varying degrees based on their exposure to the shock. Using the 2016 Panama Canal expansion as a natural experiment, we show that the expansion not only had a direct effect on shipments traveling through the canal, but importantly also affected trade flows between countries using the Panama Canal intensively. The expansion produced sizable gains from trade according to a model-based counterfactual analysis. The results

[19] We use PPP-adjusted GDP as weights. PPP-adjusted GDP for 2015 stems from the Penn World Table 9.1 (Output-side real GDP at current PPPs). The original data is denominated in constant 2011 USD, we convert it to 2015 USD using the corresponding price levels also provided in Penn World Table 9.1.

highlight the importance of trade networks for the quantification of the gains from trade.

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Appendix

A Constructing the Container Traffic Data Set

Our point of departure are the AIS data containing all port calls made by ships in 2016 that has been provided by Marine Traffic. Based on the ship categories used by Marine Traffic, we limit the data set to the ships categorized as "container ship" and "Cargo/containership". Marine Traffic provides each ship with a unique identifier (Ship ID). We start out with close to 5,300 ships based on this identifier. We use this to identify each ship's travel history. A ship also has an IMO number and an MMSI number as well as a Ship Name. We use this information to merge the AIS data set with the World Fleet register data base constructed by Clarkson, which has vessel specific information on a range of time invariant ship characteristics, such as the vessels carrying capacity measured in deadweight tonnes (dwt) and cargo capacity of container ship measured in twenty-foot equivalent unit (TEU).

Ideally there should be a perfect match between ship identifiers (IMO, MMSI and Ship ID). However, for around 5% of the ships this is not the case. The mismatch could either because of misreporting, or changing of owners (containerships typically change their MMSI number when changing the owner). We correct for both misreporting and the change of identifiers by cross checking a ship's IMO and MMSI number, as well as ship's characteristics, like its deadweight tons (dwt). We are able to correct for most of the misreporting and end up with 5,165 distinct containerships. Finally, as we want to focus on global container traffic, we introduce a threshold of 15,800 deadweight tons. This leaves us with 4,908 ships.

We then proceed by cleaning the routes of each container ship. The AIS data are very rich with information on not just ports, but also on whether the ship is on/off loading in a port, or is just in transit (e.g. due to need for additional fuels). In addition the data set has information on anchorages, i.e. stops made by ships in places that are not ports.

We sort trips for each ship by their time stamp, so that their travel records

are listed as Arrival-Departure-Arrival-Departure, etc. A "trip" is defined as a direct port-to-port voyage. If a ship departs a port A, makes several "in transit" stops at other ports, or stops at anchorages, before finally arriving at port B, we define the voyage from A to B as one trip of the ship. We use the draught reported when the ship reaches the arrival port as the draught of the trip.

To calculate travel time between ports, we exclude trips which involve crossings of anchorages where the ship is sailing in ballast and does not indicate that it is *in transit.* Moreover, we exclude port-to-port connections where less than 5 ships were observed over the whole year. Note also that the travel time reflects the time it takes to get from port D's geofence to port A's geofence plus the time spent traveling, waiting or lading/unloading within the port area. Since we do not observe the time when ships arrive at the dock, we account for the latter by adding one half of the median time that ships spent within the geofence of port D and port A, respectively to the travel time between the geofences.

B Calculating Container Shipment

B.1 AIS based Container Shipment

Due to the availability of AIS data, the use of draught-based estimates of ships' cargo has recently emerged in the maritime transport literature, see e.g. Adland et al. (2017). We build on this approach, and as we limit the analysis to one type of ships, namely container ships, we are able to establish a relatively simple rule for the computation of the ships' container shipment. A ship sailing without cargo is referred to as a ship sailing in ballast. In practice, a ship sails in ballast if its draught is smaller than a given threshold value, which we refer to as ballast draught (H_B). Specifically, we define $H_B = 0.55H_S$, where H_S is the ship's scantling draught. Scantling draught is the draught the ship will have when it is fully loaded, and it is also referred to as design draught, as it is this draught it is build for. We have access to technical information on

ships' scantling draught as well as the vessel's carrying capacity (dwt) from the Clarkson World Fleet Database (see Section A above). We use 0.55 as the weight to define ballast draught based on the maritime engineering literature.[20] Letting H_A refer to the draught reported by the ship en route, we calculate the shipments carried by a ship on a specific voyage,as

$$B = dwt * (H_A - H_B) / (H_S - H_B), \tag{7}$$

and refer to B as *effective dwt*. A ship's draught as well as estimated cargo relates to one specific trip, i.e. to a voyage between two ports.

Table 7 shows that, based on our draught based estimates, on average container ships do merely 0.2% of their trips without cargo (in ballast). This stands in sharp contrast to other types of vessels that are typically involved in very different trades, and do not operate on "bus routes" like container ships. Brancaccio et al. (2017) focus on dry bulk ships and report that 42% of the ships travel without cargo. We also observe that there is substantial variation across trips with respect to draught, effective dwt, and across ports with respect to total incoming and outgoing cargo.

[20]The threshold for ballast water is chosen based on information from Marine Traffic supported e.g. David (2015).

Table 7: Ships, Trips and Port

Variable:	Obs	Mean	Sd	Min	Max
Ships:					
Share of trips in ballast (<55%)	4,908	0.002	0.04	0	1
Trips:					
Actual draught (% of scantling draught)	331,265	0.80	0.10	0.55	1
Effective dwt on loaded trips	331,265	26,113	24,560	1.23	199,744
Ports:					
Total incoming effective dwt in millions	515	16.80	44.30	0	498.70
Total outgoing effective dwt in millions	515	16.80	44.30	0	499.98

Note: Summary statistics are based on the port calls made by container ships in 2016. Effective dwt is calculated based on dwt and draught and is used as a measure for cargo. Only ships with deadweight tons>15,800 and trips with non-zero duration are used. Summary statistics include only routes taken by at least 5 ships and only routes between ports that appear both as arrival and departure ports.

B.2 Calculating cargo flows pre and post the Panama Canal expansion

In order to conduct the event study on the impact of the Panama Canal expansion we use the AIS data on port calls for 2016 that provide us with a comprehensive data set of all voyages made by container ships during this year. We prepare the data set in the following way:

First, we drop January and December from our analysis due to a substantial decline in the number of observations for these two months, which is due to the fact that we have no, or incomplete, information on trips that started before the beginning of our sample period (January 1st of 2016) or were completed after the end of sample period (December 31st of 2016).

Second, we split voyages into those that were exposed to the Panama expansion and those that were not. We define a trip as exposed to the expansion if it runs through the canal.

We let the date of the trip be given by the departure time of the ship as it leaves Panama before heading to a foreign destination port. If we observe a change in draught as a ship travels through the Panama Canal, we assume that the number of newly added containers at Panama is sufficiently small compared to the number of containers it carried through the Canal.

Summing the tonnage identified above by date/week/month yields the total tonnage passing though the canal. To construct our control group, we use the rest of the trips in our data and sum over the departed tonnage by country and by time.

B.3 Summary Statistics Panama Canal Exposure

Table 8: Summary statistics on Panama Canal exposure

Rank	Importer	Share of total imports passing PC	Share in world imports	Exporter	Share of total exports passing PC	Share in world exports
1	USA	52.7	14.0	USA	30.1	9.0
2	MEX	10.1	2.5	CHN	17.9	14.9
3	CAN	9.6	2.7	MEX	11.6	2.6
4	CHN	5.0	7.7	CAN	9.7	2.5
5	JPN	2.8	3.7	JPN	5.7	4.3
6	KOR	1.8	2.6	DEU	3.3	8.5
7	CHL	1.2	0.4	KOR	3.2	3.4
8	COL	1.2	0.3	GBR	1.3	2.6
9	HKG	1.1	3.4	FRA	1.3	3.3
10	BRA	1.0	0.9	ITA	1.2	3.1
11	NLD	1.0	3.0	CHL	1.0	0.4
12	PAN	0.9	0.2	BRA	0.9	1.3
13	FRA	0.9	3.8	IRL	0.9	1.1
14	AUS	0.8	1.2	PER	0.7	0.2
15	PER	0.8	0.2	COL	0.7	0.2

C Estimation Data: Summary Statistics

Table 9: Summary Statistics of the Estimation Sample

Variable	N	Mean	Std. Dev	Min	Max	Source
ln Value (in $)	68,112	15.73	3.31	2.83	25.64	monthly COMTRADE
ln Qty (in kg)	65,701	14.39	4.13	0	35.98	monthly COMTRADE
FTA	68,112	.29	.45	0	1	WTO RTA database
ln Distance	68,112	8.57	.88	4.11	9.89	CEPII
Contiguity	68,112	.03	.16	0	1	CEPII
Common Language	68,112	.13	.34	0	1	CEPII
Pan Exposure	68,112	*.08*	.24	0	1	AIS data

Note: Export data in rows 1 and 2 is aggregated from monthly to quarterly frequency and covers the period 2015Q3 - 2017Q2.

D Theory Appendix

Market potential. The change in the market potential term Φ_j is

$$\begin{aligned}
\hat{\Phi}_j &= \frac{\sum_{i\in N} T_i w'^{-\theta} {d'_{ij}}^{-\theta}}{\sum_{i\in N} T_i w_i^{-\theta} d_{ij}^{-\theta}} \\
&= \sum_{i\in N} \frac{T_i w_i^{-\theta} d_{ij}^{-\theta}}{\sum_{i\in N} T_i w_i^{-\theta} d_{ij}^{-\theta}} \hat{w}_i^{-\theta} \hat{d}_{ij}^{-\theta} \\
&= \sum_{i\in N} \chi_{ij} \hat{w}_i^{-\theta} \hat{d}_{ij}^{-\theta}.
\end{aligned}$$

Goods market clearing. Manufacturing gross production can be written as

$$\begin{aligned}
Y_i^M &= X_i^M - D_i^M \\
&= \alpha X_i - D_i^M \\
&= \alpha \left(Y_i + D_i^M \right) - D_i^M \\
&= \alpha w_i L_i + \alpha D_i^M - D_i^M \\
&= \alpha w_i L_i \left(1 - \frac{1-\alpha}{\alpha} \frac{D_i^M}{Y_i} \right).
\end{aligned}$$

The market clearing condition then becomes

$$\begin{aligned}
\alpha w_i L_i \left(1 - \frac{1-\alpha}{\alpha} \frac{D_i^M}{Y_i}\right) &= \sum_j \chi_{ij} X_j^M \\
&= \sum_j \chi_{ij} \alpha X_j \\
&= \sum_j \chi_{ij} \alpha \left(Y_j + D_j^M\right) \\
&= \sum_j \chi_{ij} \alpha \left(w_j L_j + D_j^M\right) \\
&= \sum_j \chi_{ij} \alpha w_j L_j \left(1 + \frac{D_j^M}{Y_j}\right).
\end{aligned}$$

This can be re-written to

$$w_i L_i \left(1 - \frac{1-\alpha}{\alpha} \frac{D_i^M}{Y_i}\right) = \sum_j \chi_{ij} w_j L_j \left(1 + \frac{D_j^M}{Y_j}\right).$$

Holding the trade deficit constant relative to GDP, we can write the market clearing condition in changes as:

$$\hat{w}_i = \sum_j \frac{\chi_{ij} X_j^M}{Y_i^M} \hat{w}_j \hat{\chi}_{ij}.$$