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KEY POINTS

- Policy makers need real-time information for quick and efficient decision-making in response to events. Indicators from automatic identification system (AIS) that tracks ships are increasingly used in economic monitoring and analysis.
- The AIS-based indicators such as port traffic and time in port show that maritime transport was disrupted globally during the coronavirus disease (COVID-19) pandemic and at varying degrees in different ports in Asia and the Pacific.
- AIS-derived trade-related indicators such as port call and change in draft, when compared to official statistics, show potential for estimating and forecasting international trade flows in the region's economies.
- Real-time AIS data can also support analysis and intervention in areas such as port infrastructure, shipping emissions, and impacts of climate change and disasters triggered by natural hazards.[1]

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Economic Applicability of the Automatic Identification System Data: Use Cases and the Way Forward

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INTRODUCTION

The automatic identification system (AIS) was devised for maritime traffic safety, yet data it generates are used increasingly across different applications. For instance, radio signals that ships emit to communicate with each other and with coastal authorities are increasingly being used to gauge maritime traffic, port performance, and trade volumes. AIS messages are sent multiple times daily and reveal information about a ship's position, direction, speed, and depth or payload. As more than 80% of global trade by volume and more than 70% by value is carried on board ships and handled by seaports worldwide (UNCTAD 2017), trade and maritime indicators using AIS data can therefore enable stakeholders in public and private sectors to make quicker and more efficient decisions.

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Note:
ADB recognizes "Korea" as the Republic of Korea.

Table 1: Categories of Automatic Identification System Data

Static Information (ship characteristics)	Dynamic Information (ship movement)	Voyage-related Information (current voyage)
• Maritime Mobile Service Identifier (MMSI) • International Maritime Organization (IMO) Number • Call sign • Ship name • Type • Dimensions	• Ship's position (longitude, latitude) • Speed over ground (SOG) • Course over ground (COG) • Navigation status	• Destination • Estimated time of arrival (ETA) • Draft

Source: United Nations Global Platform AIS Handbook. https://unstats.un.org/wiki/display/AIS/Overview+of+AIS+dataset.

Applications in economic analysis include estimating trade flows, assessing port performance, and monitoring fisheries and maritime carbon dioxide emissions (Arslanalp, Koepke, and Verschuur 2021). While official monthly trade data are often published with a lag of 1 to 2 months, AIS data can provide more timely estimates for international trade flows. AIS data-based indicators can serve as leading indicators of shipping costs in times of disruptions when physical ship movement and port activities are immediately affected. Reported vessel draft measurements from AIS messages can also be used as a basis for estimating ships' payload.

This brief examines the potential use of high-frequency AIS data in developing key indicators for trade monitoring and analysis. Specifically, the brief proposes indicators derived from AIS data that represent maritime performance and trade flows; assesses the impact of coronavirus disease (COVID-19) on vessel flow and waiting time in Asia's major ports, based on these derived measures; and explores their usefulness in estimating trade flows. Finally, it explores opportunities for using AIS data in evidence-based policy implementation.

OVERVIEW OF THE AUTOMATIC IDENTIFICATION SYSTEM

AIS is a vessel identification system that transmits real-time information on routes of vessels via very high frequency radio transponders (March et al. 2021). Since 2004, the International Maritime Organization (IMO) has required all ships with 300 gross tonnage or more that are engaged in international voyages (or those with 500 gross tonnage or more not engaged in international voyages) to be equipped with AIS transponders. These transponders send radio messages every few seconds or minutes to other ships and coastal authorities to enhance maritime security. Such data may include vessel type, the ship's position (latitude and longitude), size, speed, the ship's draft (vertical distance between the ship's keel and waterline, which can indicate its load), destination, and navigational status (anchored, moored, under way using engine) (Cerdeiro and Komaromi 2020). AIS is increasingly used voluntarily by smaller fishing and leisure vessels, enabling greater monitoring of a diversity of ships around the world.

AIS data contains information on ship characteristics (static), movements (dynamic), and the trips that the ships in the record have made (Table 1). The Maritime Mobile Service Identity is a unique 9-digit vessel identifier used over radio frequencies to identify a vessel based on the country of registration, while the IMO number is an identifier used by the International Maritime Organization. Similarly, the call sign is also a unique identifier to a ship which can be helpful when the reported vessel name is difficult to identify. Navigation status refers to where the ship is under way using engine, anchored, or when moored, while draft is the reading at a given time based on draft marks on the side of the ship. Along with destination, such information provides unique observations to estimate ships' payloads, maritime traffic, and port congestion.

AIS data are freely accessible to statistical offices and international organizations through the United Nations Global Platform, where worldwide data from December 2018 onward are available. The wealth of information available in AIS data, along with all other big data sources, is changing how official statistics are computed. The UN Committee of Experts on Big Data and Data Science for Official Statistics (UN-CEBD) built the UN Global Platform (UNGP) to make AIS data more accessible to those who do not have the infrastructure and skills to handle such a data set. The AIS Task Team, a global community developing research and methodologies on the use of AIS data, complements this platform.[2]

STUDIES USING AIS DATA IN THE LITERATURE

High-frequency AIS-based trade flow estimates could complement official trade data that are available only at lower frequency. Cerdeiro and Komaromi (2020), for instance,

[2] The Asian Development Bank (ADB), as a member of the AIS Task Team, utilizes the UNGP to explore potential applications of AIS data for its developing member countries. In addition, the ADB supports the UN-Committee of Experts on Big Data and Data Science for Official Statistics by providing technical assistance on AIS data architecture and maintenance of the UNGP infrastructure.

utilize machine-learning algorithms to construct trade volume indicators from AIS-based port call data and measure these against actual trade data published by the Netherlands Bureau for Economic Policy Analysis. Their resulting Global Trade Intelligence index can be used for nowcasting as well as forecasting trade flows. For the world as a whole, the calculated index has a correlation of 0.9 for monthly levels and 0.4 in quarter-on-quarter growth rates. Arslanalp, Koepke, and Verschuur (2021) found a good fit of AIS-based estimates of trade flows with official data in Pacific Island countries with limited data availability.[3]

Using the AIS data, several studies find that the pandemic caused significant disruptions in maritime activities, leading to reduced trade. Millefiori et al. (2021) find significant declines in ship mobility based on cumulative navigated miles in 2020: 5.6%–13.8% for container ships, 0.2%–9.3% for wet bulk, and 19.6%–42.8% for passenger traffic. March et al. (2021) find that ship traffic density, the number of vessel transits per square kilometer, in January and February 2020 were similar to that in same months of the previous year, but about 50% of cells showed a decrease in density by March, when the pandemic was declared. Looking into Veneto Region in Italy, which was Europe's first maritime region subjected to lockdowns, Depellegrin et al. (2020) found a 69% reduction in vessel activity during the March–April 2020 lockdowns compared with the same period in 2017. Verschuur, Koks, and Hall (2021) find that maritime trade declined by 7%–9.6% during the first 8 months of 2020 with manufacturing sectors being hit the hardest, and small island developing countries and low-income countries suffering the largest relative losses. Cerdeiro and Komaromi (2020) find that going from no restrictions to full lockdown reduced import growth by about 11%, which is suggestive of the downstream propagation of countries' lockdowns through global supply chains.

The AIS data are also widely used to address the environmental impact of international shipping. The industry contributes around 3% of global greenhouse gas emissions annually (Brown et al. 2022). The main strand of literature focuses on the estimation of shipping emissions using granular information such as ship types, distance traveled, speed, and other data sources that are combined to implement a "bottom-up" approach (Jalkanen et al. 2009; Shi and Weng 2021). Some studies focus on emissions contributed to specific ports and coastal regions (Goldsworthy and Goldsworthy 2015; Tichavska and Tovar 2015). Other applications include a monitoring system using AIS data to assess the environmental impact (e.g., oil spill risk) of shipping activities (Eide et al. 2007; Metcalfe et al. 2018). Vicente-Cera et al. (2020) measure environmental pressure exerted by the cruise sector.

AIS DATA-BASED INDICATORS

A key indicator in AIS data are port calls. Several other indicators can be derived from port calls data as they contain information on port congestion, port efficiency, and maritime trade. A port call is made when a ship (i) enters an area considered as a port, (ii) stops or slows down within the boundary of the port, and (iii) exits the port. AIS data combined with the port area and vessel dimension information results in port call data, which usually contains details on the Maritime Mobile Service Identity, IMO ship number, ship name, port name, economy, arrival date, departure date, arrival draft, departure draft, last port of call, and last port of call economy.

Draft can also be used to extract information on trade activities. Specifically, changes in draft due to goods that are loaded or unloaded from a ship can be used to estimate volume of certain types of goods predominantly transported by sea. Table 2 shows the list of possible indicators derived from the AIS data with potential for use in analytical work, including this study. The computation of the indicators is presented in Appendix 1.

ASSESSMENT OF MARITIME ACTIVITIES USING AIS INDICATORS

The emergence of COVID-19 has brought new challenges to shipping operations and management. For example, new protocols and additional border control measures at a port can result in extra waiting time for berthing operations, inland seaport transshipment operations, and hinterland transportation management. Pandemic-related restrictions were imposed on the entry and exit of vessels, and strict quarantine measures were implemented on passengers and transport workers. Disembarkation of freight ships was also restricted by such measures as disallowing crew shifts in their ports, prohibiting crews from landing, prohibiting contact with unloading personnel, and requiring crews and ships to quarantine at anchorages. Supply chain or maritime activity disruptions due to these mobility restrictions and quarantine measures led to significant movements in the AIS-based indicators.

DISRUPTIONS IN MARITIME ACTIVITIES IN 2020: WHAT DO THE AIS INDICATORS SHOW?

Port call data show that the pandemic disrupted maritime transport globally and to varying degrees in major Asian ports. Worldwide mobility restriction measures started being implemented in early 2020 and expanded rapidly (Figure 1). As a result, port call counts fell significantly and remained low

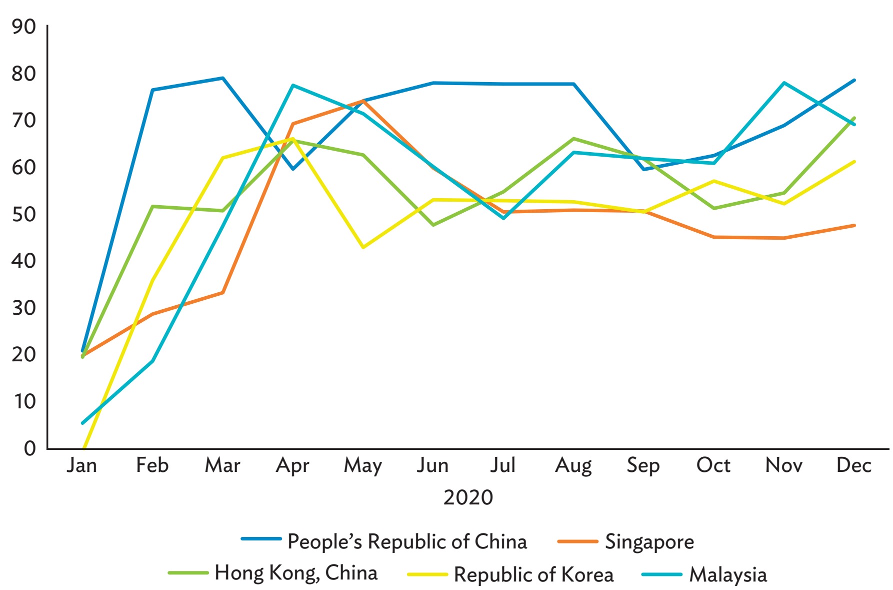
[3] As of 12 January 2023, only 12 out of 14 Pacific countries release their bilateral merchandise trade statistics in the International Monetary Fund Direction of Trade Statistics database. The two Pacific countries that are not part of the database are the Cook Islands and Niue. For the UN Comtrade database which contains data up to commodity level, only Fiji and Samoa released data up to 2021. Currently there are no data for the Marshall Islands, Nauru, Tuvalu, and Niue, while the eight remaining Pacific countries have varied outdated data.

Table 2: A Shortlist of Useful AIS-Derived Indicators

Indicator	Description
Daily Port Call	Number of ships that arrive at a particular port at a daily frequency. It can be aggregated by economy, port, and ship type
Draft Change	Difference between the arrival draft and departure draft of each ship making a port call
Daily Port Departure	Number of ships departing from a particular port at a daily frequency. It can be aggregated by economy, port, and ship type.
Time in Port	Total number of hours a ship stays in a particular port. Turnaround time includes waiting time in anchorage and service time in berth.
Laden/Unladen Port Call Count	Number of daily port calls based on the type of draft change for a ship during a port call
Passenger Carrying Ship Count	Daily port call counts for ships which are tourist-related and carry passengers during their vessel trips
Cargo Carrying Ship Count	Daily port call counts for ships which carry cargoes during their vessel trips
Trip Duration	Duration for which a ship made its last port call
Port Connectivity	An indicator that extracts a ship's origin port-economy and destination port-economy pairs. This can be aggregated by origin, destination, type of ship, and date.
Port Traffic	An indicator that determines if a particular port is experiencing an unusual increase or decrease in port traffic based on weekly benchmarks using time in port or port calls
Trade Volume	Estimated amount of cargo loaded or unloaded from a ship, with the ship's change in draft and deadweight primarily used to estimate the cargo load

Source: Authors.

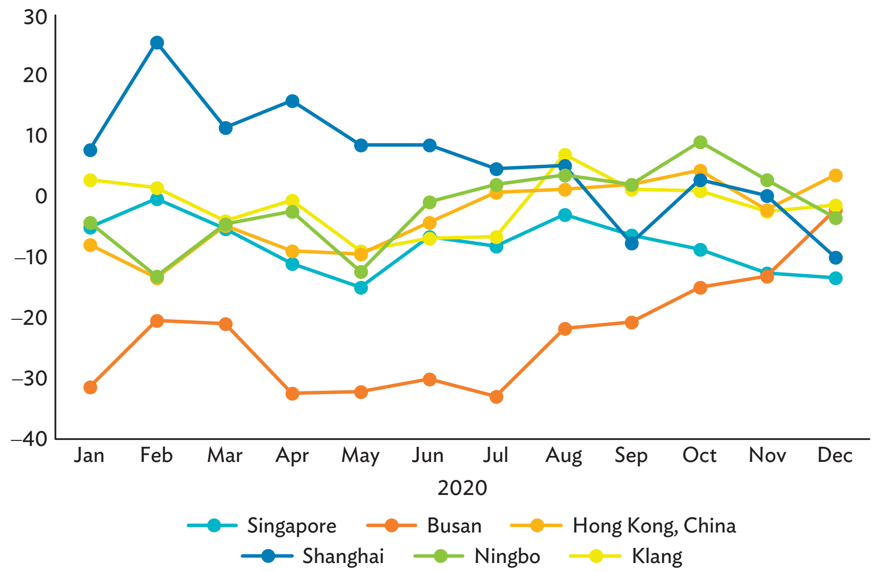
Figure 1: Monthly Government Stringency Index, 2020



Note: Cargo carrying ships only; Average waiting time of a ship = Total hours spent in port/Total vessel count. The ports chosen are among the world's top 10 based on annual throughput. For the computation of port calls, only cargo carrying ships with total hours spent in port of more than 1 hour were considered. Port calls were aggregated by port name and ship type on a monthly basis. The categorization of ship type was based on the IHS Markit ship data set.

Sources: Oxford Stringency Index; Authors' calculations based on IHS Markit data.

Figure 2: Monthly Container Ship Port Calls, 2020
(% change, year-on-year)



Note: Cargo carrying ships only; Average waiting time of a ship = Total hours spent in port/Total vessel count. The ports chosen are among the world's top 10 based on annual throughput. For the computation of port calls, only cargo carrying ships with total hours spent in port of more than 1 hour were considered. Port calls were aggregated by port name and ship type on a monthly basis. The categorization of ship type was based on the IHS Markit ship data set.

Sources: Oxford Stringency Index; Authors' calculations based on IHS Markit data.

throughout 2020 in major ports in Asia such as Singapore and Busan, while Hong Kong, China; Ningbo; and Klang recovered from the initial shock relatively sooner (Figure 2).[4] On the other hand, port calls in Shanghai were less affected, even showing positive year-on-year growth until August. This could be due to ships rescheduling their arrival to the world's largest port in anticipation of further lockdowns.

During the pandemic, the waiting time at anchorage increased, but turnaround time varied by port and ship type. Generally, the total time spent in port per ship declined in 2020 for Shanghai; Singapore; and Hong Kong, China, in part due to decreased port calls, while Busan experienced a significant rise (Figure 3a). For bulk carriers, all ports recorded lower waiting time except for Ningbo. However, products tanker, container ship, and general cargo recorded increases in the average turnaround time in most of these ports, with Busan showing the highest increase. Waiting time at anchorage, on the other hand, exhibited an overall upsurge for most ports and ship types, except for Busan (Figure 3b). The differing impacts of the pandemic for ports and ship types are possibly due to a confluence of factors like COVID-19 restriction rules, decreased availability of port staff, and particular port characteristics, among others.

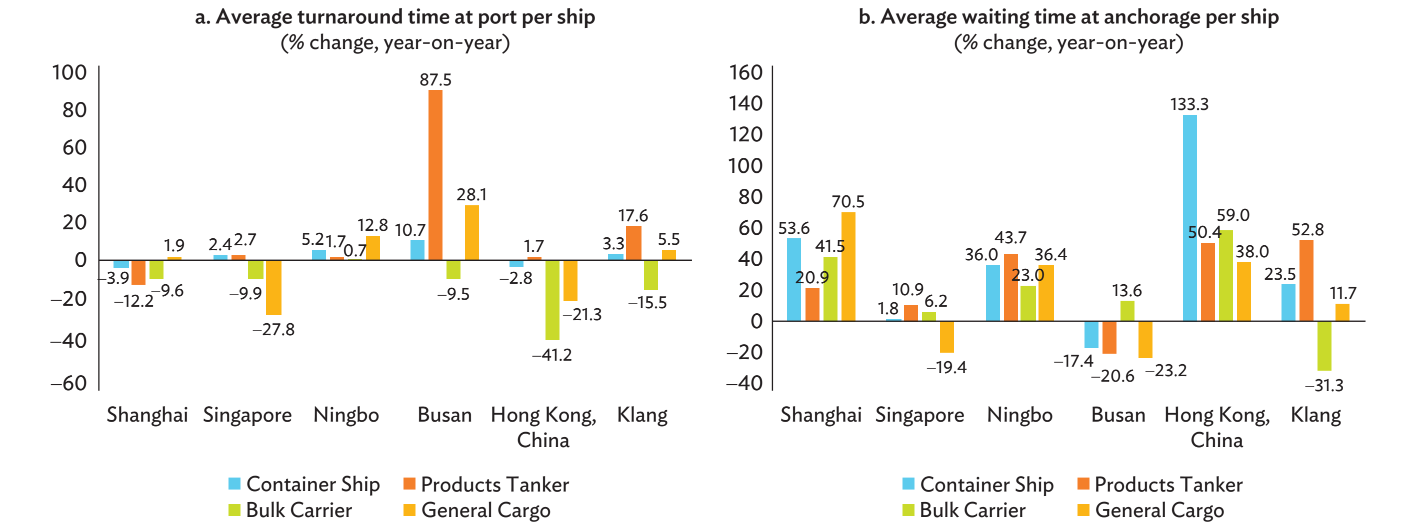
DO AIS-DERIVED INDICATORS TRACK OFFICIAL TRADE?

The AIS data-based indicators are compared with official national trade statistics to assess their potential for estimating and forecasting trade flows recorded at a lower frequency. Weekly port calls and draft change from the AIS data can be used to estimate or forecast monthly trade flows (export and import) in advance. Specifically, draft change is used to derive cargo load following Arslanalp, Marini, and Tumbarello (2019; also see Appendix 1), along with information on a ship's deadweight, its reported arrival and departure draft from a port, and its maximum draft. On a separate note, it is also important to ensure that shipping records in the AIS data used for analysis are consistent with official records managed by port authorities. The case of Busan port is discussed in Box 1.

The results show promising potential of AIS data in providing trade-related information even as they lack details on specific trade items (Figure 4). This is particularly true for Singapore as a small open economy, highly dependent on international trade as the second-busiest port in the world and leading transshipment hub. Trade flows derived from AIS data align well with official trade statistics, both for port calls and cargo loads.

[4] Appendix 2 lists the worlds' biggest 30 ports in terms of throughput.

Figure 3: Average Time at Port, 2020



Note: Cargo carrying ships only; Average turnaround or waiting time of a ship = Total hours spent in port/Total vessel count. The ports chosen are among the world's top 10 based on annual throughput. For the computation of port calls, only cargo carrying ships with total hours spent in port of more than 1 hour were considered. Port calls were aggregated by port name and ship type on a monthly basis. The categorization of ship type was based on the IHS Markit ship data set.

Source: Authors' calculations based on IHS Markit data.

Furthermore, the estimates capture the major turning points for Singapore trade in 2020 such as those in February and May.

Estimates of trade based on changes in draft have shown mixed results in predicting actual trade, and may not be more accurate than using port call information. Data for Hong Kong, China, was not as accurate as it was for Singapore, while the trade volume estimate based on draft changes better serve its purpose than data for port calls. Port calls data for Busan, on the other hand, track official trade statistics while cargo load diverged from trade flows at some point after initially being aligned. Meanwhile, estimates for Port Klang in Malaysia align with the movement of trade growth at selected periods only. Dynamics for the two ports in the People's Republic of China are similar, exhibiting volatile patterns for port calls and cargo load, although cargo load has similar alignment with the country's total trade.[5]

CASE STUDY: THE SUEZ CANAL BLOCKAGE IN MARCH 2021

The Suez Canal is a waterway in Egypt which connects the Mediterranean Sea to the Red Sea and the Indian Ocean. About 12% of global trade passes through the canal, which represents 30% of global container traffic. In March 2021, one of the world's largest container ships ran aground, blocking the canal, and caused major disruptions in maritime trade between Europe, Asia, and the Middle East.[6] The incident impacted every node in of the global supply chain, from domestic transport providers to retailers, supermarkets, and manufactures. An immediate impact was increased freight costs, while the incident also prompted the search for an economic alternate route.

To estimate the effect using AIS data, three polygons of interest are used to monitor ship movements at North Anchorage, Great Bitter

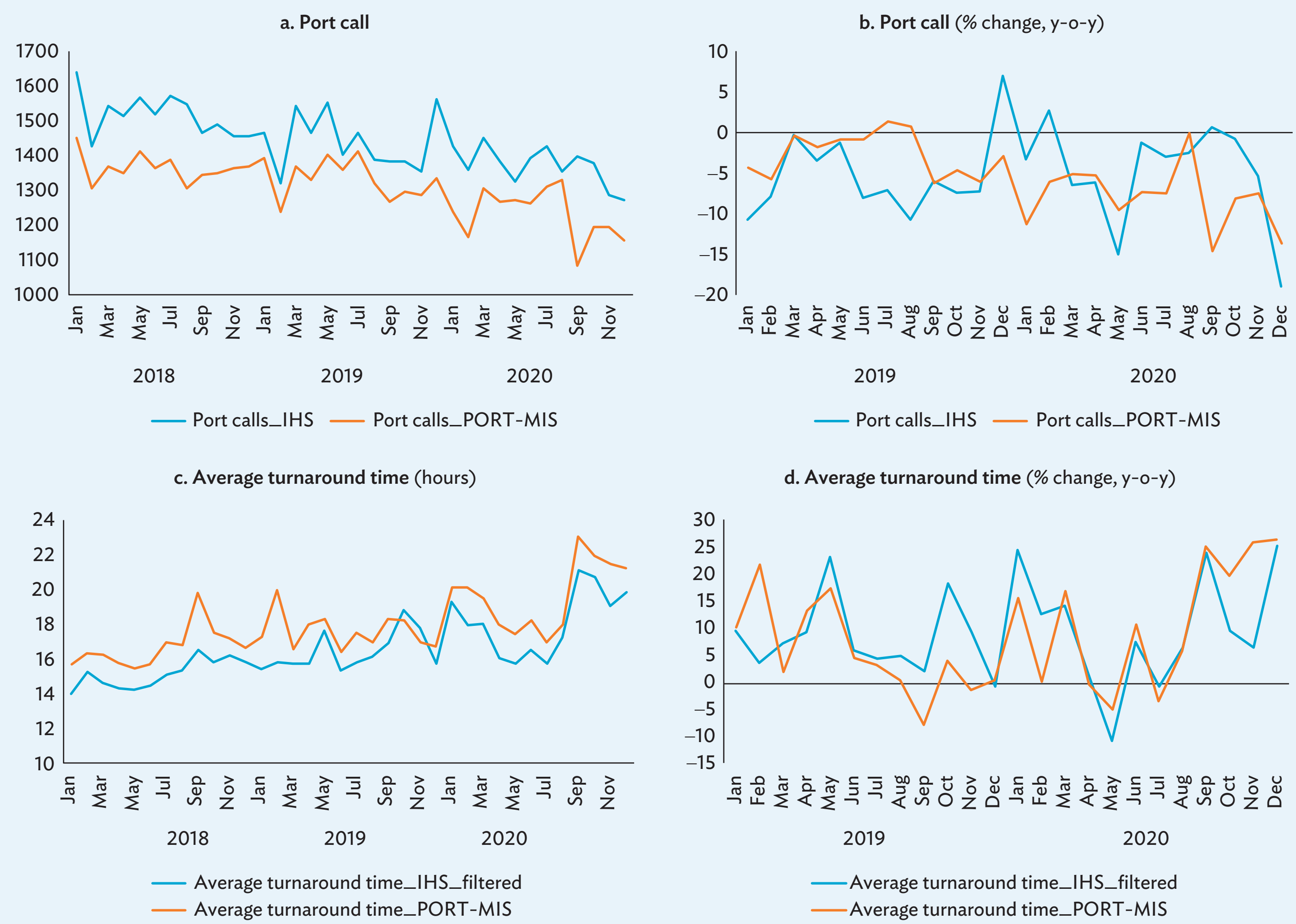
5 When comparing AIS indicators (port calls and cargo load) of specific ports (Busan, Port Klang, Ningbo, and Shanghai in this case) to the total trade value of their corresponding economies, it is important to note that a more accurate comparison can be obtained by considering data from all international ports.

6 At 05:40am GMT on 23 March 2021, the Ever Given got stuck somewhere between the South Anchorage and the Great Bitter Lake, blocking all traffic within the canal. The canal remained blocked for 6 days until the Ever Given was finally freed at 01:05pm GMT on 29 March. A total of 367 vessels were in queue before the operations resumed. Despite being freed from blockage, canal congestion persisted from 30 March to 3 April, but the situation improved as more ships were able to pass through the canal.

Box 1: Automatic Identification System Indicators Versus Official Statistics—Port Calls and Waiting Times in Busan Port

Not all port authorities release detailed statistics with enough frequency to allow for precise comparison. Busan port is chosen as an example since the Port Management Information System (Port-MIS) of the Republic of Korea provides detailed information. For container ships in Busan, port call and turnaround time data published in the Port-MIS of the Republic of Korea are compared with the derived port call and turnaround time indicators from the automatic identification system (AIS). The figure shows the number of vessels arriving at Busan port based on AIS port calls and Port-MIS data from January 2018 to December 2020. The number of ships coming into Busan port as derived from AIS data closely follows the official number of port visits from the Port-MIS. This is also the case for the average turnaround time.

Comparison between AIS-Based Indicators and Official Statistics—Port of Busan, Container Ships



y-o-y = year-on-year.

Source: Authors based on IHS Markit data and PORT-MIS of the Republic of Korea.

Figure 4: AIS-Based Trade Flows vs Official Trade Statistics (all ships; monthly)
(% change, year-on-year)

AIS = automatic identification system, PRC = People's Republic of China.

Note: Total trade is the sum of total export and total import values of the economy where the port is located. Port calls and cargo load represents all ships that have stayed in the port for at least 2 hours. Cargo load represents all ships that have stayed in the port. All are monthly figures and computed as year-on-year growth rates.

Sources: Authors' calculations based on AIS data, UN COMTRADE, and Korea Customs Service Trade Statistics (accessed 26 October 2022).

Table 3: Average Daily Arrivals and Average Transit Times during the 2021 Suez Canal Blockage

Results	BAU (1–22 Mar 2021)	Blockage (23 Mar–3 April)	% change
Average Daily Arrivals	53 vessels	43 vessels	−18.9%
Average Transit Time	31 hours	148 hours	477.4%

BAU = business as usual.

Note: The average daily transit time during the BAU is higher than the 12–16 hours average transit time reported by the Suez Canal Authority. (The authority's average only includes vessels which are going through the canal without stopping, whereas this analysis used vessels docking in nearby ports and anchorages—resulting in the higher average transit time).

Source: AIS UN Global Platform via Stealth (accessed May 2021).

Lake, and South Anchorage from 1 March to 3 April. The processing and analysis of raw AIS signals were split into two periods based on the date of transmission. The first data set covers the blockage period while the second covers business as usual in the weeks before the incident. The AIS data show there was 18% reduction in average daily vessel arrivals and nearly fivefold increase in average transit time during the blockage period (Table 3).

For further analysis, at least 50 hours of transit time was considered to determine the affected vessels count, resulting in 417 unique vessels. The blockage not only increased the average transit time through the Suez Canal but also forced about 56 unique vessels to take the longer alternative route, going around the Cape of Good Hope in South Africa, which increased their transit time by up to 2 weeks.

CONCLUSIONS AND WAY FORWARD

This study presents three applications of the AIS data: (i) estimating port calls and waiting time, (ii) suggesting a proxy for trade activities, and (iii) presenting a case study using the data. These represent just a small fraction of the applications that can be derived from the data. New areas can be explored where high-frequency, real-time data can help policy makers make informed decisions in a more focused and timely manner.

In addition to serving the purpose of real-time monitoring, AIS-based ship movement data are useful for constructing coincident or leading indicators that follow economic activities. AIS-based trade indicators supplement traditional data sources in measuring trade flows and open up a role for real-time statistics as an important tool for policy makers to understand business cycles and signal emerging challenges in trade.

AIS data contributes to enhancing transparency in supply chains by enabling stakeholders to better understand maritime activities. Accordingly, it enables decision-making to improve efficiencies in ports and trade flows, mitigating the effects of supply chain disruptions. Increasing transparency and traceability in supply chains through digitalization is a catalyst for resilient operations, while the increased availability of accurate and timely data are critical for this purpose (Kim, Endriga, and Ardaniel 2022). Furthermore, AIS data analytics can contribute to trade and transport facilitation as information from the AIS database can provide useful insights about where and when to intervene to optimize operations in trade and maritime transport.

AIS real-time data can help policy makers identify areas of intervention (such as port infrastructure, improving operational efficiency, devising policies for expedited movement) to improve competitiveness. Factors like time taken by a shipping vessel to access a port from its trunk sea route, waiting time, total time spent at the port for unloading and loading can be obtained from the AIS data. Information and awareness of such metrics of port performance are significant in determining strategies to improve port operations and provide the groundwork for port development plans. Assessing port performance in an increasingly competitive landscape is critical to help policy makers identify interventions required to maintain and raise port competitiveness (Tan and Hilmola 2012; Kavirathna et al. 2018). Furthermore, port performance influences port selection as efficiency is considered as one of the important criteria in choosing ports (Kim, Kang, and Dinwoodie 2016; Van Dyck and Ismael 2015).

The high-frequency nature of AIS data is useful for assessing the near real-time impact of disruptions from disasters triggered by natural hazards and allows governments to better respond to such scenarios. The Asia and Pacific region is highly vulnerable to natural hazards. The number and intensity of these events are expected to increase. Timely details about the extent of disruption to the maritime sector, and consequently the economy, can give governments the information they require to better prepare for and respond to these events. Such information is valuable for small island developing states that experience some of the most devastating storms and rely on maritime infrastructure to facilitate most of their trade.

The AIS data set can help quantify the gaps and address challenges that the shipping industry faces to achieve zero-emission shipping. The shipping industry has committed to having scalable zero emission fuels[7] make up 5% of international shipping fuels by 2030 to achieve zero-emission shipping by 2050 (Palmer, Baresic, and Asmussen 2022). Literature using the AIS data set has already shown the potential to track shipping emissions during coastal and international transit, which make a large contribution to emissions but are not covered by port or local authority emission inventories (Goldsworthy and Goldsworthy 2015).

7 Fuels that have net zero well-to-wake greenhouse gas emissions and have the potential to be produced at a more competitive price than fossil fuels (Smith et al. 2021)

Some challenges need to be addressed to widen applications of AIS data. A special skill set in data analytics is needed to systematically translate data from big data sources that are often unstructured and researchers and policy makers find difficult to understand. High-frequency data derived from signals can lead to errors, especially if obtained from short-term noises, and hence may lead to a sub-optimal policy outcome. Moreover, the data are yet to be standardized across organizations, leaving room to doubt their quality and accuracy. Greater collaboration is needed among stakeholders—including the private sector—to improve the quality, reliability, and application of the data.

AIS data will have greater value when supplemented by data from other existing sources. This is often about validating information obtained from AIS data analytics to increase the robustness of outcomes. While AIS data have great potential in approximating trade, the absence of additional information on cargo carried by ships reduces the quality of the estimates. Additional details on shipping records such as bills of lading can be combined with AIS data to arrive at more precise estimates and yield deeper insights from inquiry about a particular situation.

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APPENDIX 1: DEFINITIONS OF THE AUTOMATIC IDENTIFICATION SYSTEM INDICATORS

- $\textit{Time in Port}_j = \sum(\textit{ArrivalDate}_{i,t} - \textit{DepartureDate}_{i,t+1})$ where i = unique IMO ship number; j = unique port name; t = time
- $\textit{Draft Change}_{i,t} = \textit{Arrival Draft}_{i,t} - \textit{Departure Draft}_{i,t}$
- Upon getting Draft Change, port calls can then be aggregated by the Draft Status.

$$\textit{Draft Status} = \begin{cases} \textit{Unladen}, & \textit{if Draft Change} > 0 \\ \textit{Laden}, & \textit{if Draft Change} < 0 \\ \textit{No Change}, & \textit{if Draft Change} = 0 \end{cases}$$

- $\textit{Trip Duration}_{i,t} = \textit{ArrivalDateFull}_{i,t} - \textit{SailDateFull}_{i,t-1}$
- $$\textit{Port Traffic} = \begin{cases} \text{“High”} & \textit{if Daily Port Call} \geq \textit{High Traffic} \\ \text{“Low”} & \textit{if Daily Port Call} \leq \textit{Low Traffic} \\ \text{“Normal”} & \textit{otherwise} \end{cases}$$
  where,
  High Traffic = Average Weekly Port Call Count + 2 ∗ (Standard Deviation of Weekly Port Call Count)
  Low Traffic = Average Weekly Port Call Count − 2 ∗ (Standard Deviation of Weekly Port Call Count)
- $\textit{Trade Volume}_1 = U_i * DWT_i$, based on Heiland et al. (2019)

$$U_i = \frac{H_{a,i} - H_{b,i}}{H_{s,i} - H_{b,i}} \times 100\%$$

where U_i = Utilization rate of ship *i*;
DWT_i = Deadweight of ship *i*
$H_{a,i}$ = actual draft
$H_{s,i}$ = scantling or design draft of ship *i*
$H_{b,i}$ = ballast draft of ship *i*

- $\textit{Trade Volume}_2 = \sum_i DWT_{i,t} = \frac{|d^D_{i,t} - d^A_{i,t}|}{\max(d_i)}$, based on Arslanalp, Marini, and Tumbarello (2019)

where $DWT_{i,t}$ = deadweight of the ship *i* arriving in port on week *t*
$d^A_{i,t}$ = draft of ship *i* upon arrival
$d^A_{i,t}$ = draft of ship *i* departure in the same week *t*
max (d_i) = max draft reported by the ship in the sample data

- $\textit{Trade Volume}_3 = \begin{cases} (\mu_{r,out} - \mu_{r,in})DWT, \textit{if } d_{r,in} \neq d_{r,out} \\ T_{average}, \textit{if } d_{r,in} \neq d_{r,out} \end{cases}$, based on Arslanalp, Marini, and Tumbarello (2021)

where $\mu_{r,in}$ = utilization rate when entering a port
$d_{r,in}$ = draft reported when entering a port
$\mu_{r,out}$ = utilization rate when leaving a port
$d_{r,out}$ = draft reported when leaving a port
$T_{average}$ = average of all non-zero trade flows observed for a given vessel at a given port based on the vessel's history of port calls (only assigned to vessels not in transit)

$$\mu_r = \frac{(Cb_r d_r - Cb_d d_d)LW\rho_w + DWT}{DWT}$$

where L = length
d_d = design draft (i.e. max draft)
Cb_d = block coefficient at design draft
μ_r = vessel payload at reported draft
W = Width
d_r = reported draft
Cb_r = block coefficient at reported draft

APPENDIX 2: TOP 30 CONTAINER PORTS, 2020

Rank	Port	Economy	Throughput (million TEUs)	% Total world throughput	% Total economy throughput
1	Shanghai*	PRC	43.5	5.45	17.7
2	Singapore*	Singapore	36.9	4.62	100.0
3	Ningbo-Zhoushan*	PRC	28.7	3.60	11.7
4	Shenzhen	PRC	26.6	3.32	10.8
5	Guangzhou	PRC	23.5	2.94	9.6
6	Qingdao	PRC	22.0	2.76	9.0
7	Busan*	Republic of Korea	21.8	2.73	76.8
8	Tianjin	PRC	18.4	2.30	7.5
9	Hong Kong, China*	Hong Kong, China	18.0	2.25	99.9
10	Rotterdam	Netherlands	14.3	1.80	98.8
11	Dubai	UAE	13.5	1.69	69.9
12	Port Klang*	Malaysia	13.2	1.66	49.7
13	Antwerp	Belgium	12.0	1.51	85.5
14	Xiamen	PRC	11.4	1.43	4.7
15	Tanjung Pelepas	Malaysia	9.8	1.23	36.8
16	Kaohsiung	Taipei,China	9.6	1.20	65.9
17	Los Angeles	US	9.2	1.15	16.8
18	Hamburg	Germany	8.5	1.07	47.4
19	Long Beach	US	8.1	1.02	14.8
20	Ho Chi Minh City	Viet Nam	7.9	0.98	63.2
21	New York/New Jersey	US	7.6	0.95	13.8
22	Laem Chabang	Thailand	7.5	0.94	73.9
23	Tanjung Priok	Indonesia	6.9	0.86	49.0
24	Colombo	Sri Lanka	6.9	0.86	100.0
25	Tanger Med	Morocco	5.8	0.72	82.7
26	Mundra	India	5.7	0.71	34.7
27	Yingkou	PRC	5.7	0.71	2.3
28	Piraeus	Greece	5.4	0.68	94.5
29	Valencia	Spain	5.4	0.68	31.2
30	Taicang	PRC	5.2	0.65	2.1

PRC = People's Republic of China, TEU = twenty-foot equivalent unit, UAE = United Arab Emirates, US = United States, * = ports included in the analysis.

Source: UNCTAD Maritime Transport Indicators (accessed 12 January 2023; https://hbs.unctad.org/maritime-transport-indicators/); Lloyd's List One Hundred Ports 2021. https://lloydslist.maritimeintelligence.informa.com/-/media/lloyds-list/images/top-100-ports-2021/top-100-ports-2021-digital-edition.pdf.

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