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Causal Inference in Supply Chain Management: How Does Ever Given Accident at the Suez Canal Affect the Prices of Shipping Containers?

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Abstract

In March 2021, the Ever Given, a colossal 4000-meter-long container ship with a capacity of 20,000 TEUs (Twenty-foot equivalent units), became lodged in the Suez Canal for six days, causing a significant disruption. This accident blocked approximately 400 ships, impacting not only the vessel itself and the canal but also global trade and the already strained global supply chain post-pandemic. Our research leverages causal inference techniques to rigorously assess and quantify the causal effects of the Ever Given accident on the World Container Index (WCI). We conducted experiments using time series data from eight major global shipping routes, achieving statistically significant results with a confidence level of 99.89%. This research conclusively demonstrates that the Ever Given incident at the Suez Canal had a substantial impact on shipping container prices, quantifying the effect as a remarkable 40% price increase post-exposure. By offering companies the ability to apply causal inference in understanding cause-and-effect dynamics within their supply chain networks, this study equips them with the knowledge needed to make well-informed decisions, especially in times of disruption, thus facilitating the optimization of their supply chain configuration and operations.

Keywords: Causal inference; supply chain management; supply chain disruption; time series analysis; SARIMA; Prophet

1. Introduction

On March 23, 2021, the Ever Given, a massive 20,000 TEU container ship measuring 4,000 meters long, became stuck in the Suez Canal until it was finally freed on March 29, 2021 [1]. The Suez Canal, spanning approximately 200 km across Egypt from North to South, is a vital maritime link between Europe and Asia [2]. Handling around 19,000 ships annually and facilitating about 12% of global trade, it is a crucial and sensitive trade route [3]. The Ever Given incident, resulting in the blockade of approximately 400 ships for a week [4], profoundly impacted the

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already strained global supply chain in the post-pandemic period. This ripple effect continues to affect businesses and consumers today [5].

The growing complexity of supply networks, fueled by interconnectivity and rapid technology advancements, challenges supply chain efficiency. These networks consist of interrelated, sequential processes where the performance of one process affects the entire chain. This complexity makes supply chains vulnerable to unforeseen disruptions like COVID-19 and the Suez Canal's Ever Given incident. To address these issues, various simulation models, including Petri Nets, System Dynamics, Discrete-Event Simulation, Bayesian Belief Networks (BBN), Agent-Based Modeling, Interpretative Structural Modeling (ISM), Monte Carlo Modeling, and Input-Output Modeling [6], have been employed. Our research uses causal inference techniques to quantify the Ever Given incident's impact on supply chain networks, especially shipping container prices. These methods can complement established models like system dynamics and BBN, improving our understanding of supply chain dynamics and resilience.

Causal inference entails designing and analyzing data to uncover causal relationships between treatment and outcome variables. It has evolved to leverage machine and deep learning to address complex real-world problems and provide answers to previously unanswered questions. In supply chain management, causal inference has potential applications, particularly for assessing supply chain networks.

In our research, we use causal inference to assess and quantify the causal effects of the Ever Given accident on the WCI. We focus on historically assessing container freight rates across eight global maritime shipping routes (see Table 1). The data comes from Drewry, a London-based consultancy firm with over 50 years of maritime research expertise. Drewry World Container Index (WCI) is a highly trusted container shipping index used by leading global retailers, manufacturers, and government bodies. WCI traditionally supports various supply chain management analyses and planning for maritime shipping forecasting. These data provide an excellent opportunity for a causal inference experiment.

We selected these eight maritime shipping routes because they directly represent container freight rate prices, as indicated by Drewry, the study's conducting consultancy. We carefully chose routes to ensure a comprehensive analysis, encompassing those passing through and bypassing the Suez Canal. This selection guarantees comparability and representativeness. Importantly, the paper indirectly addresses potential bias from the COVID-19 pandemic's impact on freight rates by including routes likely affected by the pandemic. It mitigates bias and strengthens the foundation for examining the causal impact of events like the Ever Given incident on container freight rates.

Table 1: Drewry WCI composite eight route indices weighted for volume (in Tons) on each route representative trade.

Route	Representative Trade	Volume	Weight
Shanghai - Rotterdam	Far East to North Europe	8.740	0.248
Rotterdam - Shanghai	North Europe to Far East	3.980	0.113
Shanghai – Genoa	Far East to Mediterranean	4.850	0.138
Shanghai – Los Angeles	Far East to US West Coast	8.440	0.239
Los Angeles – Shanghai	Us West Coast to Far East	4.100	0.116
Shanghai – New York	Far East to UD East Coast	3.100	0.088
New York – Rotterdam	US East Coast to North Europe	0.920	0.026
Rotterdam – New York	North Europe to US East Coast	1.130	0.032

2. Literature Review

2.1. Supply chain disruptions

Wu et al. proposed a disruption analysis network model for examining the propagation of disruptions throughout entire supply chains and their impact on the supply chain system. This model enables detailed analysis without the computational burden of a full-scale model, streamlining supply chain management and resulting in quicker customer response times, cost reductions, improved flexibility, reduced inventories (including work-in-process), decreased obsolescence, and minimized bullwhip effect [7]. Bugert and Lasch's critical review highlighted the potential for improved analysis results by integrating dynamic and interconnected factors into disruption risk models and considering disruption propagation within supply chains [6].

Recent research has focused on the analysis of supply chain disruptions caused by the COVID-19 pandemic. Some researchers discussed how COVID-19 led to unemployment, income loss, a global stock decline, and rising oil prices, resulting in supply chain disruptions across various sectors, including food, pharmaceuticals, electronics, and automotive industries [8, 9]. Xu et al. have employed causal analysis to investigate the impact of COVID-19 on the effectiveness and responsiveness of global supply chains [10]. The Ever Given incident also caused supply chain disruptions, leading to material supply delays and container shortages [11]. However, these prior studies did not quantify the extent of these disruptions. Therefore, this paper focuses on utilizing causal inference as a method to quantify the impacts of supply chain disruptions.

2.2. Causal inference for timeseries

A time series comprises sequential real values of a variable, typically at equidistant time intervals. The central focus of time series models lies in the observations rather than time itself. Techniques for modeling time series data include Auto-Regressive Integrated Moving Average (ARIMA), which explains values using past observations, assuming stationarity and seasonality [12]. Seasonal ARIMA (SARIMA) extends ARIMA to include seasonality. Prophet, developed by Facebook, decomposes time series into trend, seasonality, and holidays [13]. It resembles a generalized additive model (GAM) and supports various trend models, flexible seasonality with Fourier series, and modeling irregular events with nonperiodic patterns using holidays [14].

In this study, we focus solely on causal effects estimation in the context of causal inference, excluding causal discovery. The choice of causal effects estimation methods depends on the experimental framework, subjects, and data limitations. Causal inference for time series presents unique challenges due to the temporal nature of the data and the suitability of techniques for estimating counterfactuals in sequential data. We categorize causality in time series data into two groups: time-invariant and time-varying treatment effects [15].

Time invariant treatment effect occurs at a specific time without subsequent changes. In time series data for the treated group, the goal is to determine the counterfactual outcome, representing how the non-treated group's time series would have evolved post-treatment. To estimate causal treatment effects, methods such as Average Treatment Effect (ATE) and Average Treatment Effect of the Treated (ATT) compare outcomes between the treated and non-treated groups. Difference of Differences (DD) is commonly used for this purpose in time series data [16]. However, DD may overfit and underestimate treatment effects when data exhibits high autocorrelation. The *Causal Impact* method was developed to address this issue. It extends DD by leveraging Bayesian Structural Time Series (BSTS) to infer causality from discrete interventions [17]. Causal Impact learns the interdependence between treated and non-treated groups in advance and uses this knowledge to generate a counterfactual outcome sequence post-intervention.

Time-varying treatment effect unfolds over multiple timestamps [18]. In such cases, time-dependent treatments call for different approaches than time-invariant ones. One such method is Marginal Structural Modeling (MSM), a variation of Structural Nested Models (SNMs) [19]. MSM handles multiple treatment possibilities by constructing counterfactuals for each using Inverse Probability of Treatment Weighted (IPTW). IPTW assigns weights to observations based on the inverse probability of treatment, often considering confounders and prior treatment data. However, linear regression-based methods like SNM and MSM may yield erroneous results when dealing with complex dependencies between treatment and outcomes. Deep learning techniques have emerged to address this challenge, including Recurrent Marginal Structural Networks (RMSN) and Deep Sequential Weighting (DWS). These methods handle nonlinearity in outcomes and learn to predict representations of hidden confounders. This demonstrates the limitations of classical statistical techniques in diverse applications [15].

3. Methodology

3.1. Data collection and description

The dataset used in this experiment comprises time series data of the world container price index across eight major global routes (see Table 1). The time series have a uniform weekly frequency, spanning 567 observations from June

23, 2011, to May 26, 2022, without missing data. The data was obtained via web scraping from the Drewry WCI source in JSON format, containing time series for the eight routes (refer to Table 1), a global composite, and route metadata. A Python class was developed to streamline data management, enabling extraction of time series, unique dimensions (e.g., date or WCI), metadata retrieval, and the creation of Pandas data frames to facilitate subsequent analysis.

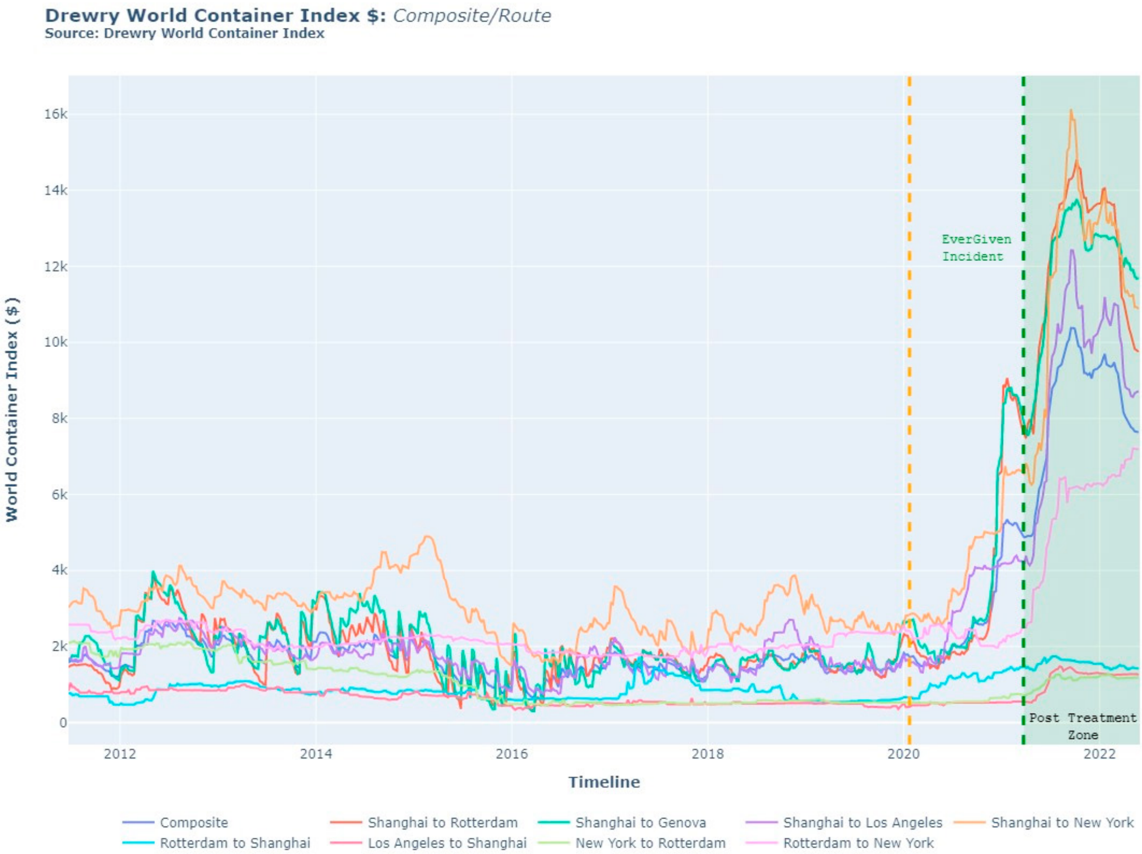


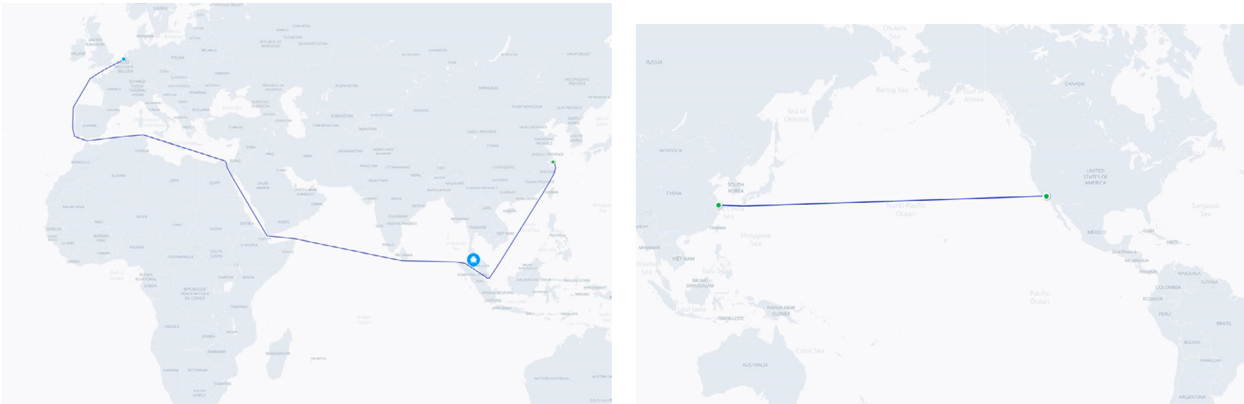
Fig. 1: Drewry WCI ($) composite and by route Including a marker (green) for the post-intervention zone.

Fig. 1 displays the world container price index (WCI) stability over nine years with minor fluctuations. Despite serving different geographical locations, the eight main routes exhibit correlated patterns. Notably, two spikes are observed: the first, denoted by a vertical orange dashed line, coincided (with a slight delay) with the onset of the COVID-19 pandemic. The second spike, marked by a vertical green dashed line, aligns with the Ever Given incident at the Suez Canal. Our analysis focuses on this second disruption, aiming to establish a potential causal link between the Ever Given accident and WCI fluctuations and estimate the accident's causal effects on WCI.

3.2. Assumptions

The assessment presented in this paper is based on several key assumptions that need to be fully and explicitly stated:

1. Causal Inference: This paper relies on causal inference techniques, like the Causal Impact model, to estimate the causal link between the Ever Given Suez Canal accident and container freight rates. This assumes that the chosen



(a) Shanghai-Rotterdam maritime route passing the Suez Canal.

(b) Los Angeles-Shanghai maritime route not passing the Suez Canal.

Fig. 2: Overview of maritime routes (source: searates.com)

method is suitable for the data and adheres to its underlying assumptions, including no unmeasured confounding variables.

2. Exogeneity: We assume that the Ever Given accident occurred independently, unaffected by other factors related to container freight rates, establishing a causal connection.
3. Homogeneity of Routes: The paper assumes that selected maritime routes, with and without the Suez Canal, share similar relevant characteristics except for the accident. This ensures that observed differences in container freight rates can be attributed to the accident.
4. No Major Additional Disruptions: We assume no other significant disruptions or events affected container freight rates during the study period, except for the indirectly considered COVID-19 pandemic.
5. Data Accuracy: The analysis assumes that data from the Drewry World Container Index is accurate and reliable for this purpose, recognizing that data inaccuracies or biases could impact the results.

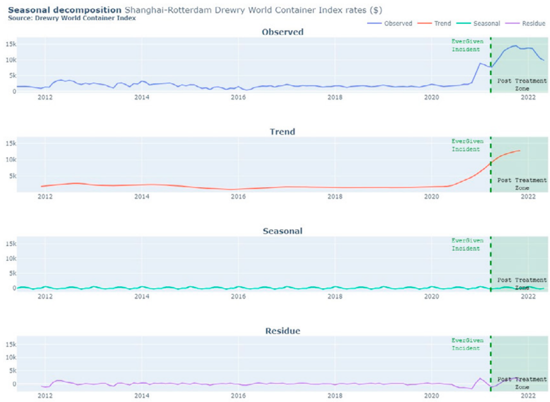
3.3. Methodology and procedure

The Ever Given Suez Canal accident resulted from a combination of weather conditions and human error, qualifying it as a randomized natural experiment with exposure assigned randomly. We selected the route from Shanghai to Rotterdam out of eight available routes, making it a potential subject to the treatment effect caused by the Ever Given accident. Fig. 2a shows the main route from Shanghai to Rotterdam.

We selected a second route to serve as a covariate based on two criteria. Firstly, it must meet the technical requirement for Causal Impact to estimate the counterfactual accurately. Secondly, it should exhibit a high correlation with the treated route [20], but not to the extent that it diverges from the assumption of natural random selection. For this purpose, the route from Los Angeles to Shanghai is chosen as the control route. This control route does not go through the Suez Canal and does not interfere with the route Shanghai-Rotterdam. Fig. 2b illustrates the route from Shanghai to Los Angeles.

After deciding upon the routes, the data was prepared for R as a time series with Y representing the Shanghai-Rotterdam, which is the route we would like to estimate the effect on from the Ever Given accident, and the Los Angeles-Shanghai route being the control time series, i.e., a time series correlated to the main route and not affected by the treatment/exposure Before running the experiment in R, the hyperparameters of Prophet and statsmodels were tuned. Prophet and statsmodel for SARIMA, namely SARIMAX, were used to assess and decompose the components of the WCI for the Shanghai-Rotterdam time series and to try and predict the counterfactual, i.e., how the time series would have evolved post-intervention if the intervention had never occurred. First, Prophet was set up to decompose the time series's seasonal-trend components and predict the counterfactual. Prophet was configured with yearly and weekly seasonality and weekly frequency. Fig. 3a shows the result of Prophet's seasonal time series decomposition of the Shanghai-Rotterdam route.

(a) Prophet seasonal-trend decomposition.



(b) Statsmodels seasonal-trend decomposition.

Fig. 3: Seasonal-trend decomposition Shanghai-Rotterdam Drewery World Container Index ($).

As seen in Fig. 3a, the time series for the Shanghai-Rotterdam route is stable until around the end of 2020, coinciding with the COVID-19 pandemic. Nevertheless, the trend is very steep around 2021, which is the first indication that there might be an event that led to the increase of the WCI. The figure also shows weekly and yearly seasonality. The yearly seasonality occurs around the end of the year, possibly due to the holiday season. For the weekly seasonality, we can see a unique trend on Thursday.

Afterward, statsmodels seasonal decompose was used to decompose the seasonal-trend components of the time series, and statsmodels SARIMAX was used to predict the counterfactual. For the SARIMAX model, the seasonality was set up to weekly. However, the other parameters were learned for a grid search operation. For this purpose, a function was written to run SARIMAX with a combination of parameters (set to 3) and then rank the results by Akaike information criterion (AIC) and the Bayesian information criterion (BIC). AIC and BIC are scores used to measure a time series model performance based on the model's performance and complexity. The SARIMAX grid search returned the following parameters (0, 2, 2), (0, 2, 2, 7). Fig. 3b is the result of statsmodels seasonal timeseries decomposition of the Shanghai-Rotterdam route.

As depicted in Fig. 3b, the time series trend drastically changes around the treatment zone, which agrees with Prophet's decomposition. Also, the seasonality is periodic and trends towards the holiday season, i.e., towards the end of the year. Finally, the model was run multiple times with different settings.

3.4. Hypothesis

Null Hypothesis (H0): There is no statistically significant causal relationship between the Ever Given accident at the Suez Canal and container freight rates on the Shanghai-Rotterdam maritime route

Alternative Hypothesis (H1): There is a statistically significant causal relationship between the Ever Given accident at the Suez Canal and container freight rates on the Shanghai-Rotterdam maritime route.

$$\begin{aligned} H0 &: Y^0 = Y^1 \\ H1 &: Y^0 \neq Y^1 \end{aligned} \tag{1}$$

where Y^0: outcome of no treatment and Y^1: outcome of treatment.

Thus, the null hypothesis states that if there is no causal relationship between the exposure and the subject, the potential outcome with or without treatment is the same. Otherwise, if the treatment does indeed affect the subject, then the outcome with and without treatment should differ. Table 2 summarizes the experiment's variables.

Table 2: Summary of experiment variables.

Variable	Definition
Y^0	Outcome of no treatment
Y^1	Outcome of treatment
Treatment (exposure)	Ever Given accident at Suez Canal
Treatment exposure date	Starts on the 23rd of March 2021 onwards

4. Implementation and Results

We chose Google's *Causal Impact* R package [21] for several reasons. Firstly, our data is time series, and the effect we are studying is time-invariant. Secondly, this package employs Bayesian Structural Time Series (BSTS), which aligns better with our experiment's assumptions compared to the Python package using statsmodels (as discussed in Section 2.2). Lastly, while various causal inference tools exist, most are not tailored for time series analysis. We conducted multiple runs of Causal Impact with varying settings, summarized in Table 3a.

Table 3: Causal Impact parameters and results.

(a) Causal Impact various runs parameters.

Number of Iterations	Number of Seasons	Season Duration	Posterior Probability of Causal Effect
Default = 1000	none	none	99.88789%
5000	none	none	99.95913%
5000	52	7	99.97983%

(b) Causal Impact results summary.

	Average	Cumulative
Actual	12119	727160
Prediction (s.d.)	8650 (1013)	518978 (60792)
Absolute effect (s.d.)	[6692, 10475]	[401527, 628496]
95% CI	3470 (1013)	208182 (60792)
Relative effect (s.d.)	[1644, 5427]	[98664, 325633]
95% CI	40% (12%)	40% (12%)
Posterior tail-area probability p	0.00112	
Posterior prob. of a causal effect	99.88789%	

Table 3a shows that the best results were obtained by increasing iterations and setting accurate seasonality patterns. This yielded a 99.98% posterior probability of a causal effect, exceeding the alpha level of 0.05, allowing us to confidently reject the null hypothesis (p-value = 0.00112), signifying statistical significance. Table 3b provides the model's summary. From Table 3b, we learn that before the Ever Given accident, the WCI averaged $12,119. According to the counterfactual, without the accident, it would be $8,650. The observed average effect is $3,470, representing a 40% increase due to the Suez Canal accident. Fig. 4 displays the results of the Causal Impact Bayesian structural time series model.

The model shows an increase in the effects of the Ever Given accident, peaking around October 2021. The effect then seems to decrease afterward, which is notable in the cumulative curve from the third row of 4, Cumulative Causal Treatment Effect. Additionally, the model's counterfactual seems to settle pre-COVID-19 pandemic levels. Also, from the second row of 4, the PointWise Causal Treatment Effect, we can see that the index has been undisrupted for years, except for a little disturbance during the COVID-19 pandemic, followed by a major one post the Ever Given accident.

Fig. 5a plots the Facebook Prophet's attempt to predict the counterfactual. Even though the model is well-fitting, the counterfactual prediction is relatively off compared to Causal Impact results. Discrepancies between counterfactual predictions from Facebook Prophet and hyperparameter-tuned SARIMAX may arise due to model complexity, how seasonality is handled, and the causal inference framework employed by Causal Impact. Variations in data preprocessing and parameter tuning also contribute to these differences. Causal Impact's specialized design for causal inference in time series data likely leads to more accurate treatment effect estimates than models lacking explicit causal modeling, including the hyperparameter-tuned statsmodels SARIMAX.

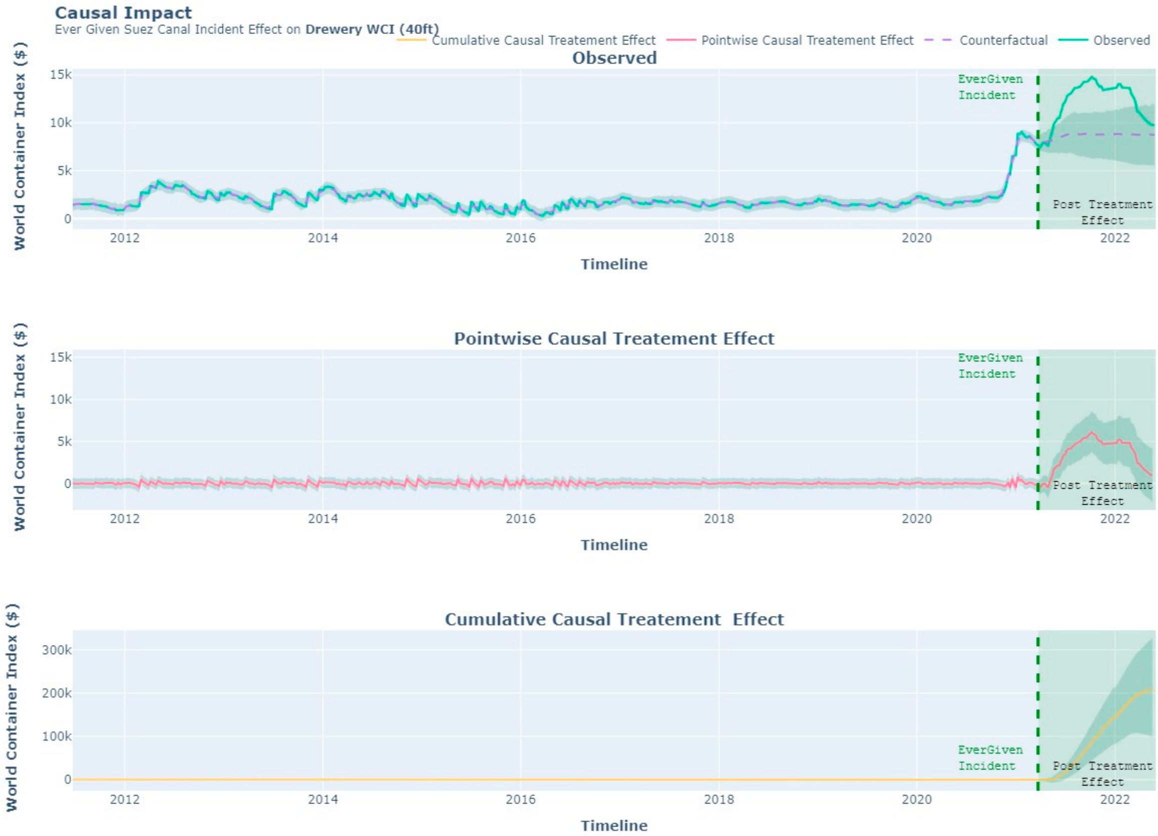
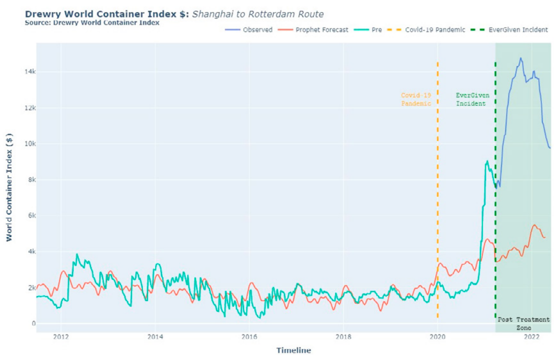
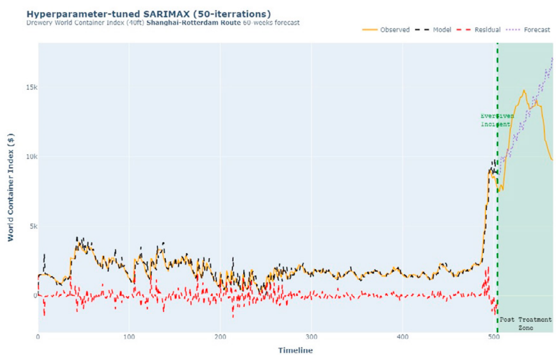


Fig. 4: Causal impact Bayesian structural time series causal effect estimation results plot for Impact of Ever Given Suez canal accident on the Drewery WCI (40-feet).



(a) Facebook Prophet counterfactual prediction attempt.



(b) Hyperparameter-tuned SARIMAX counterfactual prediction attempt.

Fig. 5: Counterfactual prediction attempts.

In evaluating an ideal model, assessing the residuals for patterns and adherence to a Gaussian distribution centered around zero is crucial. We can determine if the model is satisfactory by examining the HPT-SARIMAX model diagnostics plot in Fig. 6. The standardized residuals appear randomly scattered around zero without noticeable patterns or trends. The histogram of standardized residuals closely resembles a bell-shaped curve, indicating a normal distribution. The points in the Q-Q plot align closely with the red straight line, except for a slight deviation at the end, which is expected. This suggests that the residuals follow a normal distribution approximately. The correlogram's autocorrelation coefficients do not show statistical significance at any lag, with no significant spikes observed, indicating a lack of significant autocorrelation in the residuals. While the diagnostic plots in Fig. 6 demonstrate a strong model fit to the time series, it outperforms Facebook Prophet. However, when it comes to predicting the counterfactual, the model falls short and underperforms Prophet, as evident in Fig. 5b.

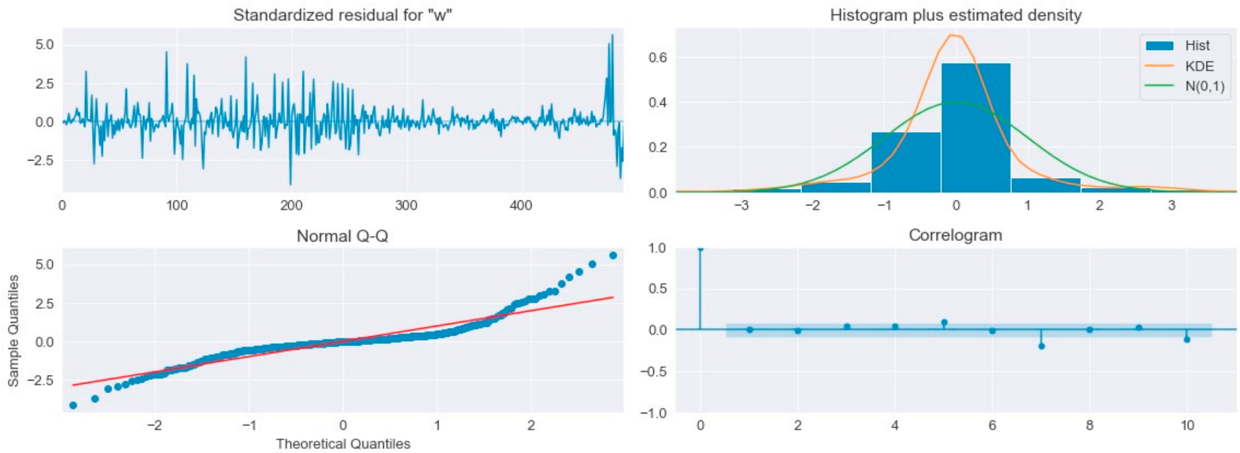


Fig. 6: HPT-SARIMAX model diagnostics plot.

5. Discussion

This study employs causal inference to assess the impact of the Ever Given incident at the Suez Canal on shipping container prices. Our analysis demonstrates a notable effect, showcasing the potential of this approach for estimating disruption consequences in Industry 4.0's data-rich environment. By understanding cause-and-effect relationships through causal inference, organizations can make informed decisions, optimize their operations, improve quality, enhance supply chain resilience, and ultimately essential in the era of Industry 4.0. This study has significant implications for supply chain management, both theoretically and practically. It advances the use of causal inference techniques to assess disruptions' impacts on supply chain variables, offering insights into how disruptions propagate. For professionals, it demonstrates the practical utility of causal inference in quantifying disruption effects on performance indicators, aiding in data-driven decision-making for risk mitigation, inventory management, and contingency planning. This approach enhances supply chain resilience, bridging the gap between theory and practice.

Acknowledging that different nations adopted diverse strategies to combat the COVID-19 virus is crucial. These varied approaches may have led to observed fluctuations in container freight rates among routes, potentially complicating the assessment of the impact of the Suez Canal incident. While our primary aim is to isolate the influence of the Suez Canal incident, other external factors, such as COVID-19-related policies and regional economic conditions, could have affected the container freight rates we examined. Initially, we considered the pandemic to be a significant disruption. However, we now assume that the impact of policies enacted by various nations is integrated into the freight rates, essentially becoming the new standard. This assumption is based on the observation that the pandemic's influence on freight rates, both before and after its outbreak, sufficiently represents our analysis.

Our research exclusively focuses on the impact of the Ever Given accident on shipping container prices. However, multiple concurrent factors, including raw material costs, geopolitical events, market dynamics, and environmental factors, influence these prices. To broaden our research, we could create a comprehensive model capturing intricate relationships among these factors, forming a causal graph. Applying causal inference to this graph would estimate causal-effect relationships among these factors. To bolster our claims, further research could entail a more comprehensive causal analysis that accounts for additional variables and potential confounding factors. This would offer a more nuanced understanding of the accident's specific influence on container freight rates within the intricate global shipping industry.

6. Conclusions

Causal inference involves designing and analyzing studies to uncover causal relationships between treatment and outcome variables. While it is commonly used in the medical field to assess the effects of medical treatments, it holds significant promise in supply chain management due to complex networks, interconnectivity, and rapid technological changes. This research centers on applying causal inference to assess the impact of the 2021 Ever Given container ship accident in the Suez Canal on shipping container prices, utilizing data from the Drewery World Container Index. We conducted the experiment using Google's *Causal Impact* R package, adhering to its key assumptions. The results, which are statistically significant at 99.89%, confirm that the Ever Given accident influenced shipping container prices, with a relative increase of 40% post-accident.

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