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Nowcasting Global Trade from Space

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ABSTRACT: We introduce a nowcasting model of global maritime trade, leveraging satellite-based big data on vessel movements. This provides a timely indicator of global trade as shipping accounts for about 80 percent of worldwide merchandise trade by volume. Our approach mimics key features of the way statisticians compile trade data—measuring the customs value of imported and exported goods, forming import and export price deflators, and then estimating import and export volumes. We show how global and regional nowcasts can be obtained using port-level data from IMF PortWatch and highlight important enhancements to the platform since its beta launch in November 2023. Finally, we demonstrate how the monthly nowcasts can be used to monitor fragmentation and regionalization in global maritime trade.

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1. Introduction

The global economy is highly reliant on trade that connects activity across borders. Understanding shifts in trade patterns in a timely manner is crucial for several reasons. First, shifts in global trade can provide early warning signs of turning points in economic activity (e.g., the global recession at the onset of the COVID-19 pandemic). Second, in an interconnected world, disruptions to global trade flows in one part of the world can have large ripple effects elsewhere (e.g., Red Sea trade disruptions; Panama Canal drought restrictions). Third, shifts in trade patterns can provide valuable insights into broader structural changes in the global economy, such as those resulting from changing geopolitical alignments. Against this background, our paper makes three contributions.

First, we introduce a nowcasting model of global maritime trade, leveraging satellite-based big data on vessel movements.[1] This provides a timely indicator of global trade as shipping accounts for about 80 percent of worldwide merchandise trade by volume. The model is built on port-level data from IMF PortWatch and generates a monthly proxy of global trade, similar to a Purchasing Managers' Index (PMI). A unique feature of our approach is that it mimics key features of the way statisticians compile trade data—measuring the customs value of imports and exports, forming import and export price deflators, and then estimating import and export volumes. This approach helps overcome a key limitation of previous studies that simply aggregate the volume of goods transported at each port to estimate trade volume (i.e. without considering differences in the unit values of shipments). In doing so, we highlight how estimates of trade based on big data can be enhanced by bringing them closer to the way official statistics are compiled.

Second, the paper describes important enhancements to IMF PortWatch since its beta launch in November 2023. These enhancements advance estimation techniques of previous studies, particularly by tackling issues related to two-way containerized trade and ships' use of ballast water. They also expand the coverage of ports and refine the historical averaging technique used to estimate incomplete observations. Together, these enhancements allow for a better alignment of PortWatch estimates with official data at the port and country level.

Finally, we show how our approach can help monitor developments in trade (fragmentation, regionalization) more promptly than traditional data sources. Our analysis finds evidence for trade fragmentation among geopolitically aligned countries in recent years, consistent with recent studies. On the other hand, while regionalization dynamics vary by region, we find no clear global trend towards regionalization, also in line with recent studies.

Related Literature. Our work builds on three strands of literature: (i) use of big data for macroeconomic and trade analysis; (ii) nowcasting using big data; and (iii) analysis of trade fragmentation and regionalization.

First, we contribute to the literature that uses vessel-level big data for macroeconomic analysis, particularly in the area of trade (Arslanalp, Marini and Tumbarello 2019, Brancaccio, Kalouptsidi and Papageorgiou 2020, Cerdeiro et al. 2020, Cerdeiro and Komaromi 2020, Deb et al. 2020, Verschuur, Koks and Hall 2021, Arslanalp, Koepke and Verschuur 2021, Furukawa and Hisano 2022, Nickelson, Nooraeni, Efliza 2022, Kim et al. 2023).

Second, we contribute to the nowcasting literature, particularly on global trade. For example, the World Trade Organization (WTO) and the United Nations Conference on Trade and Development (UNCTAD) utilize

[1] The series are available in the Trade Monitor section of IMF PortWatch, updated monthly with a lag of seven working days.

nowcasting models to analyze and forecast global trade (Hopp 2022).[2] The OECD has a nowcasting model for trade in value-added (Mourougane et al. 2023). In general, this strand of literature uses a combination of dynamic factor models (Giannone, Reichlin and Small 2008, Guichard and Rusticelli 2011, Barhoumi, Darné and Ferrara 2016, d'Agostino, Modugno and Osbat 2017, Martinez-Martin and Rusticelli 2021), machine learning tools (Hopp 2022, Chinn, Meunier and Stumpner 2023, Jaax, Mourougane and Gonzales 2024) and traditional regression models (Stratford 2013) to nowcast/forecast global trade in goods and services. Our paper contributes to this literature by leveraging satellite-based big data on vessel movements to nowcast global trade.

Third, we contribute to the literature on trade fragmentation and regionalization (Freund et al. 2024, Gopinath et al. 2024). We show that the approach described in this paper could provide a timely monitor of shifts in global maritime trade, while producing results consistent with studies based on macro data.

Finally, a word of caution. Our estimates are not a substitute for official data, but a proxy of trade. We recommend that they are used with caution and advise users to pay attention to at least three limitations of the Automatic Identification System (AIS) data that inform our estimates. First, as noted in previous studies, AIS data are subject to measurement errors. Second, AIS-based estimates of trade include transshipments, which could be significant for some ports. While this can be highly relevant for country-level trade (Adland, Jia, and Strandenes, 2017), our focus is on the trend of global trade for which we assume that the transshipment-to-trade ratio stays broadly unchanged. Third, AIS data do not account for two-way containerized trade (netting effect) and use of ballast water in ships. In this paper, we take steps towards tackling these issues, but they remain active areas of research. Finally, careful readers will note that we use the term nowcasting in a broader sense than those used in other studies that rely on specific dynamic factor or machine learning models. In this paper, nowcasting is defined broadly as monitoring economic conditions in real time and we rely on big data rather than specific models.

The rest of this paper is structured as follows. Section 2 describes our data sources for the nowcasting model. Here, we also highlight recent enhancements to the IMF PortWatch platform. Section 3 presents our nowcasting model and its goodness of fit. Section 4 shows how the resulting series could be used to monitor trade fragmentation and regionalization. Section 5 concludes the paper.

2. PortWatch: Data and Recent Enhancements

The IMF PortWatch platform was launched in November 2023 as a beta version for public use and comments. It is an open platform designed to monitor disruptions to maritime trade. It aims to help policymakers and the public assess the impact of realized and future trade shocks. To that end, the platform provides daily data on port calls and shipments (in volume terms) for 1666 ports and 24 critical maritime passages worldwide starting from January 1, 2019. Table 1 summarizes the geographic distribution of maritime activity tracked by PortWatch.

[2] The WTO Goods Trade Barometer is a leading indicator that signals changes in world trade growth two to three months ahead of the quarterly merchandise trade data release. Similarly, the UNCTAD index signals changes in world trade volume and value up to four months before the quarterly data release. Our indicator is not intended to be a leading indicator, but a monthly nowcast of global trade.

Table 1: PortWatch Estimates of Maritime Activity, 2024

	Ports	Port calls	Port calls	Imports	Exports	Port calls (%)	Imports	Exports
		(per day)	(per port per day)	(million metric tons)	(million metric tons)	(% of total)	(% of total)	(% of total)
World	1666	4732	2.8	12222	11985	100%	100%	100%
Advanced Economies	812	2458	3.0	4609	5020	52%	38%	42%
Major Advanced Economies (G7)	403	1245	3.1	2090	1817	26%	17%	15%
Euro Area (exl G7)	143	520	3.6	947	652	11%	8%	5%
Other Advanced Economies	266	693	2.6	1572	2551	15%	13%	21%
Emerging Market and Developing Economies	854	2274	2.7	7613	6964	48%	62%	58%
Latin America and the Caribbean	216	300	1.4	746	1209	6%	6%	10%
Middle East and Central Asia	146	291	2.0	904	1169	6%	7%	10%
Sub-Saharan Africa	79	100	1.3	257	285	2%	2%	2%
Emerging and Developing Asia	313	1305	4.2	5336	3571	28%	44%	30%
Emerging and Developing Europe	100	279	2.8	370	731	6%	3%	6%
Other regions								
ASEAN-5	130	550	4.2	1179	1045	12%	10%	9%
European Union	295	833	2.8	1595	1011	18%	13%	8%
Euro Area	229	720	3.1	1430	903	15%	12%	8%

Source: Authors' calculations.
Note: Based on the IMF World Economic Outlook (WEO) classification of economies. Excludes landlocked economies.

These estimates of maritime activity are based on Automatic Identification System (AIS) signals transmitted by ships, essentially a global positioning system for ships, and picked up by satellite and terrestrial receivers. The AIS is required by the International Maritime Organization (IMO) for all tanker and cargo ships greater than 300 gross tons on international voyages. Onboard AIS transponders transmit radio messages providing a periodic real-time feed including a ship's position, speed, draft, destination, and navigational status. The features of AIS data are extensively documented in previous studies, so our description here is intentionally short.

Building on Arslanalp, Koepke, and Verschuur (2021), PortWatch derives indicators of vessel and trade activity using AIS data sourced from the United Nations Global Platform. By analyzing port calls and deriving the payload of vessels entering and leaving port boundaries, PortWatch estimates shipment of goods (in metric tons) at each port. These are calculated by measuring the difference in the payload of a ship before and after a port call and multiplying it by the vessel's deadweight tonnage (the ship's carrying capacity in metric tons). On this basis, PortWatch provides daily estimates of the following indicators:

- **Port calls** are a basic indicator of maritime trade activity. The data consist of a count of ship arrivals and departures, provided for tankers and cargo ships.
- **Shipment volume** provides a more nuanced estimate of maritime trade, reported in metric tons of goods shipped at each port, based on vessel-related information such as the size and payload of a ship.
- **Transit calls and transit volume data** are available for 24 critical maritime passages, such as the Suez Canal and the Panama Canal. The transit volume data are expressed in metric tons.

Data revisions may occur for several reasons, including due to updates to the AIS source data, enhancements to the methodology, and changes in the coverage of ports and vessels. Methodological enhancements and changes in data coverage are documented in the "Data & Methodology" section of the PortWatch website.

There are several conceptual differences between AIS-derived trade estimates and official trade statistics. The former refers to maritime trade while official data generally include all modes of transportation, including air cargo, land transport and pipelines. Also, AIS data have several limitations including potentially poor reception in certain places and mismatch in the timing of trade as AIS data measure the time of port entry while official data are based on the time of customs clearance. Moreover, official trade statistics take into account what specific goods are traded, while AIS data only include information on the vessels with which they are transported. In addition, AIS-based estimates of trade include transshipments, which could be significant for some ports. Despite these and other limitations, the literature shows that AIS data capture trade trends and turning points with a reasonable degree of accuracy. That said, AIS-based estimates should be interpreted as a proxy for trade.

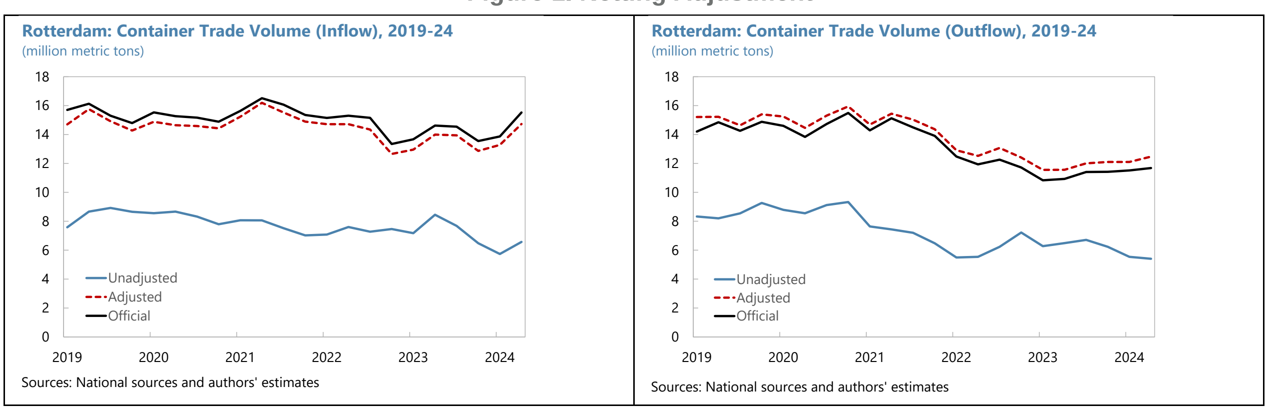
The remainder of this section lays out recent enhancements to the IMF PortWatch platform since its beta launch in November 2023. These enhancements advance estimation techniques of previous studies, particularly by tackling issues related to two-way containerized trade and ships' use of ballast water. They also expand the coverage of ports and refine the historical averaging technique used to estimate incomplete observations.

(A) Adjusting for Two-Way Containerized Trade (Netting Effect)

As mentioned in previous studies, the estimation of shipments by containerships is more challenging than other vessel types because containerships often load and unload cargo at the same time during a port call. As a result, AIS-based estimates can understate the true level of trade in such cases. We refer to this issue as the "netting effect" because only the net change in a vessel's draft is observed in the AIS data. The vessels that would be most impacted by the netting effect would be those that simultaneously load and unload cargo during port calls. This type of behavior is most characteristic of containerships, which are the focus of our netting adjustment.

Annex I details two complementary approaches for the netting adjustment. The first one is a simple approach that uses official container throughput data to complement the AIS data to estimate of the netting effect. The second one is a bootstrapping technique that could be used in the absence of container throughput data. We implement the simple approach for 83 of the largest container ports in the world that make up about two-thirds of global containerized trade (Annex I). Based on this adjustment, we observe container trade volume estimates closer to official data for those ports. Figure 1 shows the results for the port of Rotterdam, the largest container port in Europe. Annex I provides further details and validation results.

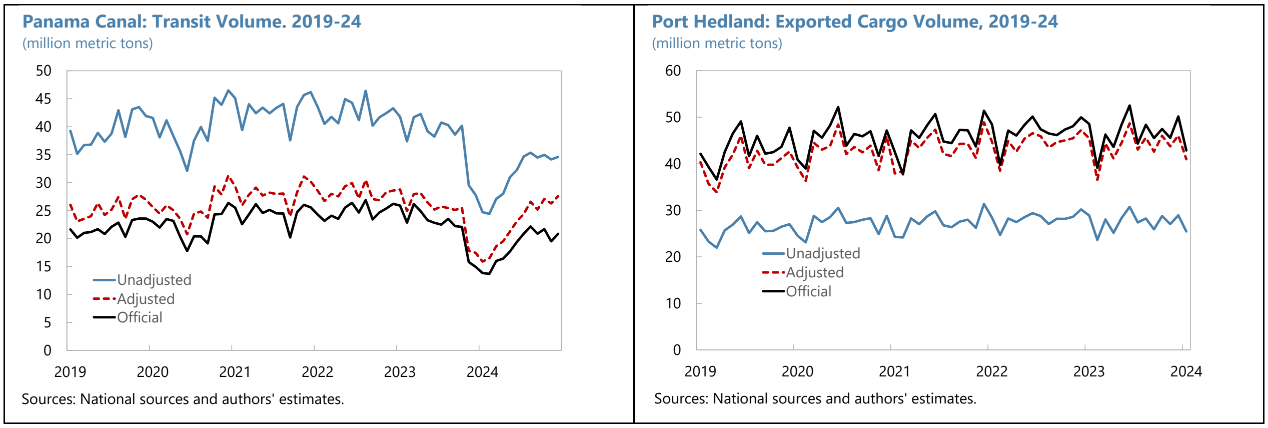
Figure 1. Netting Adjustment



(B) Adjusting for Ballast Water

The second adjustment concerns vessels' use of ballast water for stability and maneuverability. Absent an adjustment, this can lead AIS-based estimates to overstate the volume of cargo carried during a voyage (because part of the cargo is ballast water) and understate the amount of shipment that takes place at a port (because ballast water is discharged as the vessel loads cargo). As detailed in Annex II and using micro data on ship characteristic (ballast water capacity), we classify vessels into those travelling “in ballast”, “with ballast” and “laden (loaded)” to estimate their actual cargo payloads. Based on this, we observe transit and trade estimates closer to official data at specific chokepoints and ports. Figure 2 shows the results for the Panama Canal and the Port of Hedland. the world's largest bulk export port.

Figure 2. Ballast Water Adjustment



(C) Port database

The third enhancement is related to a systematic review of all ports tracked by PortWatch since its beta launch. The review expanded the original list of ports from 1378 to 1666 globally. This ensured that all the ports included in major port databases used by the ISL, Lloyd’s List, and the World Bank are fully covered in PortWatch. The review also added specialized oil terminals, drawing on Adland, Jia and Strandenes (2017).

(D) Historical averaging

The final enhancement is a refinement to the handling of incomplete draft data. Arslanalp, Koepke, and Verschuur (2021) used two techniques to bridge incomplete draft information in the AIS data: *backpropagation* and *historical averaging*. Specifically, the ship’s crew may not always update the draft information before a ship leaves the port. However, the draft information typically gets updated when the ship is about to enter the next port of call, as port authorities require vessels to broadcast their latest information before entering a port. When this is the case, backpropagation uses the vessel’s reported draft at the next port. This handles two-thirds of all incomplete draft data. For others, historical averaging is used, which is based on the vessel average shipment during prior port calls to the same port. There were two enhancements to this historical averaging technique:

- If historical data on the same vessel is not available, we use the historical data on the group of vessels of the same *vessel type* that made port calls to the same port.
- Rather than taking the simple average of shipments, we use the probability-weighted average of shipments.[3]

[3] For example, consider a vessel that for half of its port calls loads 10 percent of its deadweight tonnage (DWT), and half the time unloads 10 percent of its DWT. For this vessel, the average shipment would be zero, which would be incorrect for the purpose of historical averaging. Instead, we take the average of positive and negative shipments separately and multiply them with their relative occurrence. This yields a probability-weighted average shipment of 5 percent of DWT for exports and 5 percent of DWT for imports.

3. A Nowcasting Model for Global Maritime Trade

(A) General Approach

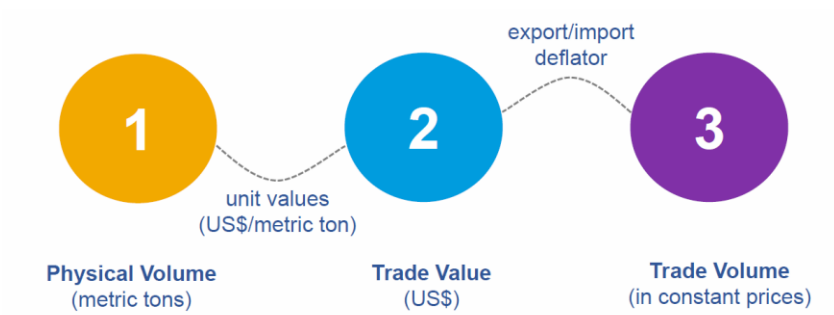
Global trade is a key indicator of economic activity, but country-level data are released with varying lags and need to be aggregated to paint a global picture. With more than 80 percent of global trade volume being transported by ships, maritime trade serves a critical role in international trade and global supply chains. Moreover, even other modes of trade (air, land) often rely on maritime trade along the global supply chains.

Our nowcasting model aims to provide a timely indicator of global merchandise trade (7 working days after the reference month), using satellite-based vessel data. It uses a methodology that mimics key features of the way official trade statistics get compiled. Specifically, trade value is estimated using data at the level of Harmonized System (HS) codes and trade volume is estimated using export/import price deflators. Our approach fits within a class of nowcast models that have produced positive results by mimicking the compilation of official data. A well-known example of this approach is the Atlanta Fed's GDPNow nowcast for U.S. GDP growth.

(B) Methodology

Our methodology is global in scope (i.e. not based on country data) and can be implemented in near real-time. It is aimed at providing early warning signs of turning points in global trade and economic activity. It is intentionally parsimonious, based on a three-step approach summarized in Figure 3.

Figure 3. From Physical Volume to Trade Estimates



We start with estimates of vessel shipments in *physical volume* (in metric tons), broken down by three main vessel types (tankers, dry bulk carriers, and containerships/other cargo vessels).[4] We then estimate *trade value* based on the average unit value of goods (US$/metric ton) transported by each of the three vessel types. Finally, we estimate *trade volume* (in constant prices) by deflating trade value with relevant export/import deflators. All series are calculated as indices with 2019 as the base year. Below, we describe each step in more detail.

[4] Tankers include oil, gas, product, and chemical tankers. Dry bulk carriers transport unpackaged bulk cargo, such as coal, iron ore and grains. The third group includes general cargo and roll-on-roll-off (roro) cargo ships, although containerships carry most (around 80 percent) of the volume of goods transported by this group. Roro cargo vessels include car carriers.

Step 1: Global Vessel Shipments in Physical Volume

For this step, we aggregate the following data for each vessel type across all the ports tracked by IMF PortWatch:

- ***Tankers.*** Metric ton of goods shipped by tankers.
- ***Dry bulk carriers.*** Metric ton of goods shipped by dry bulk carriers.
- ***Containerships and other cargo vessels.*** Metric ton of goods shipped by containerships, general cargo and roro cargo vessels.

Step 2: Global Trade Value Index

The next step involves constructing average unit values of goods (US$/metric ton) transported by different vessel types. This allows us to calculate the *global trade value*, as shown below in Equations 1 and 2.

$$V_t^i = \sum_{j \in \{tn,bc,cs\}} U_t^{i,j} * UV_t^{i,j} \qquad \forall i \in \{x,m\}, \forall t \in \{t_0, t_1, \dots, t_T\} \tag{1}$$

$$UV_t^{i,j} = UV_{t_0}^{i,j} * \left(1 + F_t^{i,j}\right) \qquad \forall i \in \{x,m\}, \forall j \in \{tn,bc,cs\}, \forall t \in \{t_0, t_1, \dots, t_T\},\ F_{t_0}^{i,j} = 0 \tag{2}$$

where V_t^x and V_t^m are global exports and imports in value terms respectively at period t, $U_t^{x,j}$ and $U_t^{m,j}$ are global export and import shipments in physical volume respectively by vessel type j at period t, respectively (obtained in Step 1), $UV_t^{x,j}$ and $UV_t^{m,j}$ are average unit values of goods exported and imported, respectively, by vessel type j at period t, and $F_t^{x,j}$ and $F_t^{m,j}$ are percentage changes in the average unit value of goods exported and imported, respectively, by vessel type j between the base period (t_o) and period t. In terms of vessel types (j), *tn*, *db*, and *cs* stand for tanker, dry bulk carrier, and containership/other cargo vessel, respectively.

To construct the unit values, we use the following data:

- ***Unit values for the base year*** *($UV_{t_0}^{i,j}$).* The CEPII BACI is a unique database that provides harmonized trade data at the country and product level (6-digit HS codes) in both value (US$) and volume terms (metric tons).[5] Complementing this data with a mapping between vessel types and HS codes (Table 2), based on Cerdeiro, Komaromi, Liu, and Saeed (2020), we can calculate the average unit value of goods exported/imported by vessel type j for the base period (2019).

- ***Change in unit values ($F_t^{i,j}$).*** To calculate the change in the average unit value of goods exported/imported globally by vessel type j on a monthly basis, we use the following:

    a. ***Tankers.*** Percentage change in the *fuel price index* (excluding coal) available from the IMF's Primary Commodity Prices database.[6] Data are released monthly with a lag of 5-7 working days.

[5] To address trade asymmetries such as in the UN COMTRADE database, CEPII (Centre d-Etudes Prospective et d'Informations Internationales) produces a balanced trade dataset called BACI (Base pour l'Analyse du Commerce International), which reconciles the asymmetric flows through statistical methods to have a single consistent figure for each bilateral flow. Valuation is also consistent, with imports and exports both measured on a free-on-board (fob) basis. Using "mirror" data reported by partner economies, CEPII is also able to improve geographic coverage. Data are available from 1995 in value and volume terms for more than 200 economies.

[6] While oil and petroleum products dominate the tanker industry, some specific types of tankers carry non-fuel commodities, such as chemicals and edible liquids. For the purposes of this paper, we assume these are negligible from a global perspective.

b. ***Dry bulk carriers.*** Percentage change in the *non-fuel commodity price index* (including coal but excluding precious metals) available from the IMF's Primary Commodity Prices database. Data are released monthly with a lag of 5-7 working days.

c. ***Containerships and other cargo vessels.*** Percentage change in the *manufactured goods price index* compiled by the WTO. Data are typically available with a lag of 3 months. For missing months, we use bridging data from two sources: (i) the US CPI index (excluding food, energy, and services); and (ii) the Cleveland Fed's US CPI inflation nowcast for the latest month.

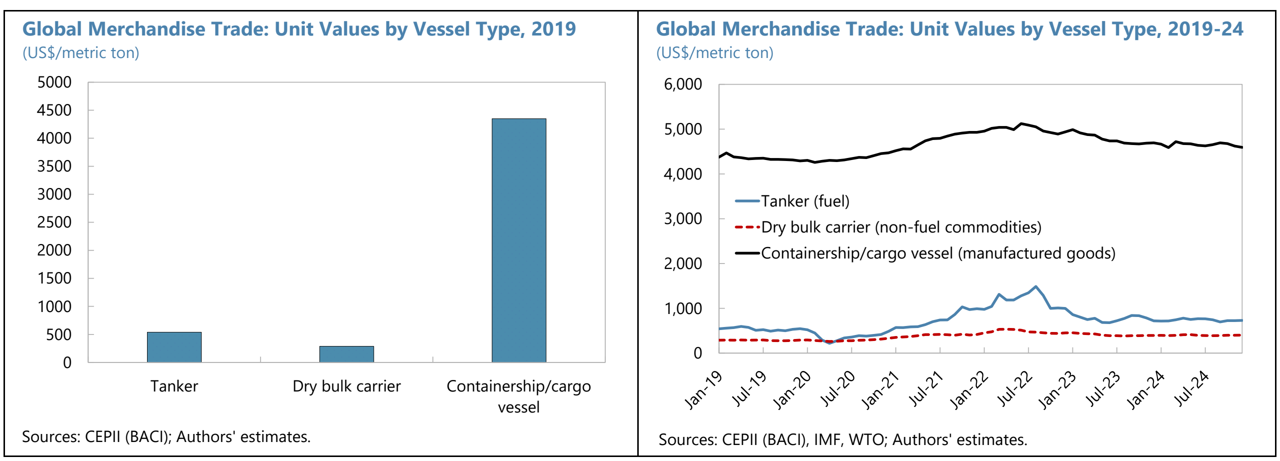
Table 2. Mapping Between Vessel Types and Harmonized System (HS) Codes

Vessel Type	Harmonized System (HS) Code
Tanker	2709-2711, 28-29
Dry bulk carrier	9-14, 17, 25-27 (except 2709-2711), 31, 68, 72-81
Containership/cargo vessel	All else except the excluded HS codes (see below)
Excluded HS codes (not transported by vessels):	
Precious metals and stones	71
Aircraft and spacecraft	88
Ships, boats, and floating structures	89
Electrical energy	2716

Source: Based on Cerdeiro, Komaromi, Liu, Saeed (2020).
Note: HS Nomenclature 2017 edition.

The result of this step is shown in Figure 4. The figure shows that the average unit value of goods transported by containerships/other cargo vessels is 8-12 times higher than those transported by tankers and dry bulk carriers. This is not surprising given that the containerships typically transport (higher value-added) manufactured goods, while tankers and dry bulk carriers transport (lower value-added) commodities. As shown in Annex III, it is important to consider this difference in unit values to measure trade values and volumes accurately.

Figure 4. Unit Values of Traded Goods by Vessel Type, 2019-24



Step 3: Global Trade Volume Index

The final step involves moving from global *trade value* to global *trade volume* using global export/import price deflators, as shown below in Equations 3 and 4.

$$Q_t^i = \frac{V_t^i}{P_t^i} \qquad \forall i \in \{x, m\}, \forall t \in \{t_0, t_1, \dots, t_T\} \tag{3}$$

where Q_t^x and Q_t^m are global exports and imports in volume terms respectively at period t, V_t^x and V_t^m are global exports and imports in value terms respectively at period t, P_t^x and P_t^m are global export and import price deflators respectively at period t.

For export/import price deflators, we use a Laspeyres-type index. This is to mimic the approach used by many national statistical agencies, including those in the euro area and the United States. The Laspeyres-type index applies the base period quantities for both the base period and the period for which the index is computed to estimate the price effect, as shown in Equation 4.

$$P_t^i = \frac{\sum_{j\in\{tn,bc,cs\}} UV_t^{i,j} \cdot U_{t_0}^{i,j}}{\sum_{j\in\{tn,bc,cs\}} UV_{t_0}^{i,j} \cdot U_{t_0}^{i,j}} \qquad \forall i \in \{x, m\}, \forall t \in \{t_0, t_1, \dots, t_T\} \tag{4}$$

where $UV_t^{x,j}$ and $UV_t^{m,j}$ are average unit values for goods exported and imported globally by vessel type j at period t, and $U_t^{x,j}$ and $U_t^{m,j}$ are global export and import shipments in physical volume by vessel type j at period t (obtained in Step 1). In terms of vessel types (j), *tn*, *db*, and *cs* stand for tanker, dry bulk carrier, and containership/other cargo vessel, respectively. Finally, t_o stands for the base period (2019).

(C) Results

In this section, we compare our global trade nowcast with official data. Table 3 provides a snapshot of official data that are widely used to monitor trends in global merchandise trade. As the table shows, they all have publication delays, not to mention revisions after first estimates.

Table 3. Data Releases on Global Trade

Release	Frequency	Delay	Coverage	Source
World Trade Monitor	Monthly	2 months	Value and volume	CBP
Direction of Trade Statistics	Monthly	3 months	Value	IMF
UN Comtrade	Monthly/Annual	Continously updated	Value	United Nations
International Trade Statistics	Quarterly	3 months	Value and volume	WTO/UNCTAD
International Trade by Commodity Statistics	Annual	9 months	Value	OECD
World Economic Outlook	Annual	In April and October	Volume	IMF

Sources: CBP, IMF, OECD, UN, UNCTAD, WTO.

For our benchmarking, we use the data compiled by the Netherlands Bureau for Economic Policy Analysis (CPB) as official data. CPB publishes a monthly index of world trade based on official data from 81 countries covering nearly 96 percent of the world trade. We focus on the CPB index because it is considered the timeliest indicator for global trade, as it is available in a monthly frequency and earlier than other data releases. CBP's first estimate of global trade (in volume and value terms) is available with a lag of two months after the reference month.

The results of our nowcasting model against the official data compiled by CBP are summarized in Figure 5 and Table 4. We provide results for both the value and volume of trade. Since the CBP index is seasonally adjusted and our nowcast is not, we focus on year-over-year changes to assess the goodness of fit between the two series. We report the goodness of fit using two frequently used measures: (i) the correlation coefficient; and (ii) the root mean squared error (RMSE):

- The correlation coefficient between the monthly year-over-year (y/y) nowcast and the official (CPB) data is 0.95 for global trade value and 0.80 for global trade volume.
- The RMSE of the monthly y/y nowcast and the official (CPB) data is 0.05 for global trade value and 0.04 for global trade volume. Excluding the COVID period (2020-21), the RMSE is 0.03 for global trade value and 0.03 for global trade volume.

The results suggest that our methodology achieves a reasonably good fit with official data. During the COVID-19 episode, the index provided reliable data in terms of identifying turning points. In particular, the nowcast clearly captures the large decline in world trade associated with the spread of the COVID-19 in early 2020 and the large rebound in trade after the outbreak. The nowcast also identifies the slowdown in world trade in 2023 and the gradual recovery since then. Having said that, one should not expect a perfect fit—for one thing, our estimates only cover maritime trade and are based on the timing of port entry, while official data cover all modes of trade and are based on the timing of customs clearance.

Overall, the nowcasting model produces results that follow changes in global trade reasonably well even when the world trade system was hit by large shocks, including the outbreak of COVID in 2020, global supply chain disruptions in 2021, and the war in Ukraine in 2022.

Figure 5. Nowcasting Global Trade Value and Volume, 2020-24

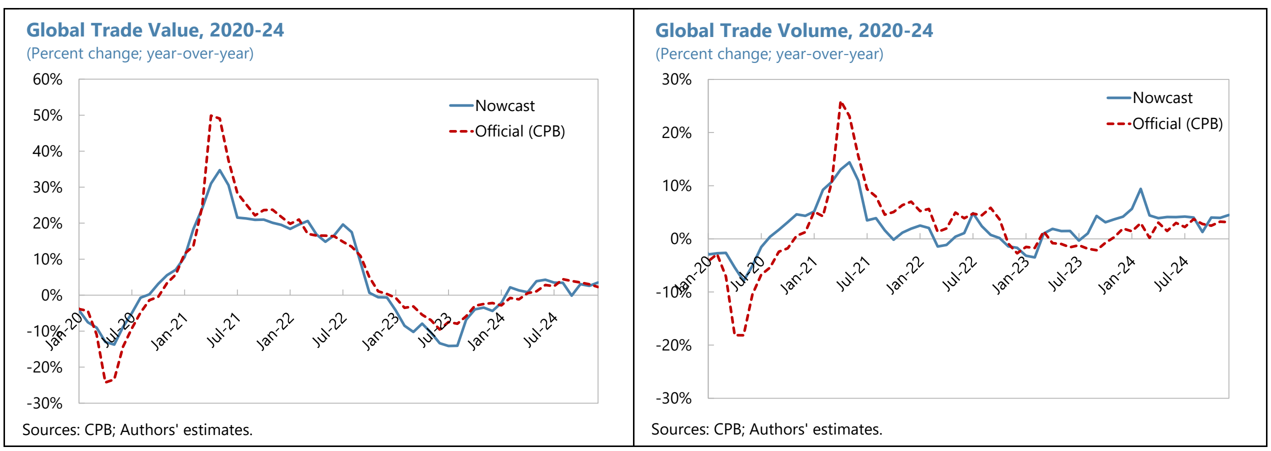


Table 4. Nowcasting Model Results

	Correlation coefficient	RMSE	RMSE (2020-21)	RMSE (2022-24)
	(value of trade)			
World	0.95	0.05	0.07	0.03
Export	0.95	0.05	0.07	0.03
Import	0.95	0.05	0.06	0.04
Advanced economies				
Export	0.89	0.07	0.08	0.06
Import	0.94	0.05	0.05	0.05
Emerging market and developing economies (EMDEs)				
Export	0.96	0.06	0.09	0.03
Import	0.91	0.07	0.10	0.05
	(volume of trade)			
World	0.80	0.04	0.06	0.03
Export	0.81	0.04	0.06	0.03
Import	0.79	0.05	0.06	0.03
Advanced economies				
Export	0.75	0.06	0.08	0.04
Import	0.71	0.05	0.06	0.05
Emerging market and developing economies (EMDEs)				
Export	0.70	0.05	0.06	0.03
Import	0.77	0.06	0.08	0.03

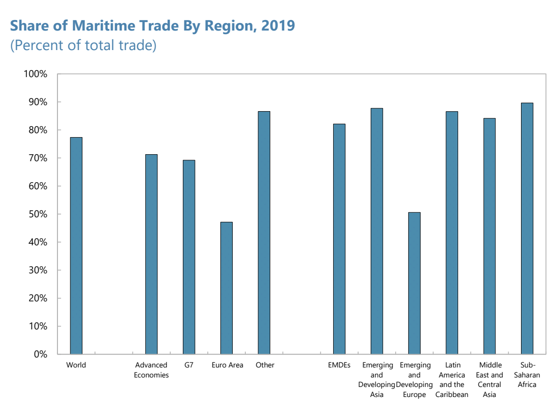
Source: Authors' calculations.

(D) Regional Breakdown of Trade

The global trade nowcast developed in this section can be broken down by region. For regions, we use the country groups defined by the IMF *World Economic Outlook* (Annex IV). For advanced economies, these include the G7, euro area, and other advanced economies (other than G7 and euro area countries). For emerging and developing economies, these include emerging and developing Asia, emerging and developing Europe, Latin America and the Caribbean, Middle East and Central Asia, and Sub-Saharan Africa.

For all regions other than Europe (euro zone and emerging and developing Europe), maritime trade represents more than 70 percent of trade in volume terms (Figure 6). This suggests that maritime trade may provide a good indication of regional trade except for Europe where most of trade is intra-regional (by land and air).

Figure 6. Share of Maritime Trade in Trade Volume by Region, 2019



The process for constructing regional trade estimates follows the same one for global trade. Specifically, we use data from IMF PortWatch for each region. For regional unit values, drawing on the methodology for global trade, we calculate the regional unit values of goods shipped by each vessel type for the base period of 2019 (Table 5) and use the previously described prices indices to estimate changes in unit values.

Table 5. Unit Values of Traded Goods by Vessel Type and Region, 2019

(US$/metric ton)

	Exports			Imports		
	Tanker	Dry bulk carrier	Containership/cargo vessel	Tanker	Dry bulk carrier	Containership/cargo vessel
World	539	288	4350	539	288	4350
Advanced economies	639	344	5117	561	406	5071
G7	635	531	5733	584	456	5829
Euro Area	875	703	4683	555	499	4246
Other	540	186	5775	539	309	4752
Emerging market and developing economies (EMDEs)	480	237	3635	505	216	3444
Emerging and Developing Asia	728	311	4755	511	190	3255
Emerging and Developing Europe	444	279	2315	535	229	3684
Latin America and the Caribbean	417	263	2582	566	249	4506
Middle East and Central Asia	449	223	2354	564	312	3180
Sub-Saharan Africa	446	77	1794	293	297	2752

Source: CEPII (BACI); Authors' estimates.

CBP's regional breakdown differs from the IMF WEO classification, so it is not possible to compare them except for (i) advanced economies and (ii) emerging and developing economies (EMDE). A comparison for these two regions shows a reasonably good fit, although somewhat less so than for global trade (Table 4). In particular:

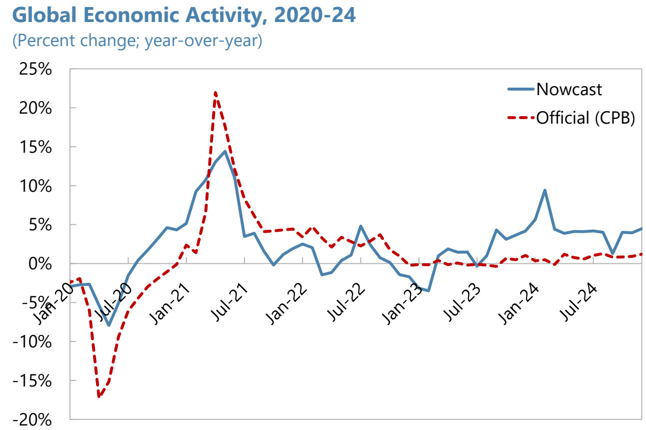
- For advanced economies, the correlation coefficient between the monthly year-over-year (y/y) nowcast and the official (CPB) data is 0.94 for the value of imports and 0.71 for the volume of imports. For EMDEs, the correlation coefficient is 0.91 for the import value and 0.77 for import volume.
- For advanced economies, the RMSE of the monthly y/y nowcast and the official (CPB) data is 0.05 for the value of imports and 0.05 for the volume of imports (and 0.05 and 0.05, respectively, excluding the COVID period). For EMDEs, the RMSE is 0.07 for import value and 0.06 for import volume (and 0.05 and 0.03, respectively, excluding the COVID period).

(E) Global Economic Activity

As trade and growth are closely associated, we explore whether our global nowcast is a good proxy also for global economic activity. For official data, we use global industrial production data compiled by the CBP (production-weighted). Similar to global trade, CBP compiles these data from official sources and releases it with a lag of 2 months. The CBP data cover 85 countries, accounting for 96 percent of global industrial production.

Figure 7 shows the results of our nowcasting model benchmarked against official data. The correlation coefficient between the monthly nowcast and the official data on global industrial production is 0.78. The RMSE is 0.03 (and 0.03 excluding the COVID period).

Figure 7. Nowcasting Global Economic Activity, 2020-24



Sources: CPB (industrial production); Authors' estimates.

(F) Seasonal Adjustment

So far, we have focused on year-over-year changes in discussing developments in global trade. Analysts monitoring short-term fluctuations in trade might also be interested in month-over-month or quarter-over-quarter changes. These would require a seasonal adjustment to our index.

To seasonally adjust our index, we recommend using the seasonal adjustment employed by the CPB. This involves applying the X12-ARIMA procedure to adjust for seasonal fluctuations and an additional adjustment to January and February pertaining to countries where the celebration of the Lunar New Year affects economic and trade activity (e.g., China, Hong Kong SAR, Korea, Singapore, Taiwan Province of China).

As an illustration, we apply this seasonal adjustment to our series and calculate the three-month-over-three-month (3m/3m) change in global trade from 2019 to 2024. Compared to CBP's own seasonally adjusted 3m/3m series, we again find a reasonably good fit.

The correlation coefficient between the two series is 0.97 for global trade value and 0.83 for global trade volume. The RMSE of the seasonally adjusted 3m/3m nowcast, compared to official data, is 0.04 for global trade value and 0.04 for global trade volume (or 0.03 for trade value and 0.03 for trade volume, excluding the COVID period).

4. Monitoring Global Trade Trends in Real Time

The methodology described in the paper could be used to monitor fragmentation and regionalization in the global maritime trade on a timely manner. To demonstrate this application, this section examines (i) fragmentation (friend-shoring) within and across geopolitically aligned blocs; and (ii) regionalization (near-shoring) patterns across eight regions defined by major regional trade agreements. We analyze these trends by vessel type to assess intra-bloc and intra-region trade at a broad product level.

On fragmentation, we demonstrate a reallocation among geopolitically aligned countries, consistent with the findings of recent studies (Alfaro and Chor 2023, Blanga-Gubbay and Rubínová 2024, Fajgelbaum et al. 2024, Freund et al. 2024, Gopinath et al. 2024). These studies highlight the growing influence of geopolitical considerations on trade patterns and the emergence of connector countries that facilitate trade between different blocs, which is consistent with the patterns that we observe in the data. On regionalization, while regionalization dynamics vary across regions, we find no significant shifts in regionalization, also consistent with other studies.

Overall, our methodology could be used to monitor fragmentation and regionalization in global trade more promptly than traditional macro-level trade data typically allow. Specifically, macro-level trade data for some countries suffer from significant delays in reporting, and bilateral trade data can be sparse in some regions, with missing values for various country pairs. This limitation restricts timely analysis and insights into current trade trends. In contrast, our methodology can provide a timelier monitor of maritime trade patterns globally.

(A) Fragmentation (Friend-shoring)

In recent years, there have been increasing concerns about fragmentation across politically aligned blocs with limited trade and capital flows with each other. This section uses our nowcast model to assess how trade (particularly maritime trade) within and between politically aligned blocs has changed in recent years. To construct trade flows between blocs, we utilize port-level trade estimates. Specifically, we calculate trade flows between countries and then aggregate them into trade within and across blocs.[7]

To identify politically aligned countries, we adopt a standard approach used in the literature (e.g., Gopinath et al. 2024) that categorizes countries into three groups based on their UN voting patterns: (i) a U.S.-leaning bloc; (ii) a China-leaning bloc; (iii) and a set of nonaligned countries.

We first examine whether trade patterns between different blocs have changed since 2019, the first year in our data series. Figure 8 shows that trade between the U.S.-leaning and China-leaning blocs as a share of trade among all three blocs has declined, consistent with the findings of earlier studies.[8] The general pattern among the three blocs reveals a decrease in trade between the U.S.-leaning and China-leaning blocs, alongside an increase in trade with the nonaligned bloc.

[7] We assume that goods are traded between two countries when their ports are visited back-to-back. For example, if a ship calls at Port X in Country A, followed by Port Y in Country B, and finally Port Z in Country C, the cargo delivered from Port X to Port Y represents exports from Country A to Country B, while the cargo delivered from Port Y to Port Z represents exports from Country B to Country C. In practice, these may include transshipments which cannot be detected in the AIS data as noted earlier in the paper.

[8] The series is defined as trade between the US- and China-leaning blocs divided by the sum of trade between the US- and China-leaning blocs, the US-leaning and nonaligned blocs, and China-leaning and nonaligned blocs. This excludes within bloc trade.

Figure 8. Share of Trade Between U.S.-Leaning and China-Leaning Blocs, 2019-24

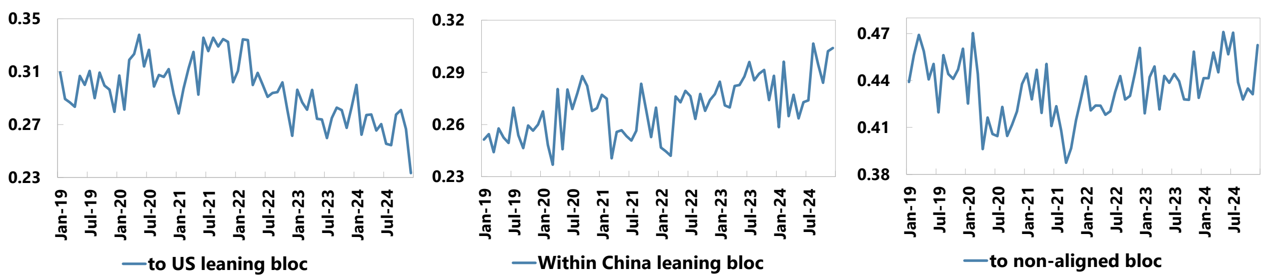
(Total trade between the two blocs as the share of total trade between all blocs; in value terms)

Source: Authors' calculations.

Figure 9 illustrates a shift in the China-leaning bloc's export dynamics, with its export share to the U.S.-leaning bloc diminishing in favor of growing shares to within the China-leaning bloc and the nonaligned bloc. This evidence is consistent with the connector country hypothesis.

Figure 9. Exports of the China-Leaning Bloc, 2019-24

(Total trade between two blocs as the share of total trade between all blocs; in value terms)



Source: Authors' calculations.

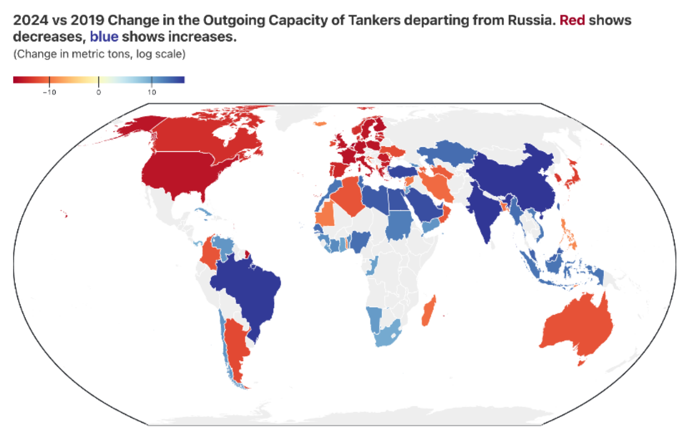
Decomposing the aggregate trade flows by vessel type indicates that a substantial portion of change in trade shares is due to changes in the trade patterns of tankers, which primarily transport oil and gas. These developments can in large part be attributed to the sanctions imposed on Russia by countries in the U.S.-leaning bloc. Box 1 provides evidence of a shift in Russia's oil trade following the war in Ukraine.

Box 1. The Shift in Oil Trade After the War in Ukraine[9]

This Box highlights the reallocation of oil trade flows in response to the sanctions on Russia after the war in Ukraine. It updates the work presented in the IMF's October 2023 World Economic Outlook *(IMF 2023).*

In response to the war in Ukraine, the European Union, the U.K. and the U.S. imposed sanctions on most imports of oil products from Russia. These sanctions included outright bans as well as stringent restrictions on dollar payments for oil shipments from Russia. Furthermore, the Group of Seven (G7) countries instituted prohibitions on transportation and insurance services for tankers carrying Russian commodities that exceed specified price thresholds.

The Automatic Identification System (AIS) data reveal substantial changes in tanker traffic patterns since the introduction of sanctions.[10] The figure below illustrates the change in the outgoing capacity of tankers departing from Russia to other countries from 2019 to 2024. Countries marked in blue indicate an increase in oil imports from Russia, while those in red indicate a decrease. Notably, China, India, and Brazil, have experienced the largest increases in imports of oil from Russia. Conversely, in accordance with the sanctions, countries such as the Netherlands, Finland, France, Germany, and Poland have drastically reduced their oil imports from Russia. This raises an important question: where are the European countries sourcing their oil now? This gap has been filled by increased imports from the U.S. and Norway. In particular, the U.S. has increased its supplies to Europe (EU and UK) the most, and now accounts for a sizeable share of the (maritime) oil imports of Europe in volume terms.



Note: For Japan, the estimates exclude LNG imports from the Sakhalin-2 project, which remained exempt from sanctions through 2024.
Source: Authors' calculations.

Conclusions. First, the sanctions on Russian oil led to a decoupling of Europe's oil trade with Russia. Second, China, India, and Brazil have emerged as key importers of Russian oil. Third, Europe has deepened its oil trade with other geopolitically aligned countries.

[9] This box covers all products transported by tankers—including crude oil, refined petroleum products, chemicals, and liquefied natural gas—but for simplicity, we refer to them collectively as "oil" throughout.

[10] In most jurisdictions, port authorities mandate that ships keep their AIS transponders active during port visits for the safety of all vessels in the port. However, to avoid sanctions, ships can deactivate their transponders to avoid detection, particularly during ship-to-ship transfers in open seas.

(B) Regionalization (Near-shoring)

While the discussion on trade regionalization is not new, it has gained renewed attention due to geopolitical tensions, the COVID-19 pandemic, concerns on supply chains resilience, and environmental sustainability concerns. A key question is whether and to what extent we observe a regionalization of global trade in the data in recent years.

Using the same approach, we examine regional trade patterns as a share of global trade over the past five years. We categorize countries based on major regional trade agreements and geographical proximity into eight distinct regions: USMCA, Latin America, Africa, Europe (EU and potential enlargement countries), Eurasian Economic Union, Middle East, East Asia, and South Asian Free Trade Area. The countries in each region are listed in Annex IV. We quantify regionalization for each region using Equation 5 below:

$$I_{reg} = \frac{\sum_{k=1}^{8}(X_{kk}+M_{kk})}{\sum_{k=1}^{8}(\sum_{j=1}^{8}(X_{kj}+M_{kj}))} \quad (5)$$

where I_{reg} is the regionalization index, X_{kj} is exports of region *k* to region *j*, M_{kj} is imports of region *k* from region *j*, and $j, k \in \{1,2,\dots,8\}$. This formula allows us to measure the extent of trade regionalization by comparing intra-regional trade to global trade.

Figure 10 shows the evolution of the regionalization index over the past five years across our defined regions. The data do not indicate a clear trend toward or away from regionalism since 2019, instead offering a nuanced perspective that questions the idea of a significant shift towards regionalization. Specifically, the index declined from the middle of 2020 to early 2022, coinciding with a surge in Asian exports driven by strong demand from advanced economies during the COVID-19 pandemic. This observed pattern aligns with insights from the DHL Global Connectedness index. However, there has been an upward trend since the war in Ukraine with the indicator returning to its pre-pandemic level.

Figure 10. Share of Regional Trade, 2019-24

Source: Authors' calculations.

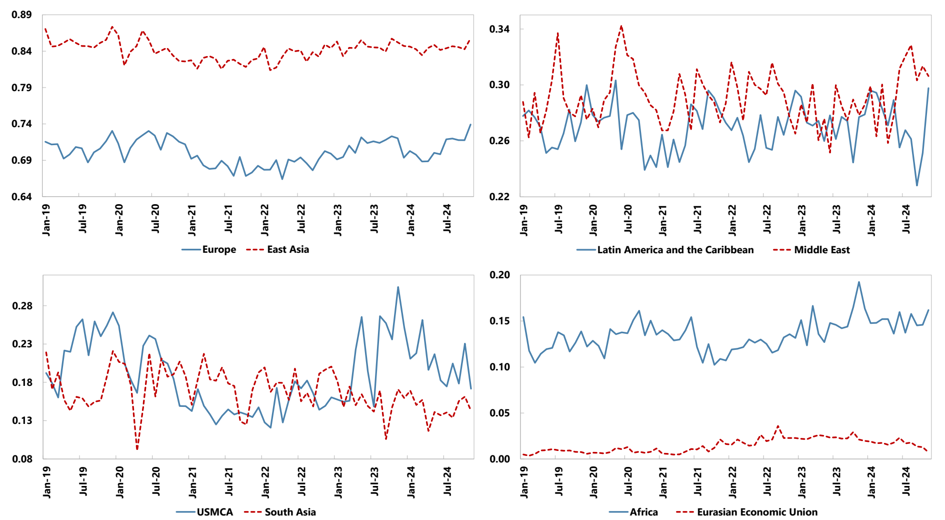
Delving deeper into the data, we examine which regions have consistently contributed to within-region trade since 2019. Our findings suggest that three quarter of this contribution comes from East Asia, and a fifth from Europe, indicating these two regions largely drive overall regionalization of maritime trade.[11]

To analyze regionalization patterns at a more granular level, we examine the extent of regionalization within each region, measured as the share of intra-regional trade relative to the region's total trade. Figure 11 presents these patterns for the eight regions included in this study. While some regions exhibit slight variations—largely mirroring the trends observed in Figure 10—there is no clear, consistent pattern at the regional level indicating a definitive shift either toward or away from regional trade.

[11] Within-region trade is larger in Europe and USMCA than in East Asia, when considering all forms of trade, not just maritime. Additionally, although a significant portion of intra-regional trade in the EU is conducted by air or land, the maritime trade remains substantial, making the EU the region with the second largest intra-regional maritime trade.

Figure 11. Regional Trade by Region, 2019-24

(Within region trade as the share of total trade of the region; in value terms)



Source: Authors' calculations.

5. Concluding Remarks

Using satellite-based port-level data, we introduced a nowcasting model of global maritime trade that aims to provide a timely indicator of global trade. The model mimics key features of the way statisticians compile merchandise trade data.

For the model, we leverage data from IMF PortWatch—an open platform launched as a beta version in November 2023 for public use and comments. We highlight important enhancement to the platform since its launch. These enhancements advance estimation techniques of previous studies, particularly by tackling issues related to two-way containerized trade and ships' use of ballast water. They also expand the coverage of ports and refine the historical averaging technique used to estimate incomplete observations. Together, these enhancements allow for a better alignment of PortWatch estimates with official data, although further research is needed to improve these estimates further at the port and country level.

Finally, we show how the nowcast model can help monitor developments in trade (fragmentation, regionalization) more promptly than traditional data sources. Our analysis finds evidence for trade fragmentation among geopolitically aligned countries in recent years. On the other hand, while regionalization dynamics vary by region, we find no clear global trend towards regionalization, also in line with recent studies.

Future avenues of research could explore the use of our proxy of global trade in other nowcasting models. With some adjustments, the approach outlined in this paper could be extended to country estimates of maritime trade, which we plan to explore in future research.

Annex I. Adjusting for Two-Way Containerized Trade (Netting Effect)

The netting effect relates to the simultaneous loading and unloading of cargo during port calls, particularly by containerships.[12] We refer to this issue as the "netting effect" because only the net change in the ship's draft (and therefore payload) is observed in the AIS data. Imagine that a containership unloads three containers for imports and loads one container for exports. Because the AIS data capture the net change in the ship's payload, this would indicate that only two containers were imported, and none were exported.

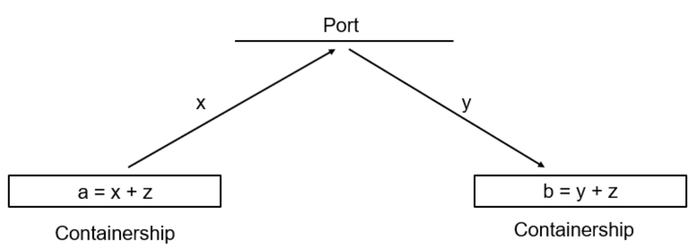
Below, we discuss two complementary approaches to adjust for the netting effect. The first one is a simple approach that uses official (container throughput) data to complement the AIS data to estimate the netting effect. The second one is a bootstrapping technique that could be used in the absence of container throughput data.

Approach #1: Netting adjustment using official (container throughput) data

Container throughput is the main metric used to report trade activity at container ports. It captures the number of containers (in twenty-foot equivalent units, or TEUs) and/or the weight of containers (in metric tons) handled at the port. We can link this information to AIS data to estimate the netting effect.

To illustrate this, assume that a containership arrives at a port with a cargo of (x + z), leaves x at the port, and picks up y from the port before departing (Figure A1.1). As discussed in Arslanalp, Koepke and Verschuur (2021), AIS data can help estimate *incoming and outgoing cargo*, which are as shown below as a and b, respectively. However, AIS data alone cannot determine x and y, which are the quantities we would like to know.

Figure A1.1. A Generic Illustration of Two-Way Containerized Trade



Essentially, this is a problem of having only two equations (a, b) for three unknowns (x, y, z). If trade were one-way, either x or y would be zero and the problem would convert to a 2x2 system of equations with a unique solution. But in the case of two-way trade, we need an additional equation to solve the problem.

By utilizing container throughput data, we can turn this problem into a 3x3 system of equations, and hence find a unique solution. Container throughput (let's call it c) is, by definition, equal to (x + y). With this additional information at hand, we now have a 3x3 system of equations (Equations A1.1-A1.3):

[12] While tankers and dry bulk carriers typically engage in one-way trade, containerships often engage in two-way trade especially at major international ports.

$$a = x + z \quad \text{(A1.1)}$$
$$b = y + z \quad \text{(A1.2)}$$
$$c = x + y \quad \text{(A1.3)}$$

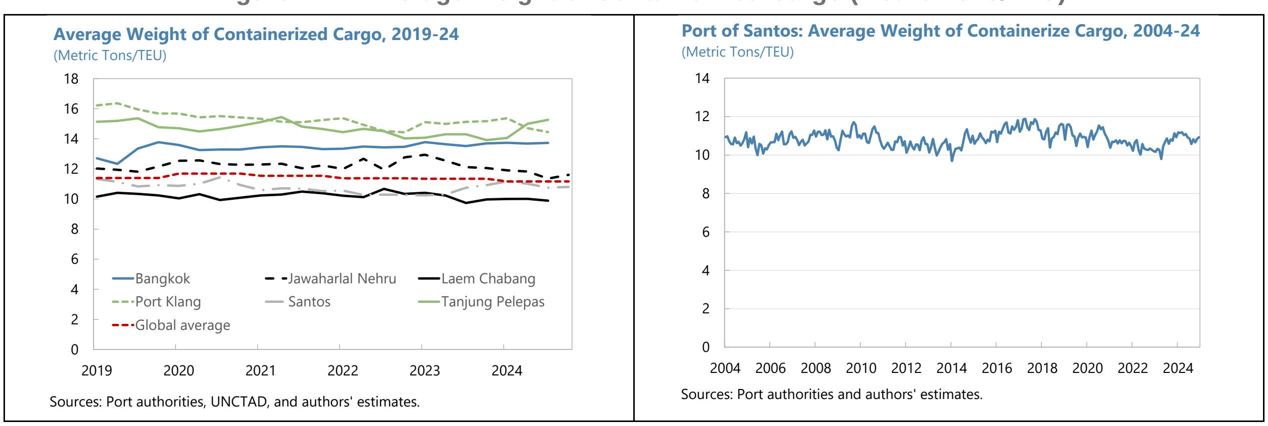
Following basic algebra, this system of equations has a unique solution (Equations A1.4-A1.6):

$$x = (a - b + c) / 2 \quad \text{(A1.4)}$$
$$y = (b - a + c) / 2 \quad \text{(A1.5)}$$
$$z = (a + b - c) / 2 \quad \text{(A1.6)}$$

As an example, if incoming cargo is 10 metric tons (a=10), outgoing cargo is 15 metric tons (b=15), and container throughput is 8 metric tons (c=8), then x, y, and z are equal to 1.5, 6.5, and 8.5 metric tons, respectively.

We implement this approach for 83 of the largest container ports in the world that make up about two-thirds of global container trade.[13] The data are published by national or port authorities and are expressed in either metric tons or twenty-foot equivalent units (TEUs). We use data in metric tons as the primary source as they align with AIS-based estimates in terms of units. This is the case for one-third of ports (and all European ports). For other ports, we use figures in TEUs which need to be converted into metric tons. For this, we use a conversion factor of 12 metric tons/TEU based on the global average of a TEU in metric tons. In practice, the conversion factor would vary across ports, depending on the type of cargo and mix of containers they handle, but tends to be stable over time for a given port (Figure A1.2). For example, the average weight of containerized cargo handled at the port of Santos (the largest container port in Latin America) has fluctuated in a tight range between 10-12 metric tons per TEU for the last 20 years (Figure A1.2). Since we focus on the trend of global trade in this paper, the global average serves our purpose. More granular data at a port level would be helpful to improve country-level estimates when container throughput data are not available in metric tons.

Figure A1.2. Average Weight of Containerized Cargo (Metric Tons/TEU)



[13] The 83 ports are Shanghai, Singapore, Ningbo, Zhoushan, Shenzhen, Qingdao, Guangzhou, Busan, Tianjin, Hong Kong SAR, Rotterdam, Jebel Ali, Antwerp, Port Klang, Xiamen, Tanjung Pelepas, Los Angeles-Long Beach, New York-New Jersey, Kaohsiung, Laem Chabang, Hamburg, Tanger Med, Jawaharlal Nehru, Savannah, Manzanillo (Mexico), Manzanillo (Panama), Valencia, Santos, Tokyo, Jeddah, Algeciras, Bremerhaven, Salalah, Piraeus, Houston, Port of Virginia, Gioia Tauro, Barcelona, Seattle, Tacoma, Felixstowe, Melbourne, Le Havre, Yokohama, Kobe, Ambarli, Charleston, Dublin, Port Botany, Nagoya, Durban, Genova, Callao, Oakland, Balboa, Osaka, Lazaro Cardenas, Mersin, Gwangyang, Gdansk, Taichung, Tekirdag, Southampton, Puerto San Antonio, Sines, Keelung, Brisbane, Colombo, Itajai, Alexandria, Bangkok, La Spezia, Veracruz, Las Palmas, Paranagua, Montevideo, Klaipeda, Koper, Gdynia, Gemlik, St. Petersburg, Trieste, Buenos Aires.

Based on this approach, we generate a scaling factor for each port that maps net imports/exports into gross imports/exports. Where container throughput data are lagging, we use a three-year historical average of the scaling factor for the respective month. The adjusted series are much closer to official data both in levels and trends. Figure A1.3 provides the results for some of the largest container ports in Asia, Europe, North America, and Latin America. The results for other ports are also available upon request.

Figure A1.3. Netting Adjustment Using Official (Container Throughput) Data

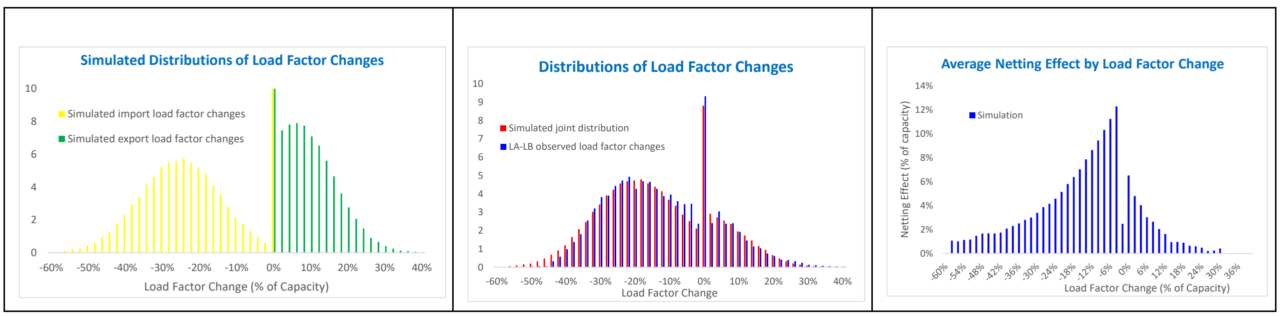
Approach #2: Netting adjustment using a bootstrapping approach

The second approach constructs a bootstrapping formula based on the statistical patterns of the payload (load factor) of incoming and outgoing vessels. In particular, the observed distribution of payload changes at a port can be thought of as the difference of two distributions: the one representing the *loading* of goods (for exports) minus the one representing the *unloading* of goods (for imports). The bootstrapping approach exploits the statistical principles underpinning the subtraction of one random variable from another, called convolution. Convolution is used for solving analytical problems in many fields such as statistics, physics, and engineering (Zou, 2023).

As an example, consider the example of the port of Los Angeles-Long Beach (LA-LB), the largest port for imports to the United States. The distribution of payload changes is heavily skewed to the left, reflecting the dominant role of imports at this port. As noted, this could be modeled as the difference of two independent distributions.

Figure A1.4 simulates the subtraction of two distributions via bootstrapping, drawing 100,000 observations from two normal distributions calibrated for the port of LA-LB (left panel). The parameters used for the two normal distributions for LA-LB are: For imports, a mean of -26% and standard deviation of 11%; for exports, a mean of 4.5% and a standard deviation of 0.1%. The red density is the joint distribution resulting from this simulation and provides a close approximation of the observed distribution (middle panel). This allows us to estimate the netting effect (right panel). We conduct similar simulations for four other ports to calibrate the bootstrapping formula that is described below.

Figure A1.4. Port of Los Angeles-Long Beach



The bootstrapping formula is based on two principals at the port-level:

- **Principle I: Magnitude of payload changes.** The greater the magnitude of payload changes at a given port, the greater the average netting effect tends to be (other things equal). This is reasonable in that larger gross imports and exports on average lead to larger offsetting effects.

- **Principle II: Symmetry of payload changes.** The netting effect is expected to be larger for ports that have a high level of *both* import and export activity. This is reasonable in that ports where only imports or exports take place would not be subject to netting.

Based on these principles, the following equations describe the bootstrapping approach (Equations A1.7-A1.9).

$$Abs(\Delta L_{orig}) < \beta \cdot Abs(\Delta L_{avg})) \tag{A1.7}$$

where ΔL_{orig} is the original payload change, ΔL_{avg} is the average payload change for imports/exports, and β is a scaling factor. This adjusts all payload changes whose absolute values are less than β times the absolute average payload for imports/exports for a particular port. This step helps ensure that ports with larger average payload changes receive a larger netting adjustment, per Principle I above. The symmetry factor (Principle II) enters the bootstrapping formula as the lower of the ratio of port calls with net exports (imports) divided by the number of port calls with net imports/exports (Equation A1.8):

$$s = Min(\frac{N_{imports}}{N_{exports}}, \frac{N_{exports}}{N_{imports}}) \quad \text{(A1.8)}$$

The final bootstrapping formula for imports is shown below in Equation A1.9. (The formula for exports is identical, but with "exports" instead of "imports".)

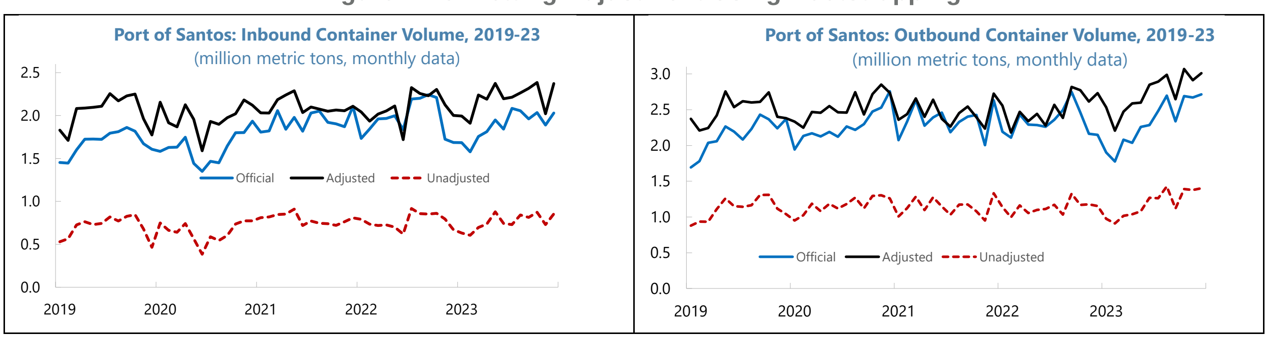
$$\Delta L_{Netting\_adj} = \Delta L_{orig} + \alpha \cdot s \cdot (\Delta L_{avg(imports)} - \frac{Abs(\Delta L_{orig})}{\beta}) \quad \text{(A1.9)}$$

where $\Delta L_{Netting\_adj}$ is the adjusted payload change. The parameter α is a scaling factor that is calibrated as 1.58 based on the calibration exercise. Similarly, β is calibrated as 3.12 based on the calibration exercise.[14] In the special case where the observed payload change is zero, the adjusted payload change would simply be $\alpha \cdot s \cdot \Delta L_{avg(imports)}$, i.e the scaling factor times the symmetry factor times the average payload for imports.

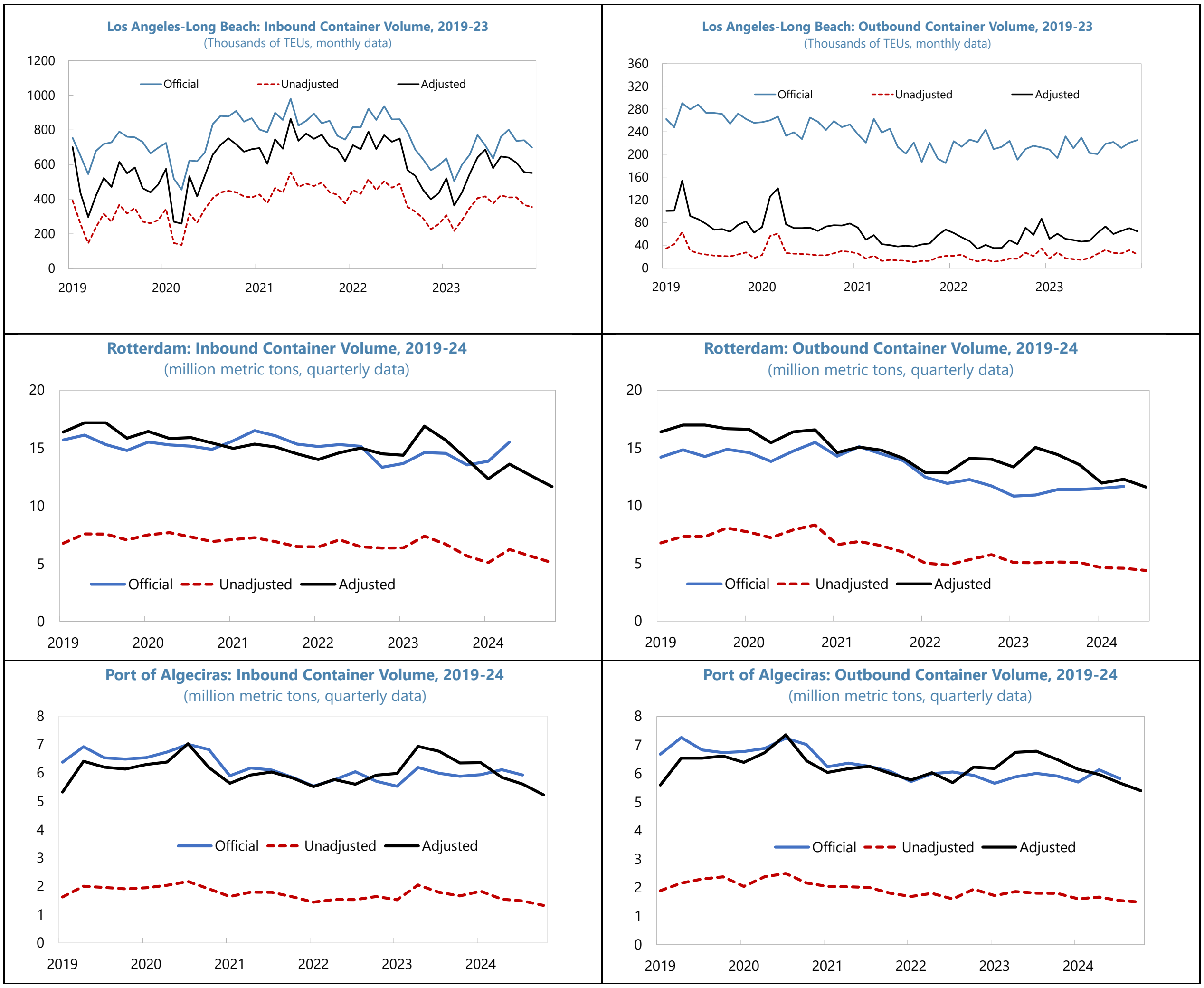
The last term in Equation A1.9 relates to a third netting principle that operates at the level of each vessel (rather than at the port level, as in the case of the first two principles). This principle is that observed payloads that are closer to zero are more likely to have been subject to (larger) netting effects. This is reasonable in that at one extreme, an observed payload change of 1 during a port call (i.e., a vessel going from full to empty) by definition cannot have been subject to netting effects (since the vessel is empty after the port call it is clear that no cargo was loaded). At the other extreme, a zero change in the payload may be the result of two (potentially large) sets of container movements of equal size in opposing directions. The bootstrapping formula captures this effect by gradually phasing out the netting adjustment as payload changes increase (in absolute terms).

Finally, the bootstrapping formula is augmented with an additional adjustment related to the weight of containers themselves. A standard TEU container weighs about 2 metric tons, or about 20 percent of the average weight of a loaded container. Accordingly, the formula is scaled by 0.8 to only capture the weight of cargo. Putting all this together, for 20 ports for which container throughput data are available in metric tons, we find that port-level container trade estimates rise from an average of 26 percent to 68 percent of official data after the adjustment. A selection of the results is shown Figure A1.5. The results for other ports are available upon request.

Figure A1.5. Netting Adjustment Using Bootstrapping



[14] Specially, α and β are calibrated by minimizing the average RMSE between actual and simulated distributions for five ports. It is worth noting that optimal values for α and β for each of the five ports fall within a narrow range of ±15% of the optimal value for all five ports collectively, suggesting that the bootstrapping formula does a reasonable job of capturing port-level variations.


Los Angeles-Long Beach: Inbound Container Volume, 2019-23
(Thousands of TEUs, monthly data)
Official
Unadjusted
Adjusted
Los Angeles-Long Beach: Outbound Container Volume, 2019-23
(Thousands of TEUs, monthly data)
Official
Unadjusted
Adjusted
Rotterdam: Inbound Container Volume, 2019-24
(million metric tons, quarterly data)
Official
Unadjusted
Adjusted
Rotterdam: Outbound Container Volume, 2019-24
(million metric tons, quarterly data)
Official
Unadjusted
Adjusted
Port of Algeciras: Inbound Container Volume, 2019-24
(million metric tons, quarterly data)
Official
Unadjusted
Adjusted
Port of Algeciras: Outbound Container Volume, 2019-24
(million metric tons, quarterly data)
Official
Unadjusted
Adjusted
2019
2020
2021
2022
2023
2024

Annex II. Adjusting for Ballast Water

Ballast is the weight placed in ships to adjust their center of gravity for improved stability and maneuverability. The concept of ballast is not new and has been followed since ancient times, when vessels would use sandbags, rocks, or iron blocks for stability (David, 2015). These would be loaded/unloaded once the cargo loading or discharge operation was finished. Today, ships carry ballast in the form of water usually in segregated ballast tanks. If a vessel needs to travel without cargo, then ballast water will be loaded up to some design level to keep the vessel upright. Some or all of this ballast water will then be discarded when the cargo is loaded. Separately, ships use ballast water to prevent tipping or listing/heeling excessively. These two different uses of ballast water are summarized in Table A2.1

Table A2.1. Typical Ballast Use of Vessels

Ballast Need	Vessel Type
Ballast replaces cargo Ballast required in large quantities, primarily for return voyage.	Tankers and dry bulk carriers
Ballast for vessel control Ballast required in almost all loading conditions to control stability, trim, and list/heel.	Containerships, general cargo, roro cargo vessels

Source: National Research Council (1996). https://doi.org/10.17226/5294.

Accordingly, in this paper, we classify vessels into two groups based on their ballast use:

- **Tankers and dry bulk carriers (Type 1 vessels)**. As noted, for tankers and dry bulk carriers, the main need for ballast water is to replace cargo. For example, a crude oil tanker or an iron ore carrier typically transports a single cargo load between two ports, then returns to its point of origin or another port without cargo (David, 2015). During empty conditions, the vessel requires ballast to operate safely—a condition referred to as being "in ballast" (National Research Council, 1996). Brancaccio, Kalouptsidi, and Papageorgiou (2020) estimate that, at any point in time, 42 percent of dry bulk carriers are traveling “in ballast.” Based on a survey by David (2015), tankers and dry bulk carriers typically use ballast water equivalent to 40 percent of their deadweight tonnage (DWT), although this number would vary by ship design.

- **Containerships, general cargo, and roro cargo vessels (Type 2 vessels)**. For containerships, general cargo, and roro cargo vessels, the main need for ballast water is vessel control. In contrast to tankers/bulk carriers, these vessels are almost always (partly) loaded between two ports, hence they require less ballast water. The use of ballast water for these ships is mainly to compensate for the unequal distribution of cargo, thereby preventing tipping or heeling (David, 2015). As a result, they use ballast water in almost all loading conditions to control for stability, trim, and heel—a condition referred to as sailing "with ballast" (National Research Council, 1996). Based on a survey by David (2015), these vessels typically use ballast water equivalent to 20 percent of their deadweight tonnage (DWT) at any given time, but again, this number would vary by ship design.

Based on these two baseline cases, we use the following criteria to classify vessels into “in ballast” and “laden” to estimate their adjusted payloads, as shown below in Equations A2.1-A2.3. We also adjust for fuel and provisions.

$$\mu_{it}^{*} = \begin{cases} 0 & if\ \mu_{it} \le b_i + f_i + \varepsilon \quad In\ ballast \\ \mu_{it} - f_i & if\ \mu_{it} > b_i + f_i + \varepsilon \quad Laden\ (without\ ballast) \end{cases} \quad \forall i \in Type\ 1\ vessels \qquad \text{(A2.1)}$$

$$\mu_{it}^{*} = \begin{cases} 0 & if \mu_{it} \le b_i + f_i + \varepsilon \quad In\ ballast \\ \mu_{it} - (b_i + f_i) & if \mu_{it} > b_i + f_i + \varepsilon \quad Laden\ (with\ ballast) \end{cases} \quad \forall i \in Type\ 2\ vessels \qquad \text{(A2.2)}$$

$$b_i = ballast\ capacity_i * \ \rho \ / \ DWT_i \qquad \forall i \in Type\ 1\ and\ 2\ vessels \qquad \text{(A2.3)}$$

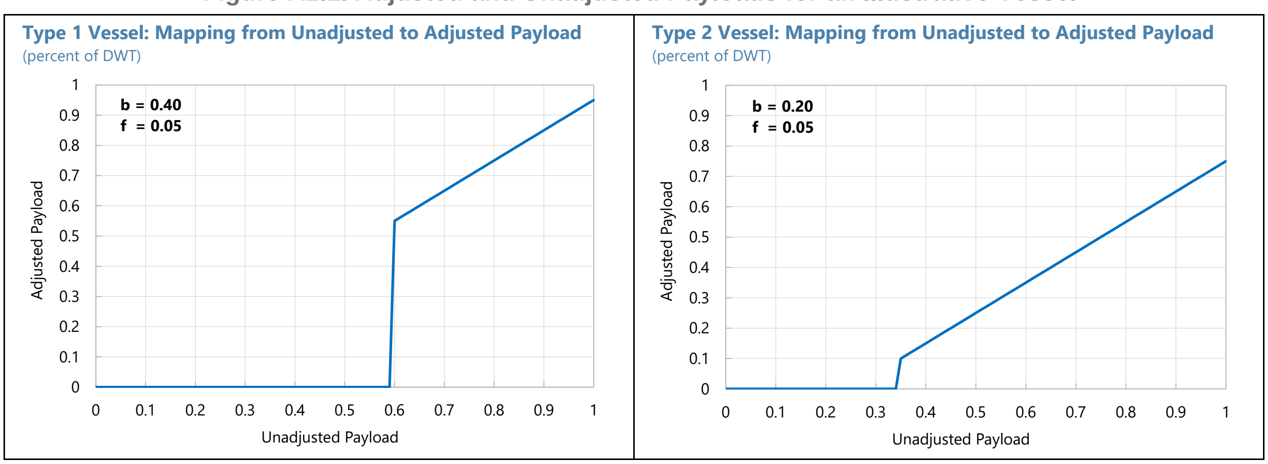
$$f_i = fuel\ capacity_i * \rho_{oil} \ / \ DWT_i \qquad \forall i \in Type\ 1\ and\ 2\ vessels \qquad \text{(A2.4)}$$

where μ_{it}^{*} is the adjusted payload of vessel *i* at time *t* (as percent of DWT), μ_{it} is the unadjusted payload of vessel *i* at time *t*, b_i is the weight of ballast water for vessel *i* (as percent of DWT), f_i is the weight of fuel for vessel *i* (as percent of DWT), $ballast\_capacity_i$ is the capacity of ballast tanks in vessel i (in m^3), $fuel\_capacity_i$ is the capacity of fuel tanks in vessel i (in m^3), ρ is the average density of salt water (1.025 metric tons/m^3), ρ_{oil} is the average density of heavy fuel oil (1.010 metric tons/m^3), DWT_i is the deadweight tonnage of vessel i (in metric tons), and ε is measurement error (as percent of DWT). [15]

While ballast water operations are highly complex and dependent on a variety of factors, for Type 1 vessels we apply a simple stepwise function with the ship traveling without ballast water beyond a certain threshold (b_i + f_i + ε). For Type 2 vessels, we apply a gradual transition with ballast water always being present for stability, in line with the stylized facts describer earlier in the Annex.

Based on this approach, Figure A2.1 shows the mapping between adjusted and unadjusted payloads for an illustrative Type 1 and Type 2 vessel. Applying this mapping, we generally observe trade and transit volumes that are much closer to official data in levels (see Section 2).

Figure A2.1. Adjusted and Unadjusted Payloads for an Illustrative Vessel



[15] The measurement error comes from the fact that, in our vessels database, we have information on ballast tank capacity for two-thirds of ships and fuel capacity for half the ships. For the rest, we apply a gap-fill method based on the median ballast and fuel capacity by vessel type and vessel size (divided into DWT bins of 10,000 metric tons). The standard deviation of this estimation is 15 percent (of DWT) for Type 1 vessels and 10 percent (of DWT) for Type 2 vessels, which is how we define ε. We also do not have information on the utilization rate of ballast and fuel tank capacity. Having said that, David (2015) notes that ballast tanks are usually filled up to maximum capacity to prevent free surface effects that could cause ships to become unstable.

Annex III. Why Are Unit Values Important for Measuring Trade Volume Accurately?

Example

Imagine a country imports 10 cars (each car is 2 tons and costs $20,000 per ton) and 20 tons of rice (at $500 per ton). Next year, the country imports 20 cars and 20 tons of rice at the same prices.

	Cars	Rice	Import Value	Physical Volume of Imports
Current Year	**20 tons** at $20,000 per ton	**20 tons** at $500 per ton	**$410,000**	**40 tons**
Next Year	**40 tons** at $20,000 per ton	**20 tons** at $500 per ton	**$810,000**	**60 tons**

In this example, the **value of imports** has increased from $0.41 million to $0.81 million in one year, or approximately by **100 percent**. As the prices of imported goods have not changed, the **import price deflator** is unchanged. Meanwhile, the **physical volume of imports** has increased from 40 to 60 tons, or by **50 percent**.

A naïve approach would take the change in the physical volume of imports (50 percent) as the change in import volume, but this would be incorrect. To calculate trade volume accurately (as in official statistics), we need to calculate the trade value first and then deflate it by a price deflator. Since import value increased by 100 percent and import price deflator is unchanged, import volume is up by **100 percent** (not **50 percent**).

This makes sense since trade volume is a hypothetical concept—it measures how much trade value would have increased if prices were unchanged (as in this example). Put differently, simply aggregating the physical volume of traded goods is not an accurate measure of trade volume when unit values differ.

What is true for specific **goods/products** (as in this example) is also true for **product groups**. As Section 3 shows, the average unit value of goods transported by containerships (manufactured goods) is an order of magnitude larger than those transported by tankers/bulk carriers (commodities). Hence, simply aggregating the physical volume of goods shipped by different types of vessels (i.e., without considering their unit values) would lead to an incorrect measure of trade volume. This would be the case especially for countries whose imports or exports are relatively non-homogenous (i.e., a mixture of manufactured and commodity products).

Annex IV. List of Economies

Table A4.1. List of Economies, by Income and Region	
Advanced Economies	Australia, Belgium, Canada, Croatia, Cyprus, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong SAR, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Macao SAR, Malta, The Netherlands, New Zealand, Norway, Portugal, Singapore, Slovenia, Spain, Sweden, Taiwan Province of China, United Kingdom, United States.
Euro Area	Belgium, Croatia, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Malta, The Netherlands, Portugal, Slovenia, Spain.
G7	Canada, France, Germany, Italy, Japan, United Kingdom, United States.
Other advanced economies	Australia, Denmark, Hong Kong SAR, Iceland, Israel, Korea, Macao SAR, New Zealand, Norway, Singapore, Sweden, Taiwan Province of China.
Emerging and Developing Economies	Albania, Algeria, Angola, Antigua and Barbuda, Argentina, Aruba, Azerbaijan, The Bahamas, Bahrain, Bangladesh, Barbados, Belize, Benin, Brazil, Brunei Darussalam, Bulgaria, Cabo Verde, Cambodia, Cameroon, Chile, China, Colombia, Comoros, Democratic Republic of the Congo, Republic of Congo, Costa Rica, Côte d'Ivoire, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eritrea, Fiji, Gabon, The Gambia, Georgia, Ghana, Grenada, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, India, Indonesia, Iran, Iraq, Jamaica, Jordan, Kazakhstan, Kenya, Kiribati, Kuwait, Lebanon, Liberia, Libya, Madagascar, Malaysia, Maldives, Marshall Islands, Mauritania, Mauritius, Mexico, Micronesia, Moldova, Montenegro, Morocco, Mozambique, Myanmar, Namibia, Nauru, Nicaragua, Nigeria, Oman, Pakistan, Palau, Panama, Papua New Guinea, Peru, Philippines, Poland, Qatar, Romania, Russia, Samoa, São Tomé and Príncipe, Saudi Arabia, Senegal, Seychelles, Sierra Leone, Solomon Islands, Somalia, South Africa, Sri Lanka, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, Sudan, Suriname, Syria, Tanzania, Thailand, Timor-Leste, Togo, Tonga, Trinidad and Tobago, Tunisia, Türkiye, Turkmenistan, Tuvalu, Ukraine, United Arab Emirates, Uruguay, Vanuatu, Venezuela, Vietnam, Yemen.
Emerging and Developing Asia	Bangladesh, Brunei Darussalam, Cambodia, China, Fiji, India, Indonesia, Kiribati, Malaysia, Maldives, Marshall Islands, Micronesia, Myanmar, Nauru, Palau, Papua New Guinea, Philippines, Samoa, Solomon Islands, Sri Lanka, Thailand, Timor-Leste, Tonga, Tuvalu, Vanuatu, Vietnam.
Emerging and Developing Europe	Albania, Bulgaria, Moldova, Montenegro, Poland, Romania, Russia, Türkiye, Ukraine.
Latin America and the Caribbean	Antigua and Barbuda, Argentina, Aruba, The Bahamas, Barbados, Belize, Brazil, Chile, Colombia, Costa Rica, Dominica, Dominican Republic, Ecuador, El Salvador, Grenada, Guatemala, Guyana, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Peru, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, Suriname, Trinidad and Tobago, Uruguay, Venezuela.
Middle East and Central Asia	Algeria, Azerbaijan, Bahrain, Djibouti, Egypt, Georgia, Iran, Iraq, Jordan, Kazakhstan, Kuwait, Lebanon, Libya, Mauritania, Morocco, Oman, Pakistan, Qatar, Saudi Arabia, Somalia, Sudan, Syria, Tunisia, Turkmenistan, United Arab Emirates, Yemen.
Sub-Saharan Africa	Angola, Benin, Cabo Verde, Cameroon, Comoros, Democratic Republic of the Congo, Republic of Congo, Côte d'Ivoire, Equatorial Guinea, Eritrea, Gabon, The Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Liberia, Madagascar, Mauritius, Mozambique, Namibia, Nigeria, São Tomé and Príncipe, Senegal, Seychelles, Sierra Leone, South Africa, Tanzania, Togo.

Note: Based on the IMF World Economic Outlook (WEO) classification of economies. Excludes landlocked economies.

Table A4.2. List of Economies, by Regional Trade Agreement and Geographical Proximity	
Africa	Algeria, Angola, Benin, Cabo Verde, Cameroon, Comoros, Côte d'Ivoire, Democratic Republic of the Congo, Djibouti, Egypt, Equatorial Guinea, Eritrea, Gabon, Ghana, Guinea, Guinea-Bissau, Kenya, Liberia, Libya, Madagascar, Mauritania, Mauritius, Morocco, Mozambique, Namibia, Nigeria, Republic of Congo, São Tomé and Príncipe, Senegal, Seychelles, Sierra Leone, Somalia, South Africa, Sudan, Tanzania, The Gambia, Togo, Tunisia.
East Asia (Regional Comprehensive Economic Partnership and Pacific Island countries)	Australia, Brunei Darussalam, Cambodia, China, Fiji, Hong Kong SAR, Indonesia, Japan, Kiribati, Korea, Macao SAR, Malaysia, Marshall Islands, Micronesia, Myanmar, Nauru, New Zealand, Palau, Papua New Guinea, Philippines, Samoa, Singapore, Solomon Islands, Thailand, Timor-Leste, Tonga, Tuvalu, Vanuatu, Vietnam.
Eurasian Economic Union	Kazakhstan, Russia.
Europe (European Union and potential enlargement countries)	Albania, Belgium, Bulgaria, Croatia, Cyprus, Denmark, Estonia, Finland, France, Georgia, Germany, Greece, Iceland, Ireland, Italy, Latvia, Lithuania, Malta, Moldova, Montenegro, Norway, Poland, Portugal, Romania, Slovenia, Spain, Sweden, The Netherlands, Türkiye, Ukraine.
Middle East (Gulf Cooperation Council and neighboring countries)	Bahrain, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, Syria, United Arab Emirates, Yemen.
Latin America and the Caribbean	Antigua and Barbuda, Argentina, Aruba, Barbados, Belize, Brazil, Chile, Colombia, Costa Rica, Dominica, Dominican Republic, Ecuador, El Salvador, Grenada, Guatemala, Guyana, Haiti, Honduras, Jamaica, Nicaragua, Panama, Peru, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, Suriname, The Bahamas, Trinidad and Tobago, Uruguay, Venezuela.
South Asian Free Trade Area	Bangladesh, India, Maldives, Pakistan, Sri Lanka.
USMCA	Canada, Mexico, United States.

Note: Excludes landlocked economies.

Annex V. Glossary of Maritime Terms

Ballast water is water that ships carry to stay stable and maneuverable.

Deadweight tonnage (DWT) indicates the maximum cargo (in metric tons) that a ship can carry without compromising its safety.

Draft (or draught) measures how deep a vessel is immersed in water. It is the vertical distance between the waterline and the bottom of the vessel's hull.

International Maritime Organization (IMO) number is a unique seven-digit number assigned to each ship when it's constructed. It is permanently associated with the hull of a ship and would not change with a change in the ship's name, flag, or owner. It is usually, but not always, included in the AIS signal transmitted by the ship.

Maritime Mobile Service Identity (MMSI) number is a nine-digit number that is assigned to the AIS system on board of a vessel. It is always included in the AIS signal transmitted by the ship. The MMSI number of a ship is not permanent and may change when a ship changes its flag or ownership.

Maximum (or design) draft indicates the legal limit to which a ship may be loaded without compromising its safety. It is shown on the hull of a ship with a mark called the international load line or the Plimsoll line.

Payload (load factor) is the share of a vessel's carrying capacity (deadweight tonnage) that is occupied by paid cargo. It can be estimated using a ship's reported draft, adjusting for ballast water.

Port call is a discrete event representing a vessel arriving at and departing from a port to load/unload cargo.

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