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Assessing the impact of China's trade policy uncertainty on the dry bulk shipping freight rates

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ABSTRACT

The impetus for our research lies in the multifaceted and pivotal role of China in the dry bulk market, encompassing its positions as a leading global exporter, a dominant shipbuilder, and a major shipowner. However, the effects of uncertainty arising from trade policy and particularly Chinese trade policy (CTPU) on the dynamics of the dry bulk market have remained unexplored by empirical studies. This study addresses this gap by analyzing the impact of CTPU on the Baltic Dry Index (BDI), a key indicator of international trade and the global economy.

Performing the Granger causality test and the impulse response function, we demonstrate a decline in sea-transportation demand and cost in the dry bulk market due to a spike in CTPU, yielding results consistent with option theory. This effect is observed across all BDI sub-indices and lasts approximately one year, by the end of which the markets fully recover. By developing artificial neural networks, we effectively avoid in-sample bias and underscore the out-of-sample predictability of CTPU on BDI, establishing it as a key determinant of the latter.

Based on our findings, we propose strategies for various maritime stakeholders and supply chain managers to maximize profitability and enhance operational efficiency in transportation.

1 Introduction

The inclusion of China in the World Trade Organization (WTO) in 2001 marked a pivotal moment in mitigating trade uncertainties and fostering a significant surge in Chinese exports to the global market, particularly the United States. Over the subsequent decade, economic ties between China and the US deepened, establishing the two nations as major trading partners. However, longstanding tensions over trade imbalances in combination with the implementation of a more confrontational US trade policy after 2016, signaled a new era for international trade. More specifically, the US adopted a more assertive stance toward China, imposing tariffs on Chinese imports. China responded by adjusting its trade policy and imposing new tariffs on US imports, resulting in an uncertain and less predictable trading environment.

In general, a rise in trade uncertainty discourages local firms from entering export markets [1]. Considering the role of China as a leading economy and exporter, it can be inferred that uncertainty regarding its trade policy has global repercussions that are amplified through maritime shipping. Although there are studies focusing on the financial consequences of the Chinese trade policy uncertainty both on China and its trading partners [2], its nexus with the global maritime supply chain remains underexplored.

Maritime shipping, a fundamental pillar of the global supply chain and the international economy, is extremely sensitive to policy uncertainty [3]. Stopford explains that political events and uncertainty influence ship demand and can contribute to shipping cycles [4]. Within the shipping industry, the dry bulk shipping market exhibits significant volatility. It is influenced by unpredictable factors, including global economic conditions, trade volumes, and national policies — all of which contribute to an unstable environment [5].

In the dry bulk segment, Baltic Dry Index (BDI) is a key indicator reflecting the level of dry bulk rates and the dynamics of supply and demand for bulk cargoes and their transportation costs. It serves as an essential indicator of global trade volumes, manufacturing activity, and international demand for intermediate and final products [6]. Its level influences decisions in both maritime and broader financial markets [7, 8]. The dry bulk market consists of five subcategories based on the carrying capacity of vessels, which are: Handysize, Handymax, Supramax, Panamax, and Capesize. Each of the markets has its own distinctive characteristics and determinants based on the type of commodity being transferred. However, spillover effects exist among them [9]. Consequently, the BDI is calculated as a weighted average of the following dry bulk rates indices: Baltic Panamax Index (BPI), Baltic Capesize Index (BCI), Baltic Supramax Index (BSI), and Baltic Handysize Index (BHSI).

The relationship between China and the dry bulk market has been well established in the literature. The Chinese manufacturing and steel production industries, which play a leading role globally, significantly impact the level of dry bulk rates [5, 10]. Furthermore, China's imports of iron ore and coal are a driving force behind the dry bulk seaborne trade [11]. In addition, China dominates in other sub-sectors of the industry such as vessel construction and vessel management. Consequently, the Chinese shipyards' output and the operations of Chinese-owned vessels influence market earnings and freight rates [12, 13]. Furthermore, Chinese financial markets also synthesize an exogenous environment for the dry bulk market and have predictive power over freight rates [14, 15]. Interest rates in China affect investments and the demand for iron ore, which eventually drives dry bulk rates [16].

China's significance for the dry bulk sector implies that its economic policies and the resulting uncertainty can lead to drastic transformations in market dynamics. However, only a few studies have examined the consequences of the broader Chinese economic policy and the related uncertainty on maritime trade, while no research focused on effects from economic uncertainty associated with trade policies. Particularly, uncertainty stemming from Chinese trade policies (CTPU) and its impact on the dry bulk market has not, to the best of our knowledge, been studied. This paper aimed to address this gap in the existing literature, by investigating the relationship between freight rates represented by BDI and CTPU. Using the CTPU index formulated through textual analysis of Chinese newspapers and suggested by Davis et al [17], we focused on its ability to diminish demand for sea-transportation and lower dry bulk rates, which represent the transportation costs for charterers. Our findings provided new evidence on how CTPU spikes influence BDI, an important benchmark for shipping companies to monitor freight rates. For our analysis we utilized the Vector Autoregressive Model (VAR) to conduct the Granger causality test and the Impulse Response Function (IRF). Thus, we explored the repercussions of trade uncertainty on the global maritime supply chain.

Furthermore, utilizing the same methodology, we were the first to demonstrate the concurrent impact of CTPU across all dry bulk freight rates markets. As a robustness check, we also replaced BDI with average bulker earnings and found analogous results. Thus, we provided novel evidence of the importance of the trade policy uncertainty index, particularly China's trade policy, for the entire dry bulk sector. In order to validate the out-of-sample predictability of CTPU on BDI, we formulated artificial neural networks (ANN) models. Our model containing the CTPU outperformed all the other formulated linear and non-linear models, rendering CTPU a BDI determinant and a valuable indicator for policy makers designing strategic decisions under uncertainty. Our findings also offered valuable insights for empiricists focusing on the design of route networks in order to mitigate risk, maritime stakeholders aiming to increase their profits in the industry, and investors from different industries who incorporate the level of BDI in their decisions.

The structure of the remaining sections is organized as follows: **Section 2** reviews the literature on economic and policy uncertainty, focusing on the nexus with the shipping industry. **Section 3** describes the data used in the study. **Section 4** details the research methodology. **Section 5** covers the descriptive statistics and the results of the tests conducted to the time series and models utilized in the study. **Section 6** provides a discussion of the results. **Section 7** concludes with a summary of the study's key results.

2 Literature Review

Prior to 2016, the body of research examining the effects of Economic Policy Uncertainty (EPU) on the broader economy and particularly on the shipping industry was notably limited, despite the critical importance of policy uncertainty in maritime operations. This research gap may have stemmed from the absence of a reliable and universally accepted indicator for assessing economic policy uncertainty during that period. To address this gap, the EPU index was introduced and quantified the influence driven by economic policy-related uncertainties. The concept of EPU was initially proposed by Baker et al. Its formulation procedure involved textual analysis of US newspapers. Therefore, they focused on various terms associated with economic policy and uncertainty, searched for them in articles in order to develop the EPU, and highlighted its cross-country variation [18]. The index was further categorized by policy type, including fiscal policy uncertainty (FPU), monetary policy uncertainty (MPU), and trade policy uncertainty (TPU). Since then, numerous researchers have explored the effects of EPU on physical and financial markets.

Studying the consequences of policy uncertainty, empiricists interpreted shifts in the economy that they considered a black box. One of the most important findings was that it can influence consumption and disrupt governmental decision-making, thereby delaying economic growth and decreasing private investments [19]. Particularly, private investments that depend on government spending or have a high degree of irreversibility are most affected [20]. Investments in vessels are also highly sensitive to global uncertainty [21]. Furthermore, the effects of EPU are evident in consumers' daily routines. An increase in gasoline and other commodity prices due to spikes in EPU leads to higher living costs [22, 23]. In addition, EPU is positively related to firms' cash holdings, which serve as a buffer against uncertain conditions [24]. Banks and financial institutions are more cautious in offering loans, rendering lending more expensive [25]. An increase in concerns regarding economic policy is associated with increasing volatility in the exchange market [26]. Global EPU also affects the maritime industry by decreasing investments in the industry and reducing the demand for vital commodities, ultimately leading to low freight rates [27, 28]. The effects of EPU are experienced regardless of whether a country is a net importer or exporter, with low-income countries being less equipped to manage uncertainty and bearing the most significant impact. However, by establishing Regional Trade Agreements (RTAs), a country can mitigate the adverse effects of EPU on its trading activity [29].

Uncertainty regarding trade policy has an even greater impact on the economy, as it reduces investments, consumption, and, eventually, Gross Domestic Product (GDP). It shifts the nation's economy toward introversion by increasing firms' profit margins due to an inflationary pricing bias, rendering exports less competitive [30]. It also constrains firms' access to credits [31]. In addition, when trade uncertainty is combined with geopolitical tensions, it can negatively shape the consumer confidence [32]. Commodities are also sensitive to trade uncertainty and can experience high volatility during periods of heightened uncertainty [33]. According to real option value theory, companies weigh the benefits of exporting against the benefits of waiting, before making a decision. TPU renders the second option more attractive, while export costs exceed the cost from holding back [34]. Crowley et al. demonstrated that aside from entering a foreign market, firms are more willing to exit existing markets during a TPU spike [35]. Therefore, trade flow is also diminished, especially in low-income countries where TPU can act as a trade barrier [36].

Chinese TPU, as mentioned earlier, was developed by Davis, adopting a similar methodology to Baker, and applying it to Chinese newspapers [17, 18]. CTPU plays a crucial role in its country's participation in global trade. The significant decline in CTPU during the interval 2000-2007 alleviated the financial constraints of agricultural firms boosting exports, mainly to developing countries [37]. Wang and Wu developed an integrated input-output model with energy and economy and demonstrated that restrictions in trade ultimately diminish China's GDP, whereas countermeasures from China can reduce the effect [38]. According to their results, manufacturing industries such as textiles, machinery, and apparel are more sensitive to TPU along with the energy sector. A decrease in TPU has also environmental implications, while it enhances the corporate environmental performance by reducing SO2 generation [39]. Commercial banks adopt a more passive risk-taking behavior, while capital markets experience liquidity constrains during periods of intense trade uncertainty [40]. Furthermore, CTPU discourages imports, leading to lower variety of foreign products and lower quality [41].

Uncertainty from economic policies in general and from trade policies in particular, are strongly related and have been used interchangeably by researchers. Their effects are multidimensional, including environment, economy and society. However, different categories of policy uncertainty have heterogeneous effect on the economy [42]. Regarding international trade, a major consequence of both types of uncertainty is the influence on countries exports and imports [29, 30, 37]. Therefore, there is a growing interest in the impact of EPU on the maritime market and particularly on the dry bulk market, whereas the effect of TPU has largely been overlooked. This study addresses this gap by focusing on the impact of TPU on the dry bulk rates and demand for dry bulk goods. Additionally, previous research has studied the relationship between China's EPU and the dry bulk shipping costs, demonstrating its insignificance [5]. Nevertheless, we provided novel evidence regarding the significant effect of CTPU on the BDI and the other dry bulk indices, highlighting the pivotal role of China across all dry bulk segments. Furthermore, we pioneered the study of the extent to which CTPU can explain out-of-sample movements in maritime transportation costs and demand.

3 Data

In order to scrutinize the effect of CTPU on dry bulk trade costs, we utilized the index proposed by Davis et al. [17] as a measure of uncertainty regarding China's trade policy at a monthly level. For the shipment costs in dry bulk shipping, we selected the BDI, BPI, BCI, BSI, and BHSI. As a robustness check, we used the average daily weighted earnings of all bulkers, denoted as EARN.

For our analysis, we selected the period from December 2008 to January 2024 to mitigate any bias from the impact of the Great Recession on the dry bulk market. The data were used in their stationary form and analyzed at a monthly frequency.

All dry bulk indices, along with EARN, were obtained from Clarksons' database, while CTPU data were downloaded from https://www.policyuncertainty.com.

4 Methodology

In order to unravel the impact of uncertainty regarding China's trade policy on the dry bulk rate indices, we performed Granger causality tests and IRF.

Specifically, we initially presented the examined time series and their distribution to demonstrate the limitations of model selection based on the data characteristics. Furthermore, we conducted stationarity tests to obtain the stationary form of the examined variables. The unit root tests that were incorporated in our study were the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test [43, 44]. Additionally, we employed co-integration tests proposed by Johansen [45] to identify any long-term equilibrium among the variables. Based on the results of the Johansen test, we determined the appropriate model for performing the Granger causality test. If the data were co-integrated, the Granger causality test was performed by employing the VAR model, whereas the absence of such relationship indicated the use of the Vector Error Correction model (VECM). Therefore, we applied the Granger causality test to assess whether CTPU has an impact on all the dry bulk rates indices.

The optimal lag for the VAR or the VECM models was determined based on the Hannan-Quinn Criterion (HQC), Final Prediction Error (FPE), Bayesian Information Criterion (BIC), and Akaike Information Criterion (AIC). To detect heteroscedasticity in the residuals for our VAR model, we applied the Breusch–Pagan test. We also assessed autocorrelation in the residuals by conducting the Breusch–Godfrey test. In addition, we conducted model stability tests by evaluating whether the inverse roots of the characteristic AR polynomial lie within the unit circle. This assessment validated that model-generated responses converge to equilibrium over time. We then performed the IRF in order to graphically illustrate and analyze the nature of CTPU's effect on the freight rates indices. As a robustness check, we repeated the same procedure (Granger causality and IRF) using the average daily weighted earnings of all bulkers and confirmed our findings regarding the influence of CTPU.

In order to demonstrate the one-step-ahead out-of-sample predictability of CTPU on BDI, we used ANN models. Specifically, we divided the model into training and test samples. In addition, we incorporated lagged values of CTPU and BDI in their original forms as input variables in an ANN model, which we defined as unrestricted. After determining the final model architecture, we compared its performance with that of the same model relying solely on the lagged values of the BDI as inputs, referred to as the restricted ANN model. Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE) were utilized as metrics to compare the unrestricted and restricted ANN models on the test set. The superiority of the unrestricted ANN model over the restricted model provided new evidence of the predictive power of CTPU regarding the seaborne activity index. To validate the robustness of the two ANN models, we compared their accuracy with that of various ARIMA models.

5 Results

5.1 Descriptive statistics

The descriptive statistics from all the examined time series are presented in the table below. Based on these findings, we partially determined the methodology by which we proceeded and analyzed the data.

The kurtosis of CTPU exceeds 3, suggesting a heavy-tailed distribution with outliers, which can introduce heteroscedasticity issues in the applied models, while the rest of the data exhibit kurtosis below 3. The rejection of the Jarque-Bera test's null hypothesis indicated that none of the data is normally distributed. This characteristic led us to employ models that did not require normally dis-

Table 1 Descriptive statistics

	CTPU	BDI	BPI	BSHI	BCI	BSI	EARN
MIN	0.00	306.90	324.19	197.19	-243.05	280.14	3635.80
MAX	1425.16	4819.95	4304.89	2019.48	7797.67	3456.19	39849.36
MEAN	223.99	1509.81	1570.20	677.75	2223.17	1210.32	13054.09
SKEW	2.16	1.33	1.17	1.58	1.27	1.37	1.41
KURT	5.97	1.67	0.86	2.35	2.62	1.43	2.21
JB	411.52***	74.42***	46.88***	117.72***	100.90***	72.10***	97.56***

Notes: JB represents the Jarque - Bera test for the normal distribution of the data. H0 assumes that the data are normally distributed. ***,**,* denote the rejection of H0 at 0.01, 0.05, 0.10 significance levels, respectively.

Table 2 Stationarity tests

	CTPU	BDI	BPI	BSHI	BCI	BSI	EARN
ADF	-1.10	-2.57***	-2.85***	-2.88**	-2.76***	-3.92*	-3.30**
KPSS	0.99*	0.28	0.28	0.24	0.26	0.25	0.31
ADF 1ST DIFF	-3.74*	-6.53*	-10.46*	-3.64*	-7.97*	-3.48*	-5.37***
KPSS 1ST DIFF	0.08	0.05	0.06	0.06	0.05	0.06	0.05

Notes: ADF and KPSS tests included an intercept. ADF H0: the data was not stationary. KPSS H0: the data was not stationary. ***,**,* denote the rejection of H0 at 0.01, 0.05, 0.10 significance levels, respectively.

tributed dependent or independent variables. In addition, as shown in **Table 1,** the BCI can take negative values. Consequently, we avoided applying logarithmic transformations to the variables included in this study.

5.2 Stationary tests

We performed the ADF and KPSS tests on the original form of the data and on their first differences. According to **Table 2**, both unit root tests provided sufficient and unanimous evidence that all the time series are stationary in their first differences or they are integrated of order one I(1).

In addition, the acceptance of the null hypothesis of the ADF tests and the rejection of the null hypothesis for the KPSS tests for the data in their original form indicated that, without preprocessing, not all data are stationary.

5.3 Co-integration tests

Table 3 presents the results of the Johansen test. The co-integration tests did not provide sufficient evidence to reject the null hypothesis at the 5% significance level, implying the absence of long-term relations among all the examined variables. The lack of cointegration among all the data indicated that the VECM could not be applied to analyze their relationships.

5.4 Granger Causality tests

In this section, we assessed whether CTPU can explain changes in dry bulk rates. The absence of long-term relations between CTPU and the freight rates indexes along with the fact that the variables were stationary in their first differences, led us to choose VAR models for conducting the Granger causality tests. In addition, this model does not require the independent variables to be normally distributed.

For examining the effect of CTPU on BDI we used a VAR model with 10 lags, as determined by AIC, BIC, FPE, and HQC. The rejection of the null hypothesis of the Granger causality test at the 10% confidence level in **Table 4** implied a causal relation between CTPU and BDI, namely the barometer of shipping demand. Our findings

Table 3 Co-integration tests

	No. of CR	Trace	0.05 CV (Trace)	Max Eigenvalue	0.05 CV (Max Eigen.)
BDI	None	15.16*	15.49	9.79	14.26
BPI	None	13.39	15.49	7.48	14.26
BSHI	None	12.81	15.49	7.44	14.26
BCI	None	15.13*	15.49	11.2	14.26
BSI	None	13.62*	15.49	8.07	14.26
EARN	None	14.80*	15.49	10.8	14.26

Notes: Johansen H0: there is no cointegration. ***,**,* denote the rejection of H0 at 0.01, 0.05, 0.10 significance levels, respectively.

Table 4 Granger Causality Test for BDI

	LAG	PVALUE	R^2	BG	BP
CTPU → BDI	10	0.07*	0.39	0.19	0.01***

Notes: Granger Causality H0: no significant causality exists between the variables. Symbols *, **, and *** indicate rejection of H0 at significance levels of 0.01, 0.05, and 0.10, respectively. BG represents the p-value from the Breusch–Godfrey test, assessing the presence of serial autocorrelation in the model's residuals. BP denotes the p-value from the Breusch–Pagan test, which evaluates the presence of heteroskedasticity in the model's residuals.

Table 5 Granger Causality Test for BDI sub-indices

	LAG	PVALUE	R^2	BG	BP
CTPU → BPI	10	0.06*	0.18	0.53	0.01***
CTPU → BSHI	10	0.01***	0.30	0.15	0.01***
CTPU → BCI	8	0.07*	0.25	0.88	0.01***
CTPU → BSI	10	0.01***	0.25	0.41	0.01***

Notes: Granger Causality H0: no significant causality exists between the variables. Symbols *, **, and *** indicate rejection of H0 at significance levels of 0.01, 0.05, and 0.10, respectively. BG represents the p-value from the Breusch–Godfrey test, assessing the presence of serial autocorrelation in the model's residuals. BP denotes the p-value from the Breusch–Pagan test, which evaluates the presence of heteroskedasticity in the model's residuals.

validated our initial hypothesis regarding the impact of uncertainty from China's trade policy on the trade volume and the behavior of shipping companies. Although dry bulk rates appeared to be unaffected by China's EPU, CTPU has a direct impact on demand in the dry bulk market [5]. This evidence supports previous findings regarding the varying effects of uncertainty rising from different policies and highlights the role of trade policy in the dry bulk market [42].

The remaining causal relationships were analyzed using VAR models with 8 and 10 lags according to the aforementioned criteria. The Granger causality test for the dry bulk rates indices yielded similar results, namely that each index is affected by CTPU. Therefore, the impact of CTPU on the dry bulk segment is independent of vessels' carrying capacity and traveling distance. Our findings underscored the dominant role of China in the dry bulk market, as its trading policies can influence decisions and demand in the market. This can be explained by China's dominant presence in multiple sectors of the maritime industry [5, 10-15].

The VAR models used in the study were free from autocorrelation in the residuals according to the Breusch-Godfrey test. Nevertheless, the rejection of the null hypothesis of the Breusch-Pagan test denoted that all the VAR models exhibited heteroskedasticity. This issue arose due to the presence of outliers in the time series. However, heteroskedasticity does not affect the consistency and unbiasedness of a model and, therefore, does not warrant model rejection [46].

5.5 IRF

Based on the VAR models formulated to investigate causality among the examined variables, we performed a cumulative IRF analysis to illustrate the response of all dry bulk indices to a shock in the CTPU. In the figures below, the vertical axis represents the magnitude of the maritime indices cumulative reaction and the horizontal axis measures time after the shock in months.

As depicted in **Figure 1**, a spike in CTPU has a negative impact on BDI. More specifically, changes in China's trade policy that cause uncertainty can negatively affect the dynamics of the dry bulk market. The effect appears to be insignificant for the first three months; it becomes negative afterward and peaks by the end of the sixth

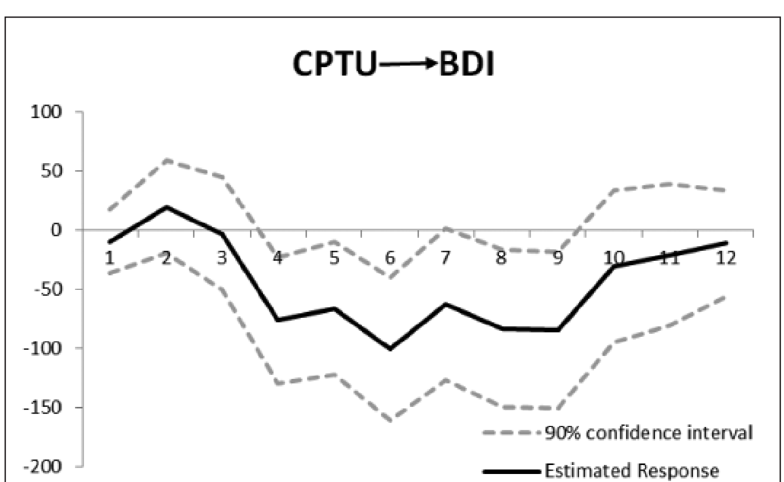

Figure 1 Accumulated Responses of BDI

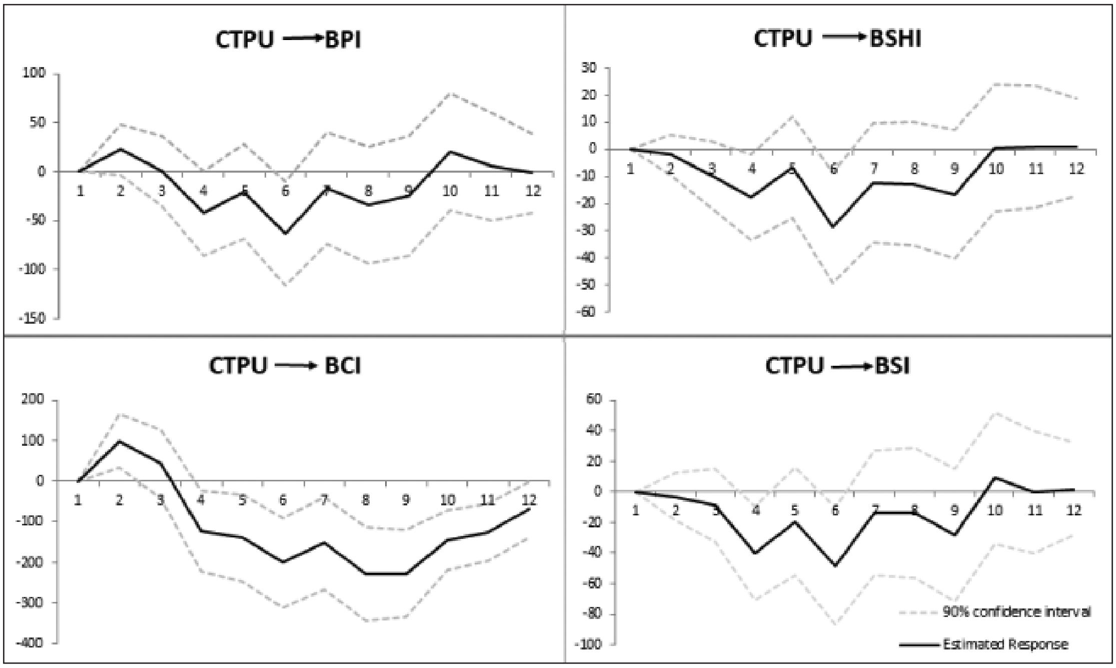

Figure 2 Accumulated Responses of Baltic Dry Index Sub-Indices.

month, when the highest decline in the seaborne activity index is observed. Subsequently, the market state begins to improve, reaching full recovery by the end of the first year.

The negative relation is likely explained by the growing uncertainty regarding trade, which renders Chinese exporters, who cover a large percentage of the market, less willing to export [29, 35]. Consequently, the trading volume in the dry bulk shipping market is reduced, pushing down demand for sea transportation and weakening the negotiation power of the shipowners. The latter become more willing to accept lower prices for chartering their vessels. In addition, reduced investments along with less access to loans and fewer self-financed projects diminish manufacturing activity and demand for goods such as iron ore and grain [22-25, 27]. The final result is a decline in the BDI, a drop in shipping costs for charters, and a reduction in trading volume among China's trading partners. Given China's prominent role in the dry bulk shipping, this outcome is the anticipated one.

The long-term nature of the effect is explained by the real option theory. Therefore, exporters facing uncertainty regarding Chinese trade policy prefer to wait, leading to a significant but temporary reduction in their exporting activity [34]. Chinese importers also choose to pause their activities due to rising uncertainty regarding trade. Once decreasing shipping costs balance the risk from CTPU and render the exporting/importing more beneficial, traders expand their activity abroad and the market recovers.

In **Figure 2**, the evolution of the main freight rates indices in response to a spike in CTPU is presented. The effect of CTPU is negative and simultaneous across all dry bulk sub-markets, becoming significant after the third month. The shock peaks again in the sixth month, after which the market starts to improve. A key difference, in comparison to the reaction of BDI, is that the sub-indices recover more quickly, fully rebounding by the end of the third quarter. The only exception is the Capesize market, in which the effect persists longer. More specifically, it peaks in the ninth month, while the market does not appear to fully recover even after the first year. Hence, the Capesize market appears to be more sensitive to Chinese trade policy, as it benefits more from economies of scale and faces steeper declines when demand drops.

Our findings align with evidence provided by prior research. More specifically, the effect of CTPU on dry bulk rates is similar to that of EPU, which causes a decrease in all the spot rates [27]. However, the effect differs in terms of duration across markets, while a spike in EPU has a longer impact. In addition, Capesizes are less affected by EPU than by CTPU. Therefore, our evidence validates the previous findings suggesting that uncertainty arising from various policy types affects markets differently [42].

5.6 Stability tests

In this section, we conducted stability tests on all VAR models to assess whether the responses of mari-

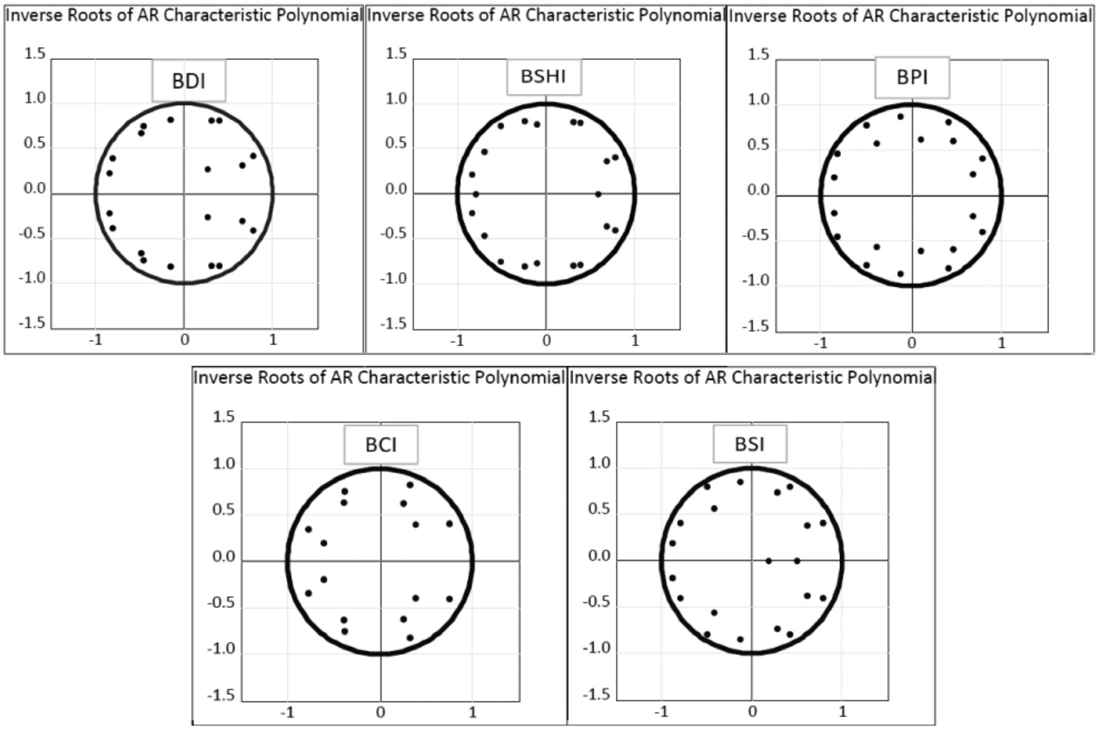

Figure 3 Stability tests

time indices to shocks of CTPU are amplified. Therefore, we calculated the roots of the characteristic polynomial. If the modulus of each eigenvalue was less than 1, the model is considered stable. In the following figure, the real components of the eigenvalues are represented on the x-axis, while the complex components on the y-axis.

Based on the results illustrated in **Figure 3,** all VAR models used in our analysis had their inverse roots inside the unit circle. Therefore, they were stable, ensuring that the models' dynamics were well behaved.

5.7 Out-of-sample predictability

In this section, our goal was to examine whether the performance of a forecasting model in terms of out-of-sample accuracy, is enhanced with the use of CTPU as an input variable. Therefore, we formulated an ANN model using the lag values of CTPU and BDI as inputs and the BDI as the target variable. In order to design a model that yields robust results and since there is no panacea in the optimization of ANN hyperparameters, we adopted the trial and error method [47].

The final ANN model incorporated one input, one hidden, and one output layer. The hidden layer had as activation function the rectified linear unit (ReLU), while the output layer used a linear activation function. The hidden layer contained 200 neurons with a dropout rate of 10%. The model was trained for 250 epochs and the learning rate was 0.00003. The loss function of the model was the MAPE. The number of training samples utilized in order to update the weights of the model during each iteration (batch size) was 15.

In order to establish the predictability of CTPU, we split the sample into training and test set, with the percentages being 70% and 30% respectively. We also formulated two ARIMA models, ARIMA(2, 1, 4) and ARIMA(0, 1, 2), based on the AIC, BIC, FPE, and HQC criteria. We then compared the out-of-sample prediction accuracy of the two ARIMA models along with the ANN Unrestricted (using CTPU as input) and ANN Restricted (without CTPU as input) models.

Figure 4 visualizes the performance of the final unrestricted ANN in one-step-ahead prediction alongside the actual values of BDI across the entire sample. The white area represents the in-sample predictions, where the model was trained and the darker area represents the out-of-sample predictions associated with the model's generalization ability. The final model successfully captures BDI's patterns, while its predictions have only minor deviations.

From **Table 6**, it can be inferred that the ANN containing CTPU as an input variable (UANN) achieved the lowest MAPE and MSE compared to the other models. Hence, it outperformed the restricted ANN (RANN) in forecasting accuracy implying that the inclusion of CTPU enhances BDI predictions. UANN also dominated all the ARIMA models, indicating that it can produce robust results. The provided evidence demonstrated the out-of-sample forecasting power of CTPU, avoiding the in-sample bias. Therefore, our results highlight China's

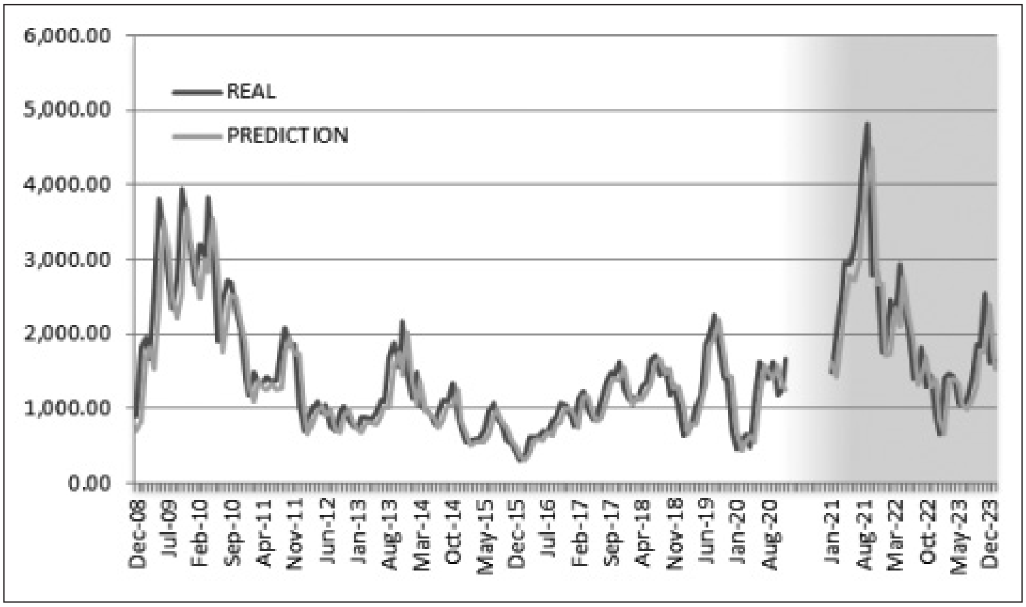

Figure 4 BDI Predictions of Unrestricted ANN model

trade policy and the subsequent uncertainty as a determinant of the BDI.

5.8 Robustness check

The effect of CTPU on BDI was re-evaluated by studying the impact of CTPU on EARN. In **Table 2**, the rejection of the null hypothesis in the ADF test and the acceptance of the null hypothesis in the KPSS indicated that the first difference of EARN is stationary. Additionally, the acceptance of the null hypothesis of the Johansen test in **Table 3** suggested the absence of cointegration between CTPU and EARN. Based on the aforementioned results, we selected the VAR model for performing the Granger causality and the IRF analyses in order to investigate the nature of CTPU's influence on EARN.

Table 4 presents the results of the Granger causality test. The selected VAR model incorporated 10 lags. The rejection of the null hypothesis at the 5% significance level indicated that CTPU also has an effect on earnings in the sector. Therefore, our findings validated the CTPU influence on the maritime transportation cost of dry bulk goods and underscored the significant role of China in the market.

The used VAR model was free from serial correlation in residuals according to the Breusch–Godfrey test. However, the Breusch–Pagan test provided sufficient evidence to reject the null hypothesis of no heteroskedasticity in the residuals.

Table 6 Prediction comparison

	UANN	RANN	ARIMA(2,1,4)	ARIMA(0,1,2)
MSE	314,892.83	318,158.77	335,277.79	372,103.21
MAPE	0.2177	0.2202	0.2243	0.23120

Notes: UANN stands for unrestricted artificial neural networks. RANN denotes restricted artificial neural networks.

Table 7 Granger Causality Test for BDI

	LAG	**PVALUE**	**R^2**	**BG**	**BP**
CTPU → EARN	10	0.04**	0.53	0.28	0.01*

Notes: Granger Causality H0: no significant causality exists between the variables. Symbols ***, **, and * indicate rejection of H0 at significance levels of 0.01, 0.05, and 0.10, respectively. BG represents the p-value from the Breusch–Godfrey test, assessing the presence of serial autocorrelation in the model's residuals. BP denotes the p-value from the Breusch–Pagan test, which evaluates the presence of heteroskedasticity in the model's residuals.

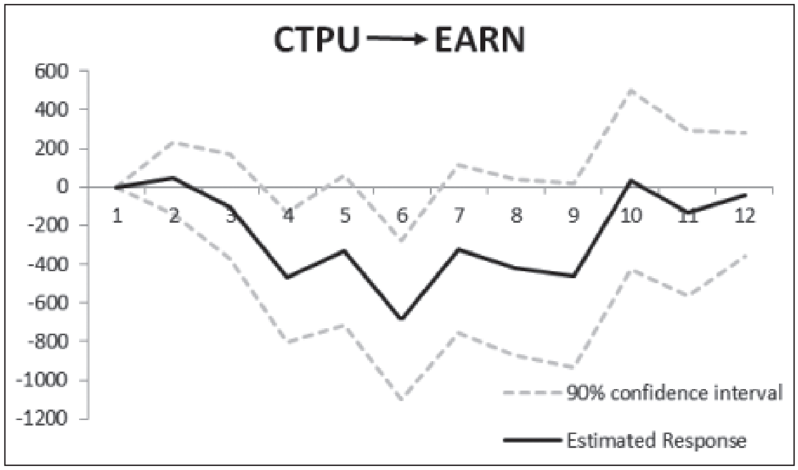

Figure 5 Accumulated Responses of EARN

Figure 5 illustrates the CTPU effect on EARN. The IRF revealed that the impact is similar in timing and duration to that on the BDI. More specifically, the effect is negative, becomes significant in the third month, leads to the greatest decline in earnings by the sixth month, and the market fully rebounds by the end of the first year. Therefore, our findings are independent of the measure of market performance and any potential biases from bunker prices [27]. Moreover, they validate the decrease in demand for dry bulk products, which leads to a decrease in spot rates and eventually, in the earnings of shipping companies.

Figure 6 presents the inverse roots of the characteristic polynomial of the VAR model used for the CTPU-EARN relationship. More specifically, the modulus of all the root values lies inside the unit circle. Therefore, the VAR model satisfies the stability condition, and its IRF is valid.

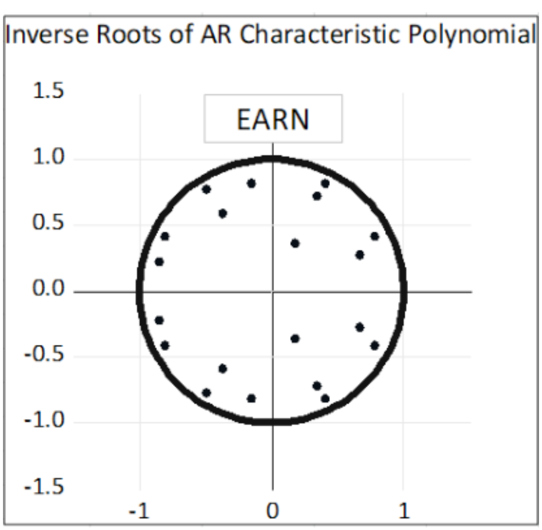

Figure 6 Stability for EARN

6 Discussion

This study focused on the dry bulk rates, particularly the BDI, a barometer of global trade demand and a critical metric used by shipping companies for strategic planning. It introduced the concept of CTPU in the dry bulk sector and analyzed its relationship with dry bulk rates for the first time. The results indicated that CTPU exerts a significant impact on the BDI, leading to its decline. Notably, dry bulk rates are affected by the end of the third month, and the effect persists approximately for a year before the market fully recovers. The CTPU effect on spot rates differs from that of the Chinese EPU, which appears to leave the market unaffected [5]. Therefore, our analysis emphasized the heterogeneous effects of uncertainty stemming from different categories of policies. This heterogeneity underscores that EPU and its subcategories should not be used interchangeably by policymakers and researchers [42]. Furthermore, our results implied that CTPU discourages exporters and reduces the demand for dry bulk shipping. Additionally, it diminishes shipowners' negotiating power for higher freight rates, thereby contributing to a sustained negative effect on seaborne trade activity. Our findings align with the real option theory proposed by Bernanke [34], suggesting that uncertainty renders exports less attractive and decreases trade volume until conditions become more beneficial. Therefore, the impact of CTPU is temporary in terms of maritime trade.

The IRF demonstrated consistent results across all markets, highlighting the importance of TPU and China's role in the dry bulk market. An increase in uncertainty in addition to reducing exports/imports, limiting access to capital, and lowering investments in the industry, can ultimately reduce the demand for sea transportation and cost of dry bulk freight regardless of vessel capacity. However, the effect on the Capesize market appears to persist for a longer period, given that this type of vessel depends more heavily on economies of scale. Furthermore, the decline in freight rates and demand due to a spike in CTPU increases the competition among shipowners and eventually reduces the average earnings per vessel.

Policymakers in China should consider establishing RTAs to diminish the effect of CTPU, as the country's economy is particularly vulnerable to this type of uncertainty [29, 38]. RTAs can also mitigate the impact on exports/imports, thereby reducing the impact on dry bulk market, in which China has a significant share [5, 10-15]. Therefore, RTAs or other similar measures will have multiple benefits for China.

For practitioners, we presented the concept of leveraging trade policy uncertainty for forecasting freight rates and improving the accuracy of BDI predictions. Therefore, shipowners and charterers should consider CTPU when designing a profitable chartering strategy. During periods of high uncertainty, shipowners should prefer the time-charter contracts and charterers the spot market. Conversely, during periods of low uncertainty shipowners should opt for the spot market and charterers should focus on the time-charter contracts.

Since heightened uncertainty tends to suppress the BDI by dampening demand for dry bulk sea transportation, supply chain managers should integrate CTPU into their investment planning, capacity regulation, and inventory management in order to achieve more economically sustainable and resilient transport operations. They should also incorporate CTPU into their flexible pricing policies. This can help balance costs and mitigate risks in anticipation of periods of high and low uncertainty. Empirical researchers should also include CTPU in their route planning models in order to optimize resource allocation and enhance operational efficiency.

7 Conclusions

Our research investigated the TPU index and its impact on the maritime shipping industry, a topic that has received limited attention compared to the more widely studied EPU index. Specifically, we concentrated on the influence of Chinese TPU on dry bulk trade, which has been underexplored by researchers despite China's pivotal role in global maritime shipping. To address this gap in the literature, we employed the Granger Causality test and IRF, examining whether and how CTPU affects the dynamics of the dry bulk shipping market.

Hence, our study expanded the understanding of CTPU's impact on the economy by assessing it separately across all the segments of the dry bulk rates market. We revealed, for the first time, its adverse implications for shipowners and its significance for the industry. Furthermore, we underlined the influence of China on the maritime trade and contributed to a more holistic understanding of seaborne activity indices movements. Utilizing ANN, we demonstrated the out–of-sample predictability of CTPU for BDI, mitigating in-sample bias, and expanding the literature regarding the determinants of BDI. From a practical perspective, considering the importance of BDI for financial markets and the real economy [6, 7, 8], our findings provided valuable insights for policymakers and investors who rely on BDI values to inform investment strategies and decision-making across various industries. Our study offered them a new variable and a predictive model, enabling them to achieve more accurate predictions of BDI and, subsequently, formulate more efficient decisions.

Future researchers should further investigate the effect of CTPU on emissions from dry bulk vessels, given that an increase in TPU reduces the environmental performance of corporations across various industries [39]. Furthermore, the impact of the uncertainty from other types of policies, namely monetary and fiscal, should also be studied.

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