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Quantifying the impact of Typhoon Phanfone on Philippine port activity using automatic identification system data

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QUANTIFYING THE IMPACT OF TYPHOON PHANFONE ON PHILIPPINE PORT ACTIVITY USING AUTOMATIC IDENTIFICATION SYSTEM DATA

Madhavi Pundit, Immanuel Sin, Paolo Magnata, R. Duncan McIntosh, and Priscille Villanueva

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ABSTRACT

The automatic identification system (AIS) is a short-range coastal tracking system used to identify ships and their speed and location worldwide. This case study leverages high frequency AIS data to analyze the impact of typhoons on port activity in the Philippines. Maritime transport plays a pivotal role in facilitating trade and transportation of goods and passengers in an archipelago like the Philippines. The Philippines typically encounters 20 tropical cyclones each year, with significant impacts on port operations and economic activity. We study Typhoon Phanfone (known in the Philippines as Typhoon Ursula) that hit the Philippines in December 2019. Disruptions in maritime activity based on daily ship traffic were measured using AIS data over a 2-year period for the Philippines and its top trade partners. A Bayesian structural time series model was employed to build a counterfactual for quantifying the impact of Typhoon Phanfone on specific Philippine ports. This analytical framework that harnesses the potential of AIS data provides policymakers and stakeholders with a tool for near real-time impact assessment that informs planning regarding port operations, scheduling, and resource allocation, and can feed into medium-term disaster risk management decisions.

Keywords: AIS data, daily ship traffic, Bayesian structural time series model

JEL codes: C11, C32, C55, Q54

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1. Introduction and Motivation

Maritime trade is a crucial driver of the global economy, acting as a catalyst for international commerce and fostering economic expansion. According to the United Nations Conference on Trade and Development (UNCTAD), more than 80% of global trade volume is transported by sea, highlighting maritime transport as vital for international trade and the global economy (UNCTAD, 2022). This underscores the essential role of ports as pivotal hubs in facilitating the exchange of goods and commodities between and within economies.

Ports serve as gateways, linking domestic and international markets and connecting producers and consumers. But their location in coastal areas makes them susceptible to the impacts of extreme weather events (Verschuur et al., 2020; McIntosh and Becker, 2017; Becker et al., 2013; Ng et al., 2015; Notteboom and Rodrigue, 2008). The efficiency and functionality of ports are important for facilitating maritime trade, which is one of the drivers of economic growth and development especially for island economies. Any disruptions to port operations, such as those induced by typhoons, can have far-reaching consequences on trade flows, supply chains, and economic activity (UNCTAD, 2017).

The occurrence of typhoons poses significant challenges to maritime trade and port operations (Balakrishnan et al., 2022; McIntosh and Becker, 2019). Typhoons, known for their regularity and intensity, have a disruptive impact on port activities, leading to delays in vessel schedules and logistical complexities. They can also wreak havoc on port infrastructure, causing damage to docks, warehouses, and cargo handling equipment, thereby impeding the smooth flow of goods (Verschuur et al., 2020; Lam et al., 2017; Ng et al., 2015; Rose and Wei, 2013).

Frequent typhoons are a common occurrence in Asia and the Pacific, causing significant disruptions, especially in locations along the Pacific Rim such as the Philippines. The country already experiences an average of approximately 20 typhoons each year, and climate change is anticipated to decrease their overall frequency while intensifying their severity (Cinco et al., 2016; Merz et al, 2024). When Typhoon Phanfone (locally known as Typhoon Ursula) hit the Philippines in December 2019, it affected 3.4 million people and damaged 594,214 houses (NDRRMC, 2020). In addition, 23,789 passengers, 3,253 rolling cargoes, 157 vessels, and 46 motorbancas were reported stranded in various ports nationwide. The economic damage to infrastructure and agriculture was estimated at ₱5.7 billion or \$98 million. Understanding the magnitude and quantifying the impact of typhoons on port activities are essential for implementing effective disaster preparedness measures, enhancing port resilience, and mitigating the economic impact of future typhoon events.

By convention, disaster risk management offices often rely on post-disaster needs assessment (PDNA) reports to quantify the impact of typhoons or any other disaster. However, conducting a PDNA poses challenges, including producing a high-quality assessment report quickly, coordinating diverse partners under government leadership, and navigating fluid political environments (Jeggle and Boggero, 2018). These challenges can hinder timely decision-making and resource allocation for response and recovery efforts as the report becomes available several months after the disaster. As a result, there is a growing recognition of the need for more efficient and real time data collection methods to improve the responsiveness and effectiveness of disaster risk management (Ghaffarian et al., 2023).

The study seeks to assess the impact of typhoons on seaports using AIS data, focusing on Typhoon Phanfone. A measure of port activity is constructed to measure the extent of disruptions by comparing the actual ship count during the typhoon against a counterfactual. The statistical framework developed in this study is designed to be replicable and scalable, facilitating its application to other case studies aimed at providing initial insights on the impact of typhoons on ports or countries of interest, especially in the absence of PDNAs.

2. Related Works

2.1. Measuring Trade Flows Using Automatic Identification System Data

Since the 1990s, advancements in technology have gradually enhanced the ability to track movements of various ships worldwide. This improvement is primarily attributed to the integration of the automatic identification system (AIS). In 2004, the International Maritime Organization (IMO) mandated that all major commercial vessels (over 300 gross tons) carry AIS transponders. This requirement aims to enhance vessel safety by helping them avoid collisions and enabling port authorities to better manage maritime traffic.

As a self-reporting system that tracks vessel locations intermittently, AIS produces a large scale, granular dataset containing information on vessel characteristics, destination, and other onboard information, such as location, speed, and heading. Before generating indicators to monitor port activities, it is important to thoroughly understand the complexities involved in handling this large dataset. These include identifying the relevant variables necessary for deriving insights and considering computing power requirements.

In an International Monetary Fund working paper proposing high frequency indicators derived from AIS data, Arsanalp, Marini, and Tumbarello (2019) approach this problem by

focusing on port calls as the basis for constructing indicators. They reason that port call data would significantly reduce the size and complexity of the data without compromising accuracy, as the signal coverage of AIS receiving stations tends to be better near ports (Arnsanalp et al., 2019). However, they also note that port boundaries must be defined properly to ensure data accuracy. In that study, they rely on a commercial AIS data aggregator, MarineTraffic, for both AIS data and port boundary information to obtain port calls.

Building on port calls, Arnsanalp, Marini, and Tumbarello (2019) propose a two-step approach to measure economic trade activity using AIS data which is tested in Malta. First, several conditions are used to filter AIS data to focus on vessel activity that is related to maritime trade. Second, high frequency indicators are then derived using the aggregate count and load of ships passing through. The derived indicators are then compared against official maritime and trade volume statistics for Malta, which allows them to conclude that AIS data may serve as a useful proxy to capture port activity information which can be used to nowcast trade flows in real time (Arnsanalp et al., 2019).

Beyond this, several other studies highlight the versatility of an AIS-based approach in measuring trade flows. Cerdeiro and Komaromi (2020) also found that AIS-derived indicators can serve as a good proxy for low frequency trade volume indicators in the Netherlands. In addition, Arslanalp, Koepke, and Verschuur (2021) found similarly satisfactory results after comparing AIS-derived metrics against official trade data in Pacific Island countries.

2.2. Estimating Causal Impact Using Bayesian Structural Time Series Models

To objectively evaluate the impact of an external intervention such as a typhoon, it is best to utilize a robust framework. In the context of econometrics and marketing, Brodersen, Gallusser, Koehler, Remy, and Scott (2015) proposed utilizing Bayesian time series models to assess the causal effect of a given market intervention. By generalizing the difference-in-differences approach in a time series context, a counterfactual can be explicitly modeled using a synthetic control obtained through model averaging. This method works best for cases where there is a large control group available for modeling this counterfactual (Brodersen et al., 2015).

These methods have been implemented beyond commercial settings as well. In a previous study conducted by the ADB Institute, Bayesian structural time series (BSTS) models were utilized by Yabe, Zhang, and Ukkusuri (2020) to measure the economic impact of Hurricane Maria on businesses in Puerto Rico using mobility data. Interestingly, the structure of mobility data is comparable to that of AIS data, as it consists of a large dataset of pings sent anonymously

by mobile phones across a wide area. Significant data manipulation is necessary to be able to produce usable indicators just as working with AIS data would entail. The utilization of BSTS models enabled researchers to specifically quantify which types of businesses were significantly impacted by the presence of Hurricane Maria based on store visits derived from mobile phone location data. Ultimately, the availability of large scale mobility data enables unprecedented spatiotemporal granularity to inform relevant authorities where disaster relief and preparation are most needed (Yabe et al., 2020). These causal inference methods have been extensively applied across a wide variety of fields from socioeconomics (Harvey et. al., 2017), political science (Brandt and Freeman, 2006), to healthcare (De Vocht, 2016).

The unique characteristics of AIS data prove to be another suitable setting for the implementation of such BSTS models. Because AIS data have a comprehensive coverage of vessel activity both spatially and temporally, this wealth of data can serve as a large control group from which the counterfactual can be modeled. This control group can be formed by aggregating AIS-derived indicators across ports worldwide over a sizable period pre- and post-intervention of Typhoon Phanfone. Past studies have also shown the versatility of this approach beyond commercial settings, which means it would be suitable for this study to estimate the causal impact of typhoons on port activity.

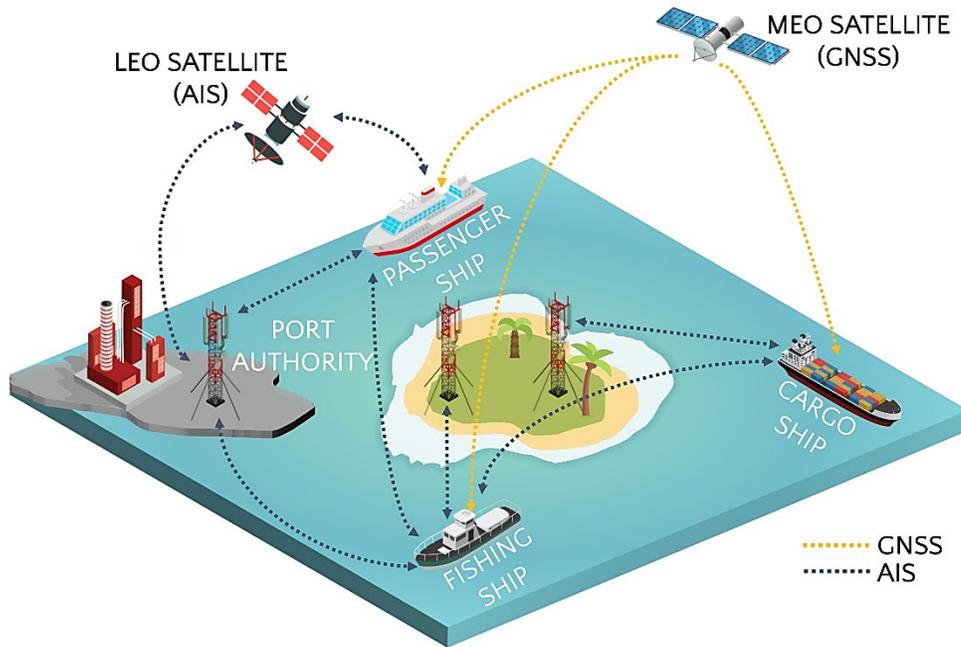
3. Data and Methodology

3.1. Data

3.1.1. Automatic Identification System

AIS is a short-range coastal tracking system used to identify ships, along with their movement and location. After acquiring unique identification and position data through global navigation satellite system technologies, AIS relays this information via radio signals to track the precise position, heading, and speed of each ship (Figure 1). This system was initially developed to improve maritime traffic safety and prevent potential collisions with support from IMO, but in recent years the data generated have proven useful in other areas. AIS data provide granular information on how various vessels move spatially and temporally.

Figure 1. Overview of the Automatic Identification System Communication Architecture



AIS = automatic identification system, GNSS = global navigation satellite system.

Source: Adopted from Aziz et al., 2020 (Figure 1).

For this study, AIS data obtained from the United Nations Global Platform (UNGP) and IHS Markit were used to construct indicators to measure port activity. UNGP is a publicly available data source containing raw AIS data whereas IHS is a privatized data source where some proprietary preprocessing methods are used. The extracted data cover vessel activity globally over a 2-year period from 1 January 2019 to 31 December 2020.

3.1.2. World Port Index

The World Port Index (WPI) is a nautical publication of the United States (US) National Geospatial-Intelligence Agency which serves as an online database of maritime port information for general reference. The database provides detailed location coordinates of 3,801 ports across 195 economies worldwide and is updated monthly. In this study, the location coordinates were used to define port areas in a standardized manner across all ports in the Philippines and its trade partners—more specifically, 1,984 ports in the Philippines and its top trade partners (Appendix A).

3.1.3. International Best Track Archive for Climate Stewardship

The International Best Track Archive for Climate Stewardship (IBTrACS) project, managed by the US National Centers for Environmental Information, is the most comprehensive historical database of tropical cyclones worldwide. It merges recent and historical tropical cyclone data from multiple agencies to create a unified, publicly available, best track dataset that improves interagency comparisons. The project consolidates weather report data gathered by 16 different agencies of the World Meteorological Organization and the US from 1842 to the present and is updated twice a week. In this study, IBTrACS datasets were used to identify which ports in the Philippines were directly affected by Typhoon Phanfone in December 2019.

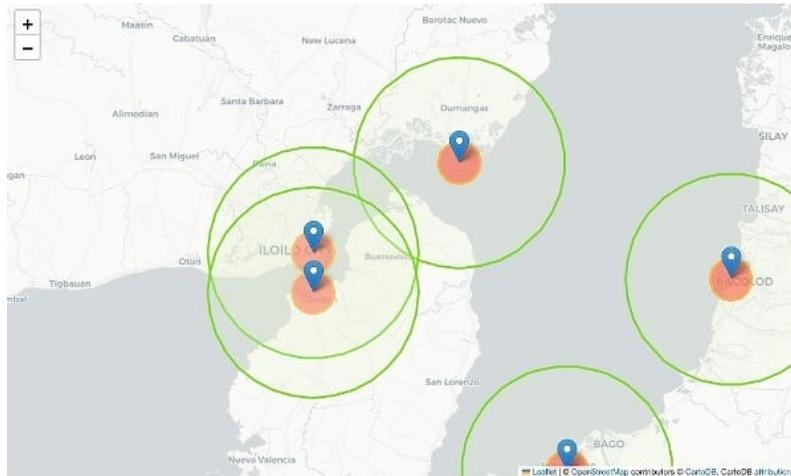
3.2. Methodology

3.2.1. Defining Port Areas

Based on location coordinates from WPI, there are 1,984 ports between the Philippines and its trade partners. Three methods can be employed to define port areas for identifying port calls: a manual approach, a distance approach, or a cluster-based approach (ADB, 2023). Although a manual approach to defining port boundaries for each port would have the highest accuracy, it would be too tedious and time-consuming to apply to approximately 2,000 ports worldwide. Similarly, a cluster approach will require considerable time and effort to train, test, and validate the clustering model on AIS signal data across the same number of ports worldwide. To ensure scalability and reproducibility of the analysis, a more efficient distance-based approach was employed to define port areas. This involved creating circular buffers around the port coordinates with radii of 2km and 10km. The choice of radii for this approach was arbitrary and can be adjusted in future studies to better suit specific needs or improve accuracy.

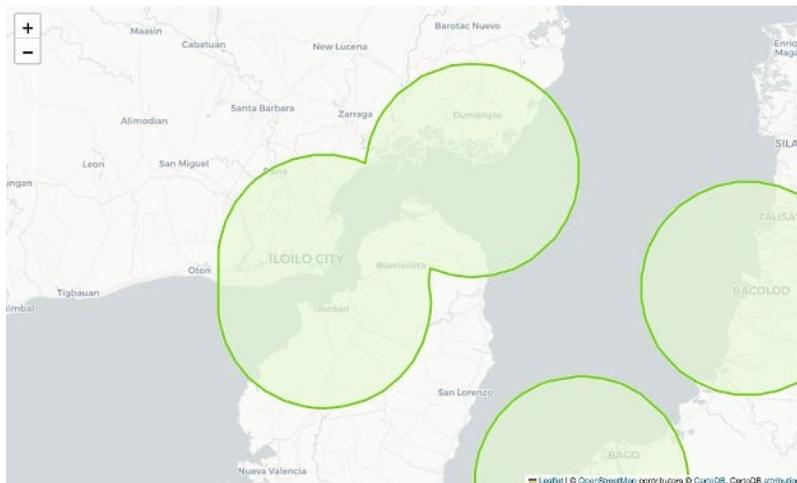
The 2km buffer region represented by the orange circle in Figure 2 was used to identify and clean up possible duplicate ports during data preprocessing. This approach ensures that each set of port coordinates indeed represents a distinct port in the real world. Subsequently, the 10km buffer region, depicted by the green circle in Figure 2, was employed to identify overlapping port areas and spatially merge them. This means that if two or more port areas overlap at the 10km buffer level, they will be merged and collapsed into one big port area (Figure 3). This is a necessary step to prevent the double counting of ship traffic flow passing through regions where multiple ports are close to each other. As a result, this approach reduces the 1,984 unique ports originally identified by WPI to 1,450 port areas.

Figure 2. Sample Ports in the Philippines with 2km (Orange) and 10km (Green) Circular Buffers



Source: Authors' estimates.

Figure 3. Sample Overlapping Ports in the Philippines Merged at 10km (Green) Circular Buffers



Source: Authors' estimates.

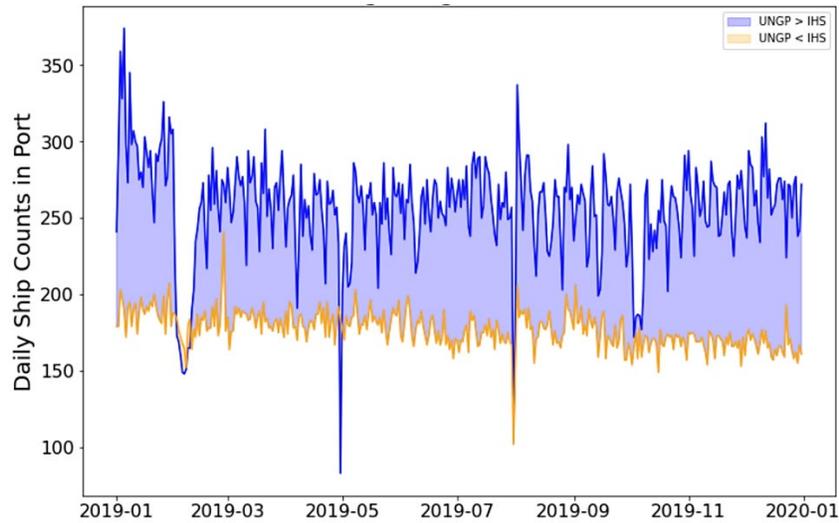
3.2.2. Measuring Port Activity

The raw AIS data were extracted to generate port call data for the identified 1,450 port areas. The port call data were aggregated to determine the number of unique ships that pass through each defined port area on a given day. This provides a relative measure of port activity to observe changes over time. Specifically, this is referred to as the unique ship count. This metric gauges maritime traffic at different ports based on ship volume.

To check for accuracy, a data validation exercise was conducted by comparing the generated indicators using AIS data obtained from UNGP versus the data from the commercial provider IHS Markit. The validation exercise only focused on singular port areas (i.e., ports that remained standalone following the methodology to define port areas). This was done so that ship counts could be easily compared and matched between UNGP and IHS Markit. Due to differences in identification conventions between WPI and IHS Markit ports, port names had to be used as the mapping criterion across the two sets of data resulting in 480 direct matches (approximately 33% of the 1,450 port areas involved in this study). This is a sufficient sample to evaluate how the resulting indicators from our two AIS data sources compare. For these 480 ports, the unique ship count indicator data were aggregated daily for the full year of 2019 from both UNGP and IHS Markit.

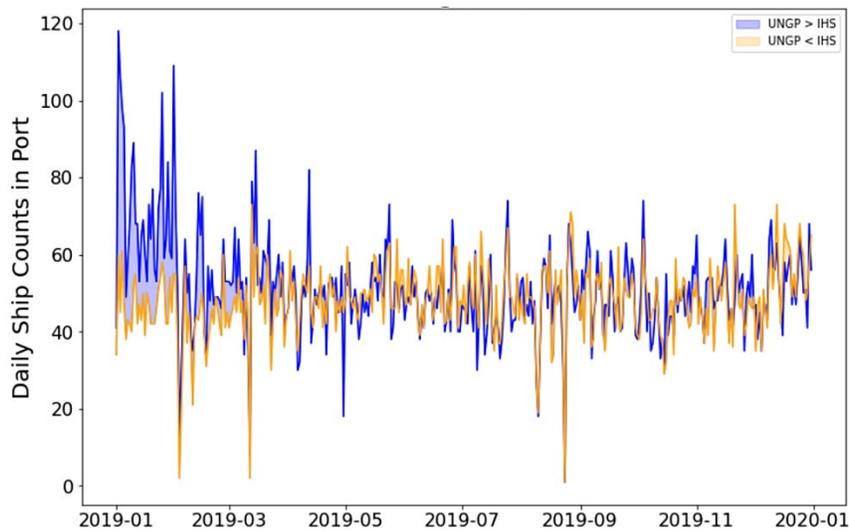
Several statistical methods were used to compare the quality of the indicators derived from the two data sources. First, a handful of singular ports were picked out to directly compare the daily ship counts observed throughout 2019. It was noticed that while the magnitude of the daily ship counts varied between the two AIS data sources, the overall trend of the time series was similar. For certain ports, UNGP-derived AIS indicators reported a higher daily unique ship count while for other ports, IHS Markit-derived indicators were higher. This variation is likely due to the arbitrary distance-based approach used to define port areas when calculating UNGP-based indicators as compared to the more detailed port boundary mapping used by IHS Markit. Figures 4.1 to 4.3 illustrate the variation in reported daily unique ship counts between the two AIS data sources.

**Figure 4.1. Daily Ship Count in 2019 for the Port of Hong Kong in Hong Kong, China
Based on the United Nations Global Platform and IHS Markit**



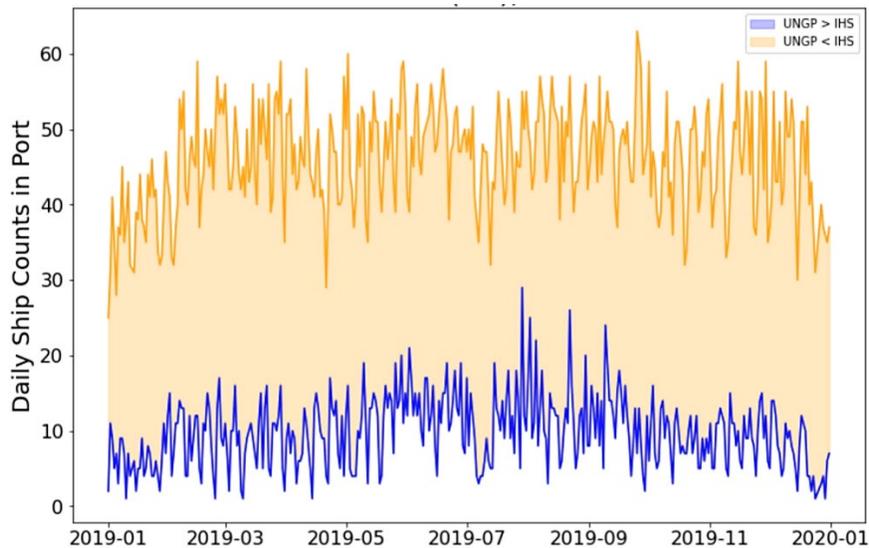
UNGP = United Nations Global Platform.
Source: Authors' estimates.

**Figure 4.2. Daily Ship Count in 2019 for the Port of Kaohsiung in Taipei,China
Based on the United Nations Global Platform and IHS Markit**



UNGP = United Nations Global Platform.
Source: Authors' estimates.

**Figure 4.3. Daily Ship Count in 2019 for the Port of London in the United Kingdom
Based on the United Nations Global Platform and IHS Markit**



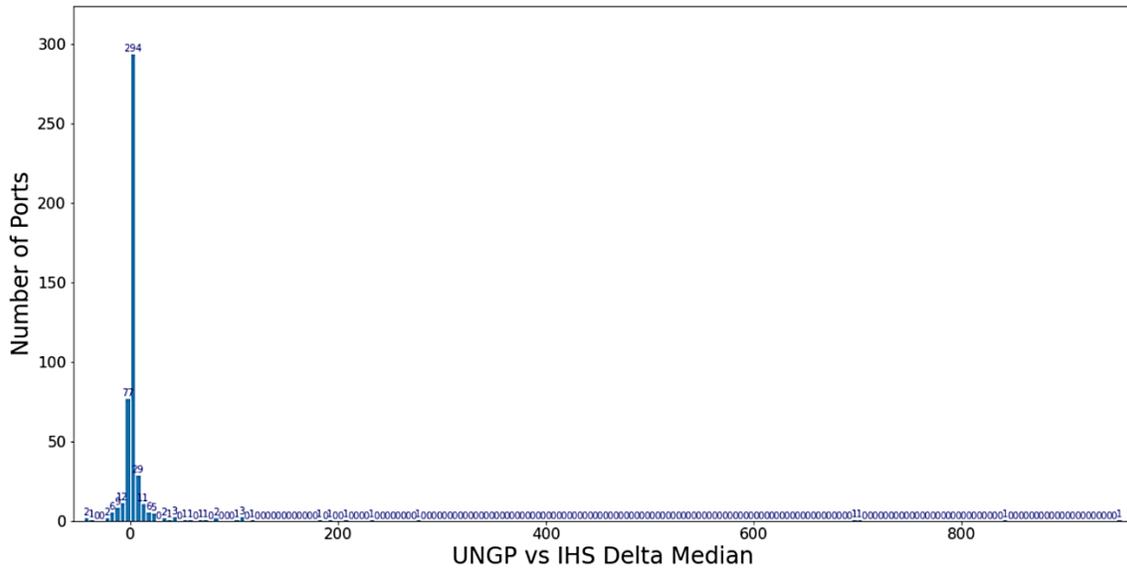
UNGP = United Nations Global Platform.
Source: Authors' estimates.

As the indicated daily unique ship count metrics vary significantly between the two AIS data sources, more generalized descriptive statistics were used to perform a comparison of the derived indicators. The median of the difference between the daily unique ship count values from UNGP and IHS Markit AIS data was obtained across all days in 2019 for each given port. Compared to the mean, this metric would be far less likely to be influenced by sporadic spikes in the data.

Using the median daily unique ship count difference, the distribution across all 480 singular ports was plotted (Figure 5). It can be observed that there are a handful of outlier ports where UNGP indicates more than 100 daily unique ships observed as compared to IHS Markit. However, such outliers are expected as the generalized distance-based approach would have its limitations versus a more nuanced approach.

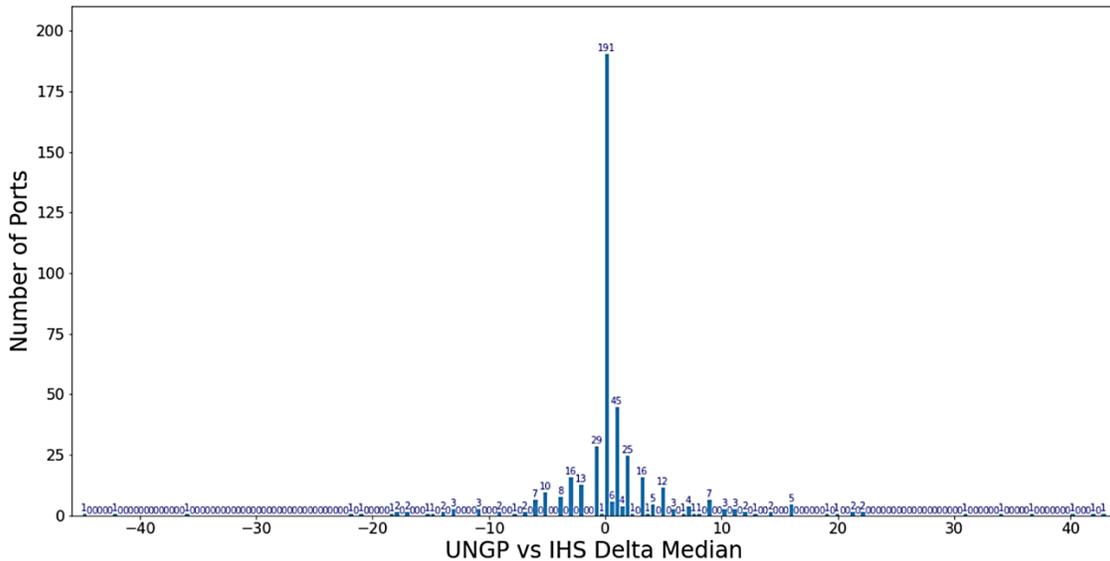
Narrowing down our view of this distribution further to the range where the median daily unique ship count difference statistic is at most 50 ships, it is observed that 191 ports (40%) have a median difference of 0 and an additional 81 ports (17%) have a median difference of ± 2 ships (Figure 6). This tells us that for approximately 60% of our sample of 480 ports, the median daily unique ship count difference is close to 0.

Figure 5. Distribution of Median Daily Ship Count Delta Between the United Nations Global Platform and IHS Markit in 2019



UNGP = United Nations Global Platform.
 Source: Authors' estimates.

Figure 6. Narrowed Distribution of Median Daily Ship Count Delta Between the United Nations Global Platform and IHS Markit in 2019



UNGP = United Nations Global Platform.
 Source: Authors' estimates.

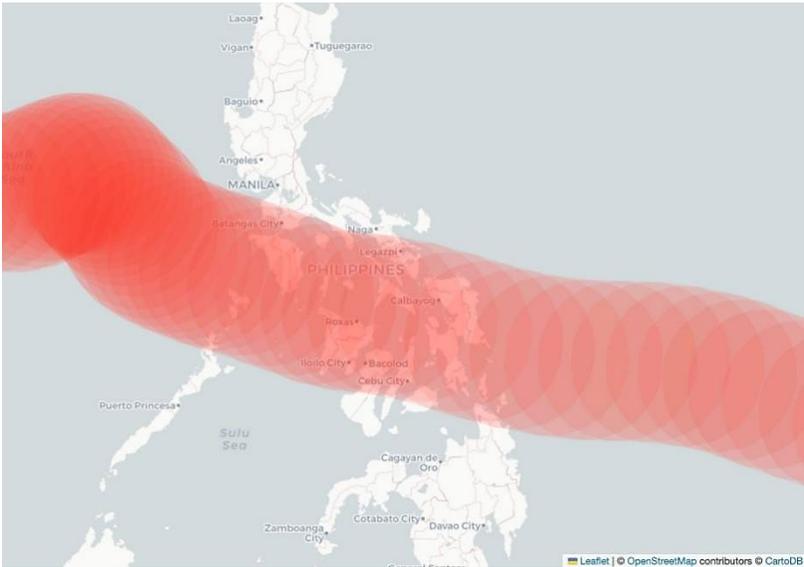
The AIS indicators derived from UNGP were used in this study to measure the causal impact of Typhoon Phanfone on Philippine ports following the outcome of the validation exercise. UNGP data can be efficiently scaled to cover a broad range of ports and geographic areas that are readily accessible and integrate well with various analytical tools and nowcasting frameworks. It is also cost effective and reduces the financial burden associated with data acquisition, making it a practical choice for ongoing research and future studies, particularly when working with a limited budget.

3.2.3. Identifying Treatment and Control Ports

Historical weather data from IBTrACS are used to determine the path of Typhoon Phanfone. IBTrACS only provides a time series of location coordinates mapping the typhoon's trajectory. Hence, a method is needed to determine the extent of the affected area, as the dataset does not specify the size of the impact zone for a given typhoon. A 200km buffer from the eye of the typhoon is applied to define the region directly affected by the typhoon following the methodology used in a previous ADB study to measure typhoon impact on vegetation (ADB, 2023). Since the intensity of each typhoon can vary, a distance-based assumption is applied. This parameter can be adjusted in future studies based on the specific characteristics of each typhoon.

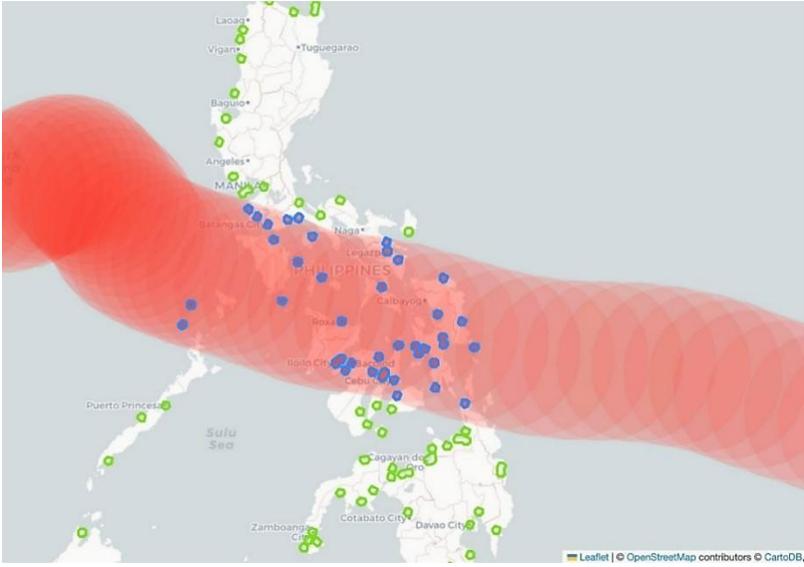
All ports that fall within the 200km zone, highlighted in red in Figure 7, are classified as the treatment group of affected ports. Ports located outside this 200km zone comprise the control group. The treatment group consists of 48 port areas, while the control group comprises the remaining 1,402 port areas, including those outside the Philippines (Figure 8). From this large control group, a synthetic control will be constructed to model the counterfactual scenario.

Figure 7. Path of Typhoon Phanfone in Dec 2019 with 200km Buffer (Red)



Source: Authors' estimates.

Figure 8. Path of Typhoon Phanfone in Dec 2019 with Treatment Ports (Blue) and Control Ports (Green)



Source: Authors' estimates.

3.2.4. Estimating Causal Impact

This study employs a BSTS model to infer the causal impact of interventions on time series data, following the methodology proposed by Brodersen, Gallusser, Koehler, Remy, and Scott (2015). This approach offers a robust framework for estimating the causal effect of an intervention

in a wide variety of settings. Utilizing observational time series data along with a defined intervention period, the model can be readily implemented using a premade R package developed by Brodersen, Gallusser, Koehler, Remy, and Scott (2015). In this study, the daily unique ship counts constitute the observational time series data and Typhoon Phanfone is the intervention whose causal impact will be estimated for a given port.

This BSTS-based approach builds on the concept of counterfactual reasoning, where the objective is to estimate what would have happened in the absence of an intervention. This is achieved through a state–space model comprising an observation equation and a state equation, which collectively describe how the observed data relate to latent states and how these states evolve over time. The model can be formally defined as follows:

The **observation equation** is given by:

$$y_t = Z_t^\top \alpha_t + \epsilon_t$$

where y_t represents the observed data at time t , α_t is the latent state vector, Z_t is the design matrix, and $\epsilon_t \sim N(0, \sigma_t^2)$ is the observation noise.

The **state equation** is given by:

$$\alpha_{t+1} = T_t \alpha_t + R_t \eta_t$$

where T_t is the transition matrix, R_t is the control matrix, and $\eta_t \sim N(0, Q_t)$ is the system noise.

The state vector α_t can be decomposed into several components, each capturing distinct aspects of the time series dynamics:

The **local linear trend** captures the underlying trend in the data:

$$\mu_{t+1} = \mu_t + \delta_t + \eta_{\mu,t}$$

where $\eta_{\mu,t} \sim N(0, \sigma_\mu^2)$ and $\eta_{\delta,t} \sim N(0, \sigma_\delta^2)$.

Additionally, **seasonal components** address regular seasonal patterns in the data and **regression components** incorporate the effect of contemporaneous covariates, accounting for external factors influencing the observed data.

To estimate causal impact, the model constructs a synthetic control by combining multiple time series that are predictive of the target series before the intervention but are unaffected by the intervention itself.

First, the BSTS model is fitted onto the pre-intervention period data to learn about patterns, relationships, and the underlying structure of the data. Next, the fitted model predicts the counterfactual time series for the post-intervention period without an intervention. The causal impact is the difference between the observed data and the counterfactual predictions during the post-intervention period, which can be expressed as:

$$Impact_t = y_t - \bar{y}_t$$

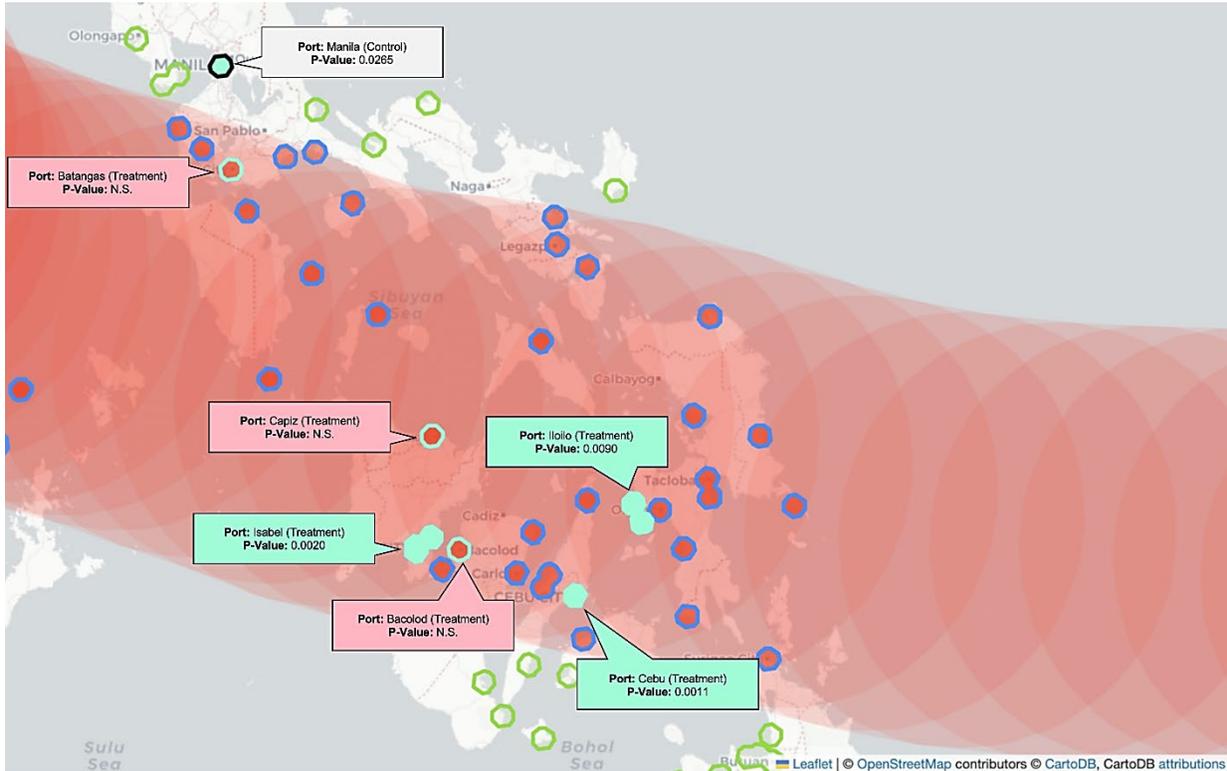
where y_t is the observed post-intervention data and \bar{y}_t is the predicted counterfactual.

In this study, the process of estimating the causal effect of Typhoon Phanfone on daily ship counts is implemented through the CausalImpact R package (Appendix B). Because this model assumes that the set of covariates is not itself affected by the intervention, the treatment ports identified in [3.2.3. Identifying Treatment and Control Ports], except for the port being analyzed, are removed from the dataset prior to each run. All remaining ports are then fed into the model as covariates to construct the synthetic control.

4. Analysis and Results

Daily ship counts were obtained over a 2-year period from 2019 to 2020 across all 1,450 port areas and fed into the BSTS model to evaluate the causal impact of Typhoon Phanfone on the time series. The model was then run for each study port. Daily unique ship counts were used as the primary variable for statistical analysis.

Figure 9. Path of Typhoon Phanfone in Dec 2019 with Selected Treatment Ports and Control Ports



Source: Authors' estimates.

Table 1. Summarized Statistical Results for Select Treatment and Control Ports After Typhoon Phanfone

Port	Manila	Cebu	Iloilo	Isabel	Batangas	Bacolod	Capiz
Group	Control	Treatment	Treatment	Treatment	Treatment	Treatment	Treatment
Counterfactual avg daily ship counts	21.6	27.0	5.5	7.8	10.4	4.5	10.4
Actual avg daily ship counts	23.7	17.5	4.7	4.1	10.5	4.2	10.5
% change (actual vs counterfactual)	10%	(35%)	(14%)	(47%)	1%	(6%)	1%
P-value	0.0265	0.0011	0.0090	0.0020	N.S.	N.S.	N.S.

() = negative.

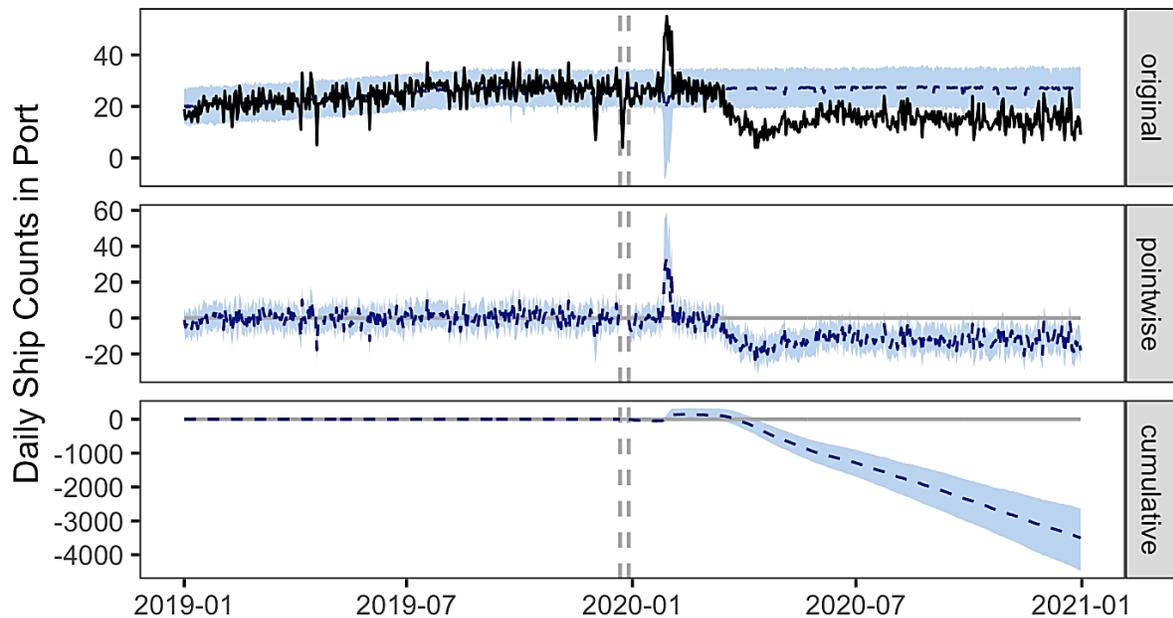
Note: The counterfactual statistic is the prediction of the BSTS model for the period after Typhoon Phanfone. Please see Appendix C for detailed results for each of the selected ports above.

Source: Authors' estimates.

For the seven selected individual Philippine ports, it can be observed that the difference between the predicted average daily ship count or the counterfactual and the actual average daily ship count varied. During the post-typhoon period, Cebu Port had an average daily ship count of approximately 17.49. By contrast, in the absence of a typhoon, we would have expected an average daily ship count of 27.02. The 95% interval of this counterfactual prediction is [24.40, 29.76]. Subtracting this prediction from the observed response yields an estimate of the causal effect the typhoon had on the daily ship counts. This effect is -9.53 with a 95% interval of $[-12.27, -6.91]$.

Post-Typhoon Phanfone (in 2020), Cebu Port saw a total of 6,450 ship calls. By contrast, had the typhoon not taken place, we would have expected a sum of 9,970. The 95% interval of this prediction is [9,000, 10,980]. In relative terms, the daily ship counts showed a decrease of -35% during the post-typhoon period. The 95% interval of this percentage is $[-41\%, -28\%]$. This means that the negative effect observed during the intervention period is statistically significant with a posterior tail-area probability of $p = 0.00101$.

Figure 10. Typhoon Phanfone Causal Impact on Cebu Port



Note: Daily ship counts before and after the typhoon for Cebu Port. Panel 1 shows the data (black solid line) and the counterfactual prediction (blue dashed line). The typhoon intervention is represented by the vertical dashed lines. Panel 2 shows the pointwise causal effect, which is the difference between the observed data and the counterfactual predictions. Panel 3 shows the cumulative effect, which is the sum of the pointwise contributions from the second panel.

Source: Authors' estimates.

Iloilo and Isabel ports also exhibited a lower number of actual average daily ship counts after Typhoon Phanfone as compared to the counterfactual. The reduction in the number of vessels at these ports is statistically significant, as indicated by p-values of less than 0.01. This evidence strongly suggests that the typhoon had a substantial impact, significantly reducing port traffic.

For other selected treatment ports, the same conclusion cannot be drawn. Specifically, for Batangas, Bacolod, and Capiz, there was no significant change in the average daily number of ships based on the counterfactual. This implies that not all treatment ports necessarily saw port traffic go down due to Typhoon Phanfone.

In analyzing the patterns of vessel traffic across various ports, a notable divergence in trends emerges. Ports like Manila and Nasugbu experienced cumulative increases in vessel count, while others, such as Cebu and Iloilo, saw declines. This raises the question of whether these shifts are a direct response to the adverse impacts felt by certain ports. Considering that some ports were more severely affected, it is reasonable to infer that vessel traffic was redirected to less impacted ports. This shift suggests a tendency for shipping routes and operational preferences to adapt to prevailing conditions in ways that may contribute to longer-term changes in traffic patterns, even after the immediate crisis has passed.

Moreover, the post-typhoon spikes in ship count observed at specific ports likely correlate with increased relief efforts. In the aftermath of a disaster, surging humanitarian needs drive a sharp increase in demand for shipping and logistics support. The resulting influx of vessels could reflect a coordinated response to deliver essential supplies and aid to affected areas. This reinforces the role of ports not only as transit points but also as critical hubs for disaster recovery. Together, these dynamics illustrate how external shocks can significantly reshape maritime activity and influence the broader dynamics of regional trade and relief logistics.

5. Conclusion

These results show that AIS data can be useful for nowcasting daily ship traffic across typhoon affected ports. In the case of Typhoon Phanfone that hit the Philippines in 2019, it was observed that the typhoon had a significant causal impact that led to a reduction in daily ship traffic levels in affected ports, namely Cebu, Iloilo, and Isabel. However, there were also some affected ports, namely Batangas, Bacolod, and Capiz, where the results of the causal impact analyses proved not to be statistically significant.

While AIS data can be used for nowcasting purposes in the event of a typhoon, there is still room to improve the precision of this approach. One area for improvement would be to utilize more precise port area boundary definitions to capture port-specific ship traffic more accurately. It was observed that there are clusters of ports worldwide that are less than 10km away from one another, which makes isolating port traffic more challenging. Should a specific port authority intend to use this framework, it can improve the accuracy of AIS-derived indicators for specific ports by using more precise mappings of port boundaries.

Another area for improvement would be to conduct this study over a wider variety of indicators such as ships' cargo tonnage or time spent in port which can also be derived from AIS data. Extending the study to such indicators would give a more holistic understanding of other aspects of port activity that may be impacted by typhoons. This can provide more detailed recommendations as to how port authorities can better manage activity in the event of typhoon disruptions.

Lastly, this methodology can be extended to other case studies of ports affected by other typhoons in the past. This will further evaluate the robustness of the developed framework to nowcast ship traffic through various ports as this study only focused on how one specific typhoon affected a set of ports in the Philippines.

Overall, measuring and understanding the impact of typhoons on port activity worldwide can help improve port resiliency and guide policy to reduce disruptions in the delivery of goods and minimize losses. This would improve overall maritime trade efficacy, especially in times where there are potential disruptions due to adverse weather conditions.

APPENDIXES

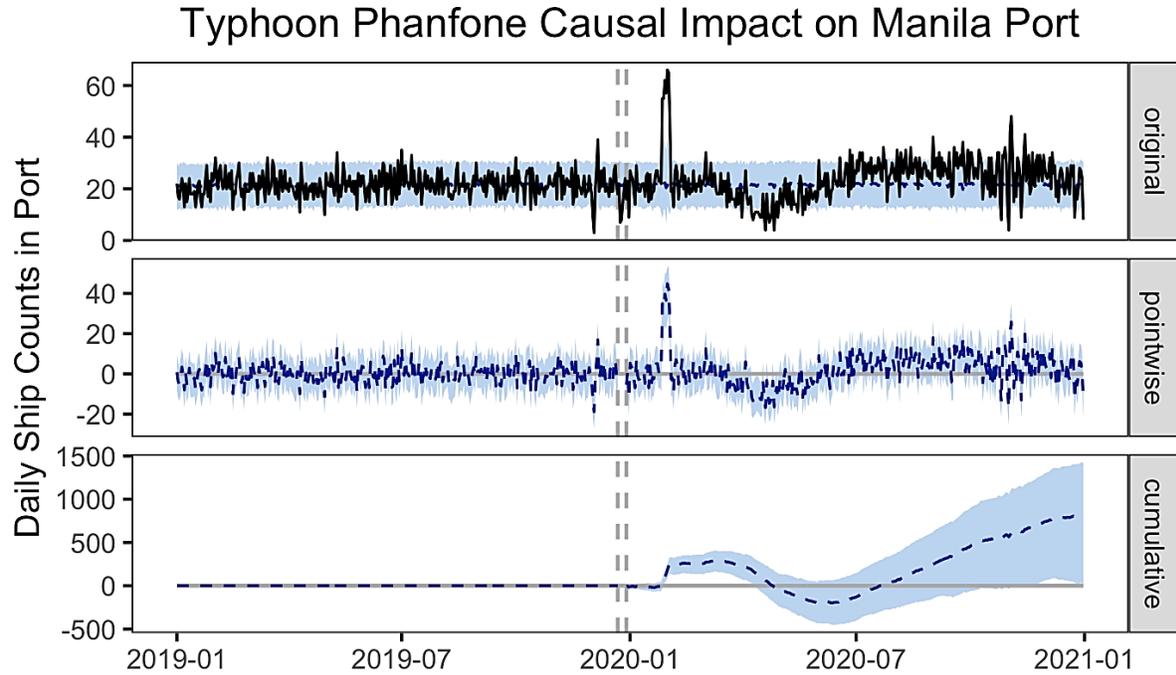
Appendix A. List of Top Trade Partners of the Philippines

Code	Economy
AE	United Arab Emirates
AUS	Australia
CAN	Canada
PRC	People's Republic of China
FRA	France
GER	Germany
HKG	Hong Kong, China
IND	India
INO	Indonesia
JPN	Japan
KOR	Republic of Korea
KW	Kuwait
MAL	Malaysia
NET	Netherlands
RU	Russia
SA	Saudi Arabia
SIN	Singapore
TAP	Taipei, China
THA	Thailand
UKG	United Kingdom
US	United States
VIE	Viet Nam

Appendix B. CausalImpact R Package authored by Kay H. Brodersen and Alain Hauser:
<https://google.github.io/CausalImpact/CausalImpact.html>

Appendix C. Detailed Statistical Results for Selected Ports in the Philippines

Port of Manila (Control)



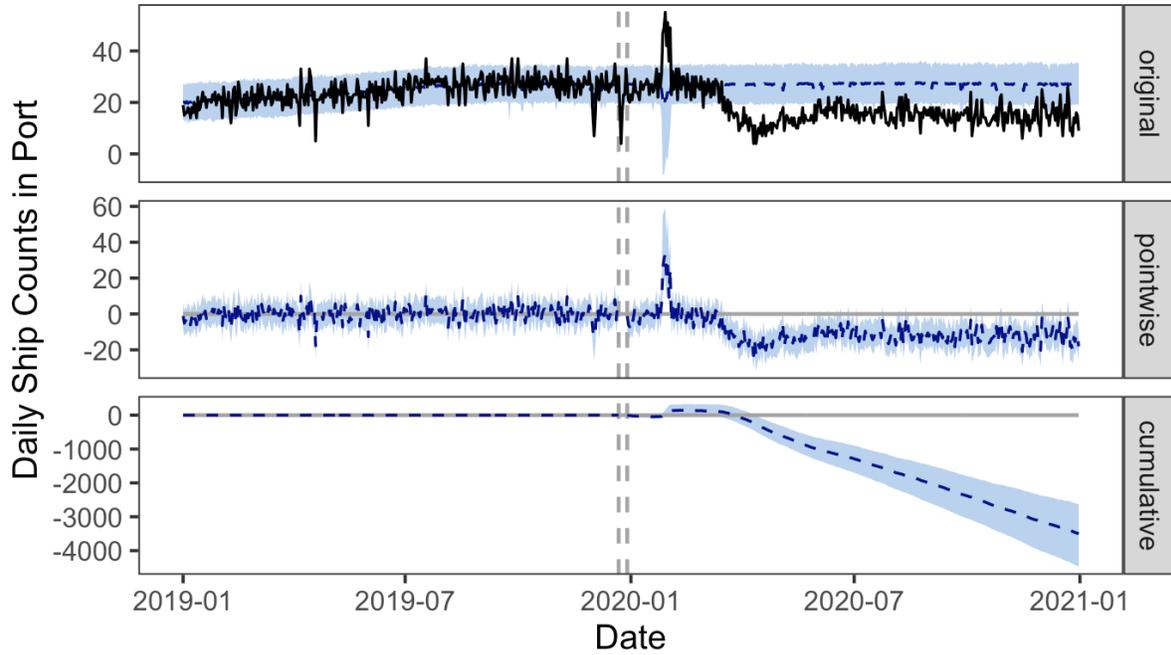
	Average	Cumulative
Actual	23.73	8,757
Prediction (s.d.)	21.60 (0.96)	7,972 (354.34)
95% CI	[19.89, 23.63]	[7340, 8720]
<hr/>		
Absolute effect (s.d.)	2.13 (0.96)	785.5 (354.34)
95% CI	[0.10, 3.84]	[36.9, 1417.0]
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Relative effect (s.d.)	10% (4.9%)	10% (4.9%)
95% CI	[0.42%, 19%]	[0.42%, 19%]
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Posterior tail-area probability p:	0.02442	
Posterior probability of a causal effect	97.558%	

CI = causal impact, s.d. = standard deviation.

Source: Authors' estimates.

Port of Cebu (Treatment)

Typhoon Phanfone Causal Impact on Cebu Port



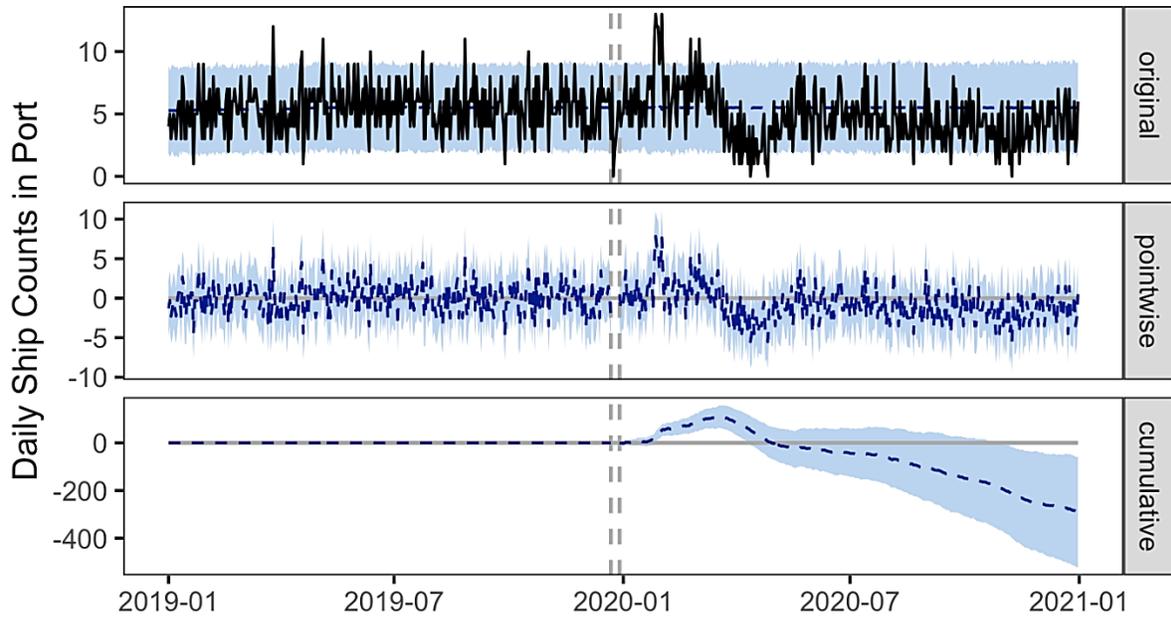
	Average	Cumulative
Actual	17.49	6,454
Prediction (s.d.)	26.99 (1.3)	9,959 (485.7)
95% CI	[24.68, 29.71]	[9106, 10964]
Absolute effect (s.d.)	-9.50 (1.3)	-3,504.6 (485.7)
95% CI	[-12.22, -7.2]	[-4510.0, -2651.7]
Relative effect (s.d.)	-35% (3.1%)	-35% (3.1%)
95% CI	[-41%, -29%]	[-41%, -29%]
Posterior tail-area probability p:		0.00106
Posterior probability of a causal effect		99.894%

CI = causal impact, s.d. = standard deviation.

Source: Authors' estimates.

Port of Iloilo (Treatment)

Typhoon Phanfone Causal Impact on Iloilo Port



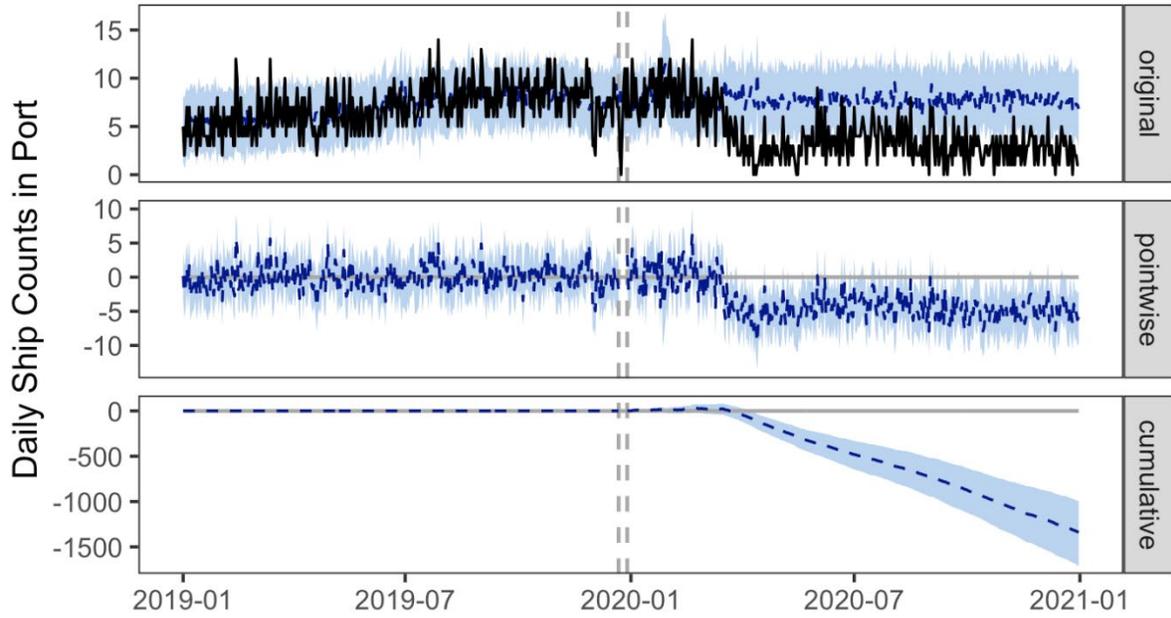
	Average	Cumulative
Actual	4.72	1,743.0
Prediction (s.d.)	5.51 (0.32)	2,031.6 (118.44)
95% CI	[4.91, 6.10]	[1811.2, 2250.3]
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Absolute effect (s.d.)	-0.78 (0.32)	-288.55 (118.44)
95% CI	[-1.37, -0.18]	[-507.3, -68.17]
<hr/>		
Relative effect (s.d.)	-14% (5.1%)	-14% (5.1%)
95% CI	[-23%, -3.8%]	[-23%, -3.8%]
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Posterior tail-area probability p:		0.00902
Posterior probability of a causal effect		99.098%

CI = causal impact, s.d. = standard deviation.

Source: Authors' estimates.

Port of Isabel (Treatment)

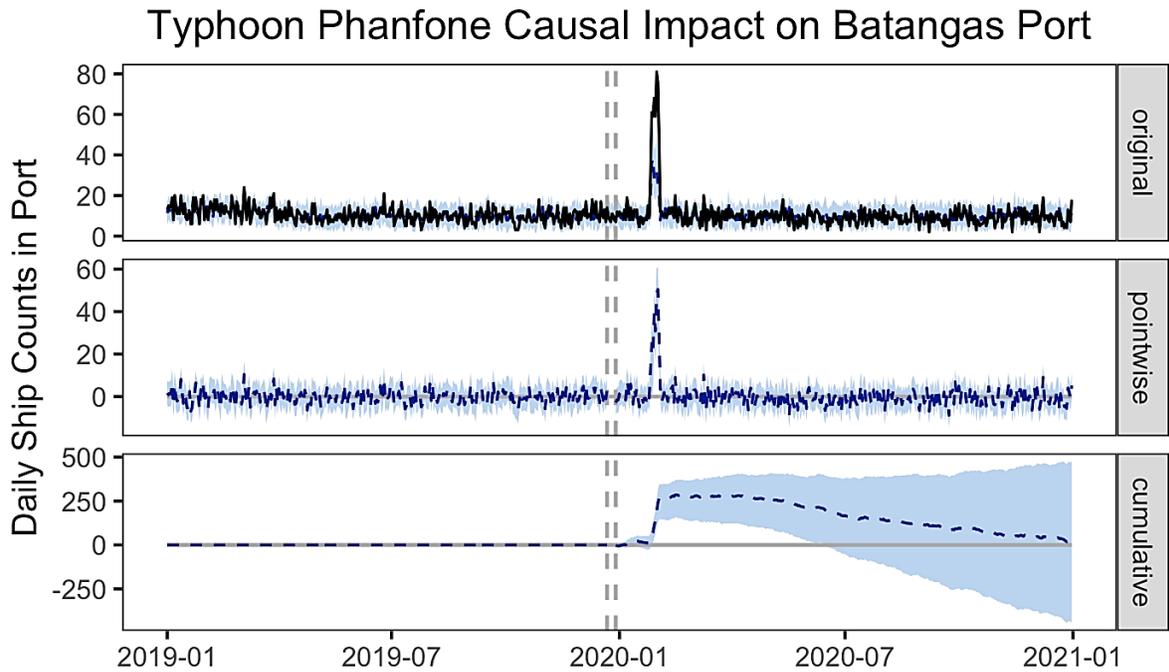
Typhoon Phanfone Causal Impact on Isabel Port



	Average	Cumulative
Actual	4.13	1,524.0
Prediction (s.d.)	7.76 (0.51)	2,863.2 (189.43)
95% CI	[6.85, 8.74]	[2527.4, 3225.9]
<hr/>		
Absolute effect (s.d.)	-3.63 (0.51)	-1,339.2 (189.43)
95% CI	[-4.61, -2.72]	[-1701.9, -1003.4]
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Relative effect (s.d.)	-47% (4.4%)	-47% (4.4%)
95% CI	[-53%, -40%]	[-53%, -40%]
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Posterior tail-area probability p:		0.00200
Posterior probability of a causal effect		99.800%

CI = causal impact, s.d. = standard deviation.
 Source: Authors' estimates.

Port of Batangas (Treatment)

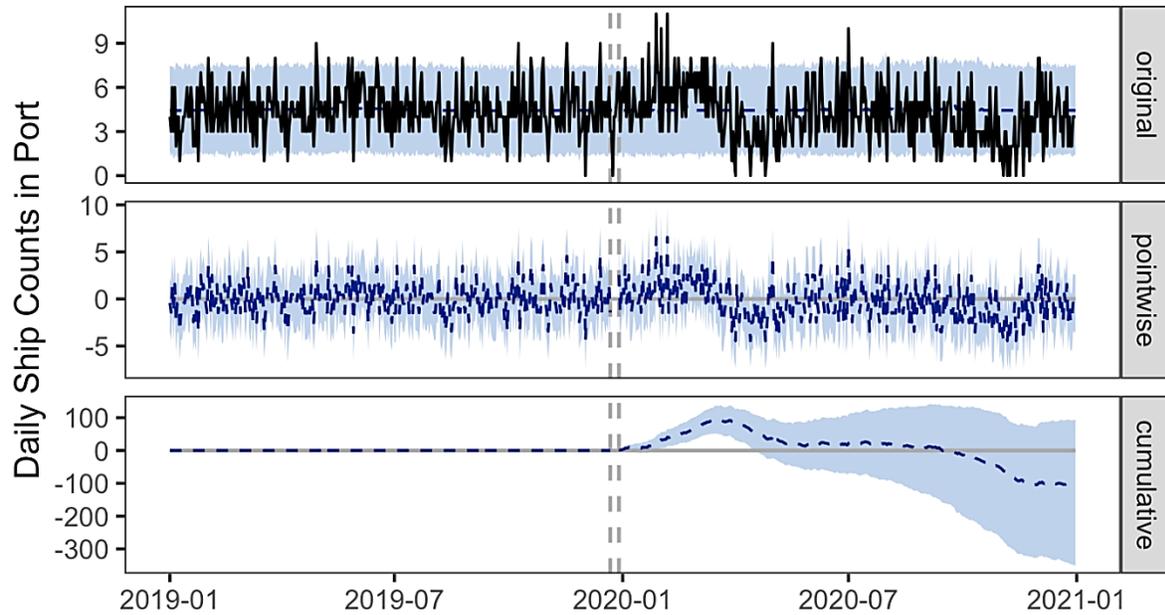


	Average	Cumulative
Actual	10.51	3,879
Prediction (s.d.)	10.43 (0.72)	3,850 (265.95)
95% CI	[9.12, 11.74]	[3365.3, 4333]
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Absolute effect (s.d.)	0.077 (0.72)	28.554 (265.95)
95% CI	[-1.23, 1.39]	[-453.9, 513.7]
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Relative effect (s.d.)	1.3% (8.5%)	1.3% (8.5%)
95% CI	[-10%, 15%]	[-10%, 15%]
<hr/>		
Posterior tail-area probability p:		0.46285
Posterior probability of a causal effect		53.715%

CI = causal impact, s.d. = standard deviation.
 Source: Authors' estimates.

Port of Bacolod (Treatment)

Typhoon Phanfone Causal Impact on Bacolod Port



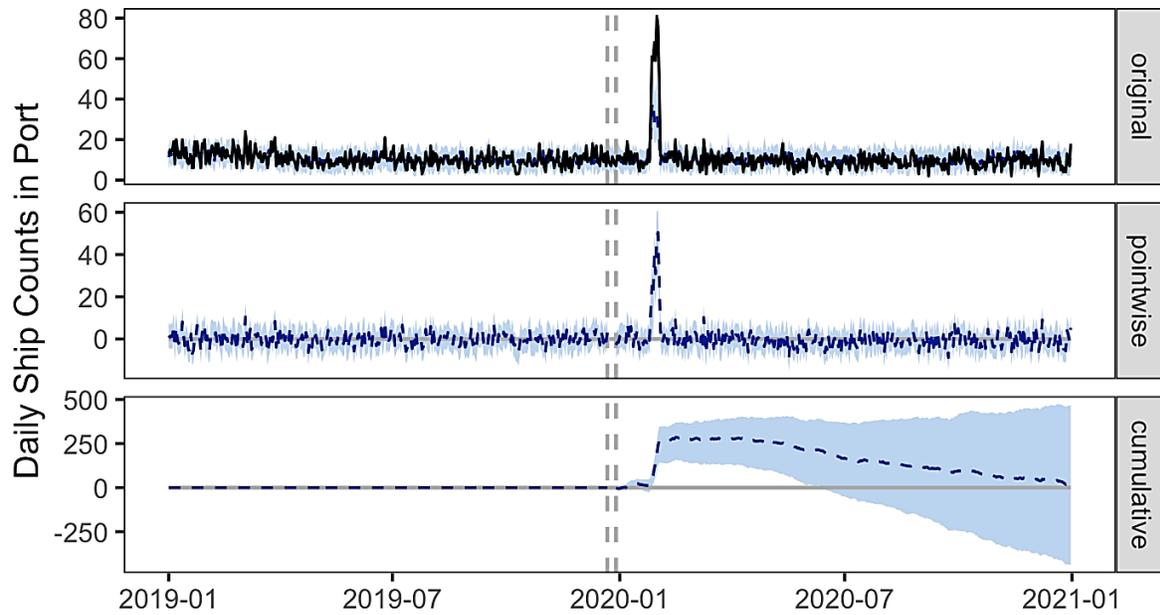
	Average	Cumulative
Actual	4.16	1,535.0
Prediction (s.d.)	4.46 (0.32)	1,646.1 (119.05)
95% CI	[3.91, 5.11]	[1444.4, 1885.7]
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Absolute effect (s.d.)	-0.30 (0.32)	-111.1 (119.05)
95% CI	[-0.95, 0.25]	[-350.72, 90.59]
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Relative effect (s.d.)	-6.2% (7.5%)	-6.2% (7.5%)
95% CI	[-19%, 6.3%]	[-19%, 6.3%]
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Posterior tail-area probability p:		0.15130
Posterior probability of a causal effect		84.870%

CI = causal impact, s.d. = standard deviation.

Source: Authors' estimates.

Port of Capiz (Treatment)

Typhoon Phanfone Causal Impact on Capiz Port



	Average	Cumulative
Actual	10.51	3,879
Prediction (s.d.)	10.43 (0.71)	3,850 (261.23)
95% CI	[9.22, 11.69]	[3400.7, 4314]
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Absolute effect (s.d.)	0.077 (0.71)	28.554 (261.23)
95% CI	[-1.18, 1.30]	[-434.7, 478.3]
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Relative effect (s.d.)	1.2% (8.4%)	1.2% (8.4%)
95% CI	[-10%, 14%]	[-10%, 14%]
<hr/>		
Posterior tail-area probability p:	0.46687	
Posterior probability of a causal effect	53.313%	

CI = causal impact, s.d. = standard deviation.
 Source: Authors' estimates.

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Quantifying the Impact of Typhoon Phanfone on Philippine Port Activity Using Automatic Identification System Data

This paper explores how high frequency automatic identification system (AIS) data can be leveraged to assess the near real-time impacts of typhoons on maritime activity. The analysis centers on Typhoon Phanfone, which struck the Philippines in December 2019. Using a Bayesian structural time series model to analyze daily ship traffic, the study quantifies disruptions at ports affected by typhoons. The proposed framework provides a valuable tool for rapid impact assessment, aiding disaster risk management, port operations planning, and resource allocation.

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