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The effect of economic policy uncertainty and geopolitics on LNG freight rates across different market conditions

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ABSTRACT

This paper examines the effects of economic policy uncertainty and geopolitics on LNG freight rates under different market sentiments, employing Markov – switching Vector Autoregressive (MS-VAR) models. Considering the crucial role of diversification and security of energy supply, we aim to fill this gap in the literature, referring to the transportation cost of LNG. Economic policy uncertainty impacts in a negative way the freight rates in the USA-China trading route and increases the freights at the USA-Europe trading route despite the market conditions. We found that the effect of a shock on National security index is more pronounced at the USA-Europe route. A shock on Geopolitical indices creates an upward trend in the freight rates for both routes under bullish market conditions, which is more intense in the USA-Europe trading route. Our results bear significant implications for both shipowners and charterers related with the LNG trade. This article is a revised and expanded version of the respective research which presented at the International Association of Maritime Economics (IAME) 2024 annual conference, Valencia, in June 2024.

1 Introduction

Kilian et al. [1] stated that the economic environment and geopolitics are crucial for the shipping industry as there are tight links between the Baltic Dry Index (BDI) and global economic activity through commodity demand. According to Baker et al. [2], Caldara et al. [3], and Gulen et al. [4], both economic and geopolitical shocks can deteriorate industrial production, which might result in lower industrial rates. Such economic events in recent history have been the trade war between the USA and China in 2018 and the COVID-19 pandemic, which decreased global economic growth. Regarding the geopolitical shocks that affected the shipping industry, the more recent cases are the Russian invasion to Ukraine and the tension of the Red Sea.

In the case of natural gas, geopolitics are more significant than other sectors. They can impact Liquefied Natural Gas (LNG) shipping in two ways. Initially, when the trading route is disrupted, the vessels must identify alternative routes to unload their cargo. The second ways involves the disruption of gas flows through pipelines. In such cases, importers need to find alternative natural gas suppliers. Hence, the high competition for the available cargo frequently results in elevated freight rates in the spot market.

The latter describes the European energy crisis in 2022. During the 1st half of 2021, the combination of the rapid decarbonization of the European Union (EU) with the industrial recovery of COVID-19 restrictions, led to a deficit of 60 bcm of natural gas. At this time, there were no gas flow disruptions from Russia. The only available source was the LNG, with the global LNG capacity was 484 bcm, of which 290 bcm were committed to long-term contracts. Consequently, the Europeans endeavored to assimilate 60 of the 194 available bcms. As a result of the escalating prices of gas in Europe, LNG vessels were redirected from Asia to Europe. Due to higher prices, 65% of American LNG was redirected from Asia to Europe according to the International Group of LNG Importers (GIIGNL) [5]. International Energy Agency (IEA) [6] denotes that the global use of gas for industrial production increased by 30 billion cubic meters (bcm) in 2023, while the corresponding increase in the Asia-Pacific region was 10 bcm. The industrial sector in China led nearly 40% of the country's overall increase in natural gas demand. In the second half of 2023, the industrial sector in Europe experienced a moderate recovery in gas demand, which increased by over 10% year-over-year, despite remaining 15% below 2021 levels, due to the reduced natural gas prices.

Turning to geopolitics, Tamvakis [7] highlighted that in 2014, the pro-European Ukrainian government signed a treaty with the EU, and Russia annexed Crimea, which led to a conflict along the eastern borders of the European Union. In 2022, Europeans experienced a loss of 167 of Russian gas because of the European embargo on Russian gas, which was implemented in response to the Russian invasion of Ukraine. Almost 80 bcm were intended to be covered through LNG. The demand for LNG in Europe led to a 68% increase in imports, which in turn displaced supplies from other countries, including Bangladesh, India, and Pakistan. The USA experienced a 159% increase in exports to Europe. France was the dominant LNG importer, more than doubling LNG imports (64% from US). The imports of LNG increased in Spain, UK, Netherlands, and Italy increased LNG imports by 43%, 75%, 98% and 44% respectively. The absence of regasification facilities in Germany resulted in the importation of insignificant LNG volumes until the first FSRU was operational towards the end of 2022. Qatar, Russia, and Nigeria were the next three dominant exporters of LNG to Europe according to the International Gas Union (IGU) [8].

British Petroleum (BP) [9] described how the war highlighted the focus on energy security issues, as well as the need for diversification of natural gas supply, due to the vulnerability of the European energy system to geopolitical events. The supply and price shocks that followed the Russia-Ukraine conflict resulted in a 12% decrease in Europe's gas demand. The reduced gas demand in Europe was significantly influenced by the moderate 2022-23 winter, as well as significant reductions in industrial demand, gas-to-coal switch, and renewables integration according to the Hellenic Association for Energy Economics [10]. Demand in Asia fell 1.9%. In South Asia, LNG prices were unaffordable, causing switching to coal wherever possible. During the 1st half of 2023, the US was the leading LNG exporting country, accounting for 21% of global supply. USA, Australia and Qatar represented 60% of the global supply. In terms of destination markets, the geographical structure of LNG supplies from some of the top exporters underwent substantial changes. The geographical structure of exports in Australia and Malaysia is relatively undiversified, with Asia serving as the primary destination for their cargoes. The United States, Qatar, and Russia act as global balancing suppliers that export substantial LNG volumes to both Europe and Asia, responding to the supply-demand and pricing dynamics of the regional markets. The most rapid and extensive response to the European gas crisis was achieved by the United States as a result of the adaptable commercial structure of its LNG exports according to IGU [8]. So, the intra-Atlantic LNG flows increased from 19.8% in 2019 to 27.9% in 2022, while the Atlantic-Pacific flows decreased from 11.4% to 9.5%.

The importance of our research lies in the maritime sector. Importing countries under the need of undisrupted gas flows, want to mitigate their exposure to economic and geopolitical risks, through diversification of suppliers. Hence the shipowners will have their vessels employed, taking advantage of the above-mentioned. Moreover, we provide further aspects of the LNG freight rates' behavior under major events under different market sentiments.

There are few papers discussing the interactions among geopolitical risk and shipping markets. Drobetz et al. [11], attributed the lack of empirical research to the nature of the Geopolitical risk Index (GPR) and Economic Policy Uncertainty index (EPU) concept. Most of the academic research has been focused on the geopolitical impacts on commodity prices, and mainly on the crude oil. Regarding the shipping sector, Drobetz et al. [11] examined the effects of the geopolitical risk and the EPU on dry bulk shipping freight rates, and Michail et al. [12] focused on the geopolitical aspects of LNG trade. Monge et al. [13] studied the geopolitical impact on BDI instead of a specific trading route, while Palaios et al. [14] studied the connectedness of economic and geopolitical uncertainty with the volatility of LNG freight rates. Chen et al. [15] investigated the time-varying connectedness among LNG freight rates and LNG prices, geopolitical risk, and carbon price.

Georgoulas et al. [16] utilized a nonlinear causality test based on neural networks and indicated the strong relationship between geopolitical risk and shipping as well as the long-term effects and the disruption of maritime trade. Qin et al. [17] found that the impact of geopolitics on crude oil has been found significant but, on the gas, returns was negligible. These results were consistent with Cunado et al. [18], Li et al. [19], Khan et al. [20], Ivanovski et al. [21], and Jin et al. [22].

Liu et al. [23] found that the impact of geopolitical risk on energy commodities' volatilities is significant in the long run. These results are in line with Akram [24] and Ozcelebi et al. [25]. Jin et al. [22] confirmed the overall connectedness between energy future prices, i.e., crude oil, heating oil and natural gas, with the geopolitical risk. Apergis et al. [26] showed that the geopolitical threats drive the Henry Hub's price gas crash risk.

Monge et al. [13], examined the impact of GPR both on BDI and oil prices by employing the Autoregressive Fractionally Integrated Moving Average (ARFIMA) model and Fractionally Cointegrated Vector Autoregressive (FCVAR) framework to capture these effects using a dataset of monthly frequency from 1985 to 2021. This study indicated that GPR and BDI returned to their original trend after an exogenous shock, followed a mean reversion process. They also found a persistent effect of GPR on BDI in the long term, but weak relation in the short-run.

As for the effects of GPR and EPU on freight rates on specific dry bulk routes, Drobetz et al. [11] employed Bayesian Vector Autoregressive (BVAR) model. They demonstrated that an increase in GPR had an instant positive effect on dry bulk shipping freight rates which steadily declined over time. On the other hand, dry bulk trading routes responded negatively to positive shocks to EPU. They also showed that the impacts of these shocks can have different signs within different subperiods.

Michail et al. [12] denoted that GPR affects the freight rates. The LNG fleet and the natural gas price in USA (Henry Hub – HH) did not have any significant impact on freight rates in contrast with GPR and a macroeconomic proxy. The impact was 20% and 25% on the route from the USA to Europe and from the USA to China, respectively. The scholars utilized the Vector Error Correction model (VECM) and monthly frequency data from 2018 to 2021.

Palaios et al. [14], applied quantile connectedness methodology on a dataset of monthly observations from 2010 to 2022. The authors concluded that after a shock, the energy variables absorbed the marginal effects contrary to geopolitical and economic uncertainty. Lastly, Chen et al [15] employed a Time-Varying Parameter Vector Autoregressive model with Dynamic Shocks (TVP-VAR-DY) model and found a bidirectional connectedness between the LNG price and LNG freight rates with similar intensity. They also argued that in the U.S. and Europe market, the spillover effect of LNG freight rate on natural gas' spot price is more pronounced. On the other hand, except the outbreak of Russia-Ukraine conflict, the geopolitical risk was not found to have an obvious spillover effect on the LNG freight rates of the U.S.-Europe route.

2 Dataset and Methodology

2.1 Dataset

We employ data for the freight rates of two LNG routes (Sabine Pass to Tianjin and Sabine Pass to Zeebrugge) to capture the economic and geopolitical uncertainty on LNG freight rates as dependent variables. Neither fleet development nor the natural gas price in Henry Hub (HH) affects the LNG freight rates according to Michail et al. [12]. Conversely, the macroeconomic environment and geopolitics are significant. Therefore, in order to accurately represent the macroeconomic conditions of both regions, we implement industrial production in both China and Europe as independent variables. Additionally, we estimate the price premiums in the European and Asian natural gas markets. More specifically, we calculate the Asian premium as the difference between the Asian prices (JKM) and HH, and the European premium as the difference between European prices (TTF) and HH. As variables of interest, we utilize the Economic Policy Uncertainty Index, the National Security Index, and the Geopolitical Risk Index, as well as the sub-indices of Acts and Threats. Our data spans a six-year period from January 2018 to December 2023 in monthly frequency.

EPU index measures the relative frequency of domestic newspaper articles that include the three terms associated with the economy (E), policy (P) and uncertainty (U). The index value is directly correlated with the percentage of newspaper articles that address economic policy uncertainty in the corresponding month. Chinese index is a smooth splicing of the South China Morning Post (SCMP) and mainland newspapers' articles. We employ Chinese EPU as proxy for the Asian region. National Security index is a sub-category of EPU and is provided globally. We also constructed the EPU for Europe, as the average EPU of Germany, France, Italy, Spain, and United Kingdom.

We employ the Caldara & Iacoviello's GPR indices to capture the geopolitical sentiment. These indices are calculated by counting the volume of articles regarding adverse geopolitical events in eleven leading newspapers. GPR index reflects automated text-search results of the electronic archives of 10 newspapers: Chicago Tribune, the Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, the Los Angeles Times, The New York Times, USA Today, The Wall Street Journal, and The Washington Post. Geopolitical Threats include words regarding war threats, peace threats, military buildups, nuclear threats and terror threats. Geopolitical Acts refer to beginning of war, war escalation and terror acts. However, we do not include the Geopolitical Acts as variable to our models following the findings of Apergis et al. [26].

Data referring to freight rates, industrial production, and LNG prices are retrieved from Clarkson's Intelligence Network. EPU and National Security index obtained from the website of Baker, Bloom, and Davis (www. policyuncertainty.com).

Table 1 depicts the variables that we employ in our empirical research along with their sources, their definitions and the unit of measurement.

Table 1 List of variables

Variables	Description	Source	Units of Measurement
Sabt	Sabine Pass to Tianjin*	Clarkson's Intelligence Network	$/day
Sabz	Sabine Pass to Zeebrugge**	Clarkson's Intelligence Network	$/day
PrAs	Premium in Asian markets	Clarkson's Intelligence Network, authors' calculations	$/Mbtu
PrEu	Premium in European markets	Clarkson's Intelligence Network, authors' calculations	$/Mbtu
InAs	Industrial Production in Asia	Clarkson's Intelligence Network	% Yr/Yr
InEu	Industrial Production in Europe	Clarkson's Intelligence Network	% Yr/Yr
NatSec	National Security Index	Caldara and Iacoviello	Units
EPU_Ch	Economic Policy Uncertainty in China	Caldara and Iacoviello	Units
EPU_EU	Economic Policy Uncertainty in Europe	Caldara and Iacoviello	Units
GPR	Geopolitical risk index	Caldara and Iacoviello	Units
GPR_T	Geopolitical risk index referring to threats	Caldara and Iacoviello	Units

Notes: * Basis T/C equivalent, 55-day round trip (via Panama); ** Basis T/C equivalent, 28-day round trip.

2.2 Descriptive statistics

Table 2 provides the descriptive statistics. We observe that the average freight rates are almost identical for the two trading routes. Both routes present similarities regarding their distributions; positive skewness and extreme values in the tails (leptokurtic distribution). The Jarque-Bera [27] normality tests, indicate that the null hypothesis of normality can be rejected. We observe the same characteristics with the freight rates, to the premiums and the industrial production in both regions. EPU is normally distributed for both areas. Moreover, the EPU referring to China presents higher prices compared to European EPU. Lastly, GPR is higher when it concerns threats rather than acts.

Table 3 presents the stationarity tests. We used the Philips and Perron [28] (PP) test, as it employes a non-parametric approach contrary to the Augmented Dickey–Fuller [29] (ADF) test and is more appropriate for relatively short time series according to Michail et al. [12]. We employ the PP model under three different specifications: with intercept; with intercept and trend; and without intercept and trend. We minimize the Schwarz Bayesian Information Criterion (SBIC) to determine the lag length of the PP statistic. Under the three different specifications, the time series are I(1) except those referring to Industrial Production at 5% significance level, which have been retrieved in returns as mentioned in Table 1.

Table 2 Descriptive statistics

Variable	Mean	SD	Skewness	Kurtosis	JB
Sabt	92170.2	78846.7	2.49	11.08	0.0000*
Sabz	91003.2	76785.5	2.56	11.66	0.0000*
Pras	10.9	10.5	1.33	4.04	0.0000*
PrEu	10.2	12.2	1.96	6.91	0.0000*
InAs	5.6	6.3	2.05	15.83	0.0000*
InEu	-0.37	7.6	1.21	15.12	0.0000*
Nat Sec	113.6	58.9	1.45	5.59	0.0000*
EPU Ch	647.6	189.5	-0.45	2.83	0.2801
EPU EU	495.7	126.3	0.07	3.09	0.9552
GPR	105.98	41.27	2.62	12.95	0.0000*
GPR_T	129.91	53.24	2.85	14.2	0.0000*

Notes: Numbers in JB column indicate the p-value of Jarque-Bera test. *. **. and *** Indicate statistical significance at 1%. 5% and 10% level of significance. When the p-value is lower than the significance level we reject the null hypothesis of normal distribution.

Table 3 Phillips-Perron stationarity test

	With constant		With constant & trend		Without constant & trend	
Variables	**Levels**	**1st Differences**	**Levels**	**1st Differences**	**Levels**	**1st Differences**
Sabine Pass – Tianjin	0.0424**	0.0000*	0.1840	0.0000*	0.0645***	0.0000*
Sabine Pass – Zeebrugge	0.0376**	0.0001*	0.1235	0.0000*	0.0652***	0.0000*
Premium Asia	0.2761	0.0000*	0.3783	0.0000*	0.2316	0.0000*
Premium Europe	0.1716	0.0000*	0.3103	0.0001*	0.0973***	0.0000*
EPU Asia	0.0021*	0.0001*	0.0131***	0.0001*	0.6802	0.0000*
EPU Europe	0.0007*	0.0001*	0.0050*	0.0000*	0.6332	0.0000*
GPR	0.0150**	0.0000*	0.0215**	0.0000*	0.5138	0.0000*
GPR Threats	0.0081***	0.0000*	0.0266**	0.0000*	0.3390	0.0000*
National Security	0.0000*	0.0001*	0.0001*	0.0001*	0.0769***	0.0000*
Industrial Production China	0.0054*	0.0000*	0.0278**	0.0001*	0.0089*	0.0000*
Industrial Production Europe	0.0682*	0.0000*	0.0203**	0.0000*	0.0062*	0.0000*

Notes: *, **, and *** Indicate statistical significance at 1%. 5% and 10% level of significance.

2.3 Markov – switching Vector Autoregressive (MS-VAR)

Sims [30] developed the standard k-dimensional Vector Autoregressive (VAR(p)) process by adopting simultaneous equations. to carry out linear regression between the endogenous variables and their lag term. in order to estimate the dynamic relationship among the variables, as:

$$y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + \mu_t + e_t \tag{1}$$

where y_t refers to the k*x*1 vector of endogenous variables, $A_1 \ldots . A_p$ denote the k*x*k metrices of the estimated lagged coefficients, μ_t is the k*x*1 vector of intercepts and e_t the k*x*1 vector of residuals.

Hamilton [31] proposed the Markov switching method in order to support the existence of different characteristics within an economic system under different mechanisms states.

Krozlig [32] combined the VAR model with the Markov process. He modified equation 1 to allow for regime changes. In his approach the y_t follows a VAR process depending on the value of a discrete state variable, s_t. We assuming that there are two possible regimes, the bullish and bearish sentiment of the market. Hence, the state variable s_t follows a two-state first order Markov process. When $s_t = 1$, the market is in regime 1 in period t.

There are two forms of VAR regime dependence: the Switching Intercept model (SI) and the Switching Mean model (SM). The eq. 1 is transformed respectively to eq. 2 and 3.

$$y_t = \sum_{j=1}^{p} A_j (s_t)\, y_{t-1} + \mu_t (s_t) + e_t \tag{2}$$

$$y_t - \mu_t (s_t) = \sum_{j=1}^{p} A_j (s_t)\, (y_{t-j} - \mu_{t-j} (s_{t-j})) + e_t \tag{3}$$

SI specification results to smooth changes in the time series, and e_t depends on the current regime. In contrast, the MS specification results to immediate jump in the mean and e_t depends on the current and the previous regimes.

In Markov models it is assumed that the probability of being a regime depends on the previous state, and are time-invariant:

$$P(S_t = j \mid S_{t-1} = i.\ S_{t-2} = k\ldots) = P(S_t = j \mid S_{t-1} = i) = p_{ij}(t) \tag{4}$$

Hence, $p_{ij}(t) = p_{ij}$ for all t. The ij-th element denotes the probability of moving from regime i in the period t-1 to regime j in period t. The probabilities matrix is the following:

$$P = \begin{pmatrix} P(s_t = 1 \mid s_{t-1} = 1) = p_{11} & P(s_t = 2 \mid s_{t-1} = 1) = 1 - p_{11} \\ P(s_t = 1 \mid s_{t-1} = 2) = 1 - p_{22} & P(s_t = 2 \mid s_{t-1} = 2) = p_{22} \end{pmatrix} \tag{5}$$

The expected duration of y_t being and remaining in regime 1 equals to:

$$\frac{1}{P1.2} = \frac{1}{1 - P1.1} \tag{6}$$

Markov VAR can capture in an appropriated way the nonlinear dynamic features of macroeconomic variables and reflect the effect of macroeconomic changes on LNG freight rates fluctuations. It can also determine the economic cycles endogenously. Lastly, Markov VAR measures the probability of different regimes, and especially the transition probabilities between the regimes, as well as the switching duration.

3 Empirical results

3.1 Determination of model and lag order

Prior to the establishment of Markov switching Mean VAR (SMMA – VAR) models, we determine the lag order and the variables. We employ the Akaike criterion (AIC) and the SBIC. For each route, we tested the models including the freight rates, the geopolitical indices, the EPU with the regional specifications, the national security index, the price premium in each route, and the industrial production in each destination of the vessel. Firstly, we tested the models with two periods of lag, and with one lagged period. From a forward-looking perspective, based on the above-mentioned criteria we concluded that the one period of lag order is the more appropriate. Then, we tested which variables should be included. The AIC and SBIC criteria denote that the models with the freight rates, the geopolitical indices and EPU are the more appropriate. Table 4 presents the results where SMMA stands for Switching Mean Markov, and the number in the parenthesis denotes the number of regimes.

We also notice, according to SBIC, that for the route Sabine Pass – Tianjin, the most appropriate model is the one including GPR threats which is in line with Apergis et al. [26].

3.2 Transition probabilities

Table 5 denotes the probability transition matrix between the two regimes for the two trading routes. We present the transition probabilities for the models with the lowest AIC and SBIC values for each route. For the Sabine Pass – Tianjin trading route, the model contains the Geopolitical threats, and for the route Sabine Pass – Europe, the model includes the GPR.

Regime 1 refers to bullish market conditions, while regime 2 refers to bearish market conditions. Regime 2 can be linked with specific periods where significant events took place for the LNG shipping market. Such events include excess demand for LNG due to weather conditions, or for storage. Respectively, we can infer that Regime 1 represents stability in freight rates.

According to Eq. 6, the duration for remaining in each regime is equal, around 2 months, for both routes. This finding is rational, and we attribute it to the seasonal patterns of the freight rates in these routes. It can be inferred that the freight rates go up and down within a 4-month period, writing down a “cycle”. This finding is in accordance with Polemis et al. [33] who identified freight rate’s peaks in March, July and August. The duration for both regimes remains the same in all models for both routes.

Table 4 Model selection criteria

Route	Geopolitical Variable	Model	AIC	SBIC
Sabine Pass – Tianjin	GPR*	SMMA (2) – VAR (2)	6.17	10.28
		SMMA (2) – VAR (1)	6.03	8.5
	GPR	SMMA (2) – VAR (1)	4.37*	6.29*
	GPR Threats*	SMMA (2) – VAR (2)	6.49	10.93
		SMMA (2) – VAR (1)	6.35	8.8
	GPR Threats	SMMA (2) – VAR (1)	4.52*	6.19*
Sabine Pass – Zeebrugge	GPR*	SMMA (2) – VAR (2)	5.2	9.03
		SMMA (2) – VAR (1)	4.49	7.72
	GPR	SMMA (2) – VAR (1)	3.89*	5.49*
	GPR Threats*	SMMA (2) – VAR (2)	6.39	8.07
		SMMA (2) – VAR (1)	4.29	7.01
	GPR Threats	SMMA (2) – VAR (1)	4.25*	5.92*

Notes: * including price premium and industrial production.

Table 5 Transition Probabilities Matrix

Trading route: Sabine Pass – Tianjin		
	Regime 1	**Regime 2**
Regime 1	55.04%	44.96%
Regime 2	54.80%	45.20%
Trading route: Sabine Pass – Zeebrugge		
	Regime 1	**Regime 2**
Regime 1	47.73%	52.27%
Regime 2	47.83%	52.17%

3.3 Impulse Response Functions (IRFs)

Impulse response function can capture the shock effect of several variables within a system in the short-run. We impose a generalized shock on freight rates, the geopolitical indices and the EPU for each route. We obtain and analyze the generalized impulse response diagrams under the two regimes.

Figure 1 depicts the freight rates' response to a given shock on all other variable, for the route from USA to China, under the bullish market sentiment. Freight rates respond positively to their shocks, with an immediate significant impact. After the 1st month the impact decreases rapidly and the response dies out after the 4th month. The similar pattern is noticed for the geopolitical indices, but the range of the shock is deteriorating. More specifically, the response to a freight rates' shock is 0.5%, while the responses to geopolitical threats and GPR itself are 0.12% and 0.02% respectively. We attribute the difference between the two geopolitical indices to the methodology of constructing these indices, as GPR contains both the threats and the acts. The impacts of GPR acts, offsets the effects of GPR threats in the common GPR index. In the discussion section we will comment thoroughly the implementations of our results.

Figure 2 shows the freight rates response for the same route under the bearish regime. Similarly to the 1st regime, the freight rates respond positively to their shocks, with an immediate significant impact, but the

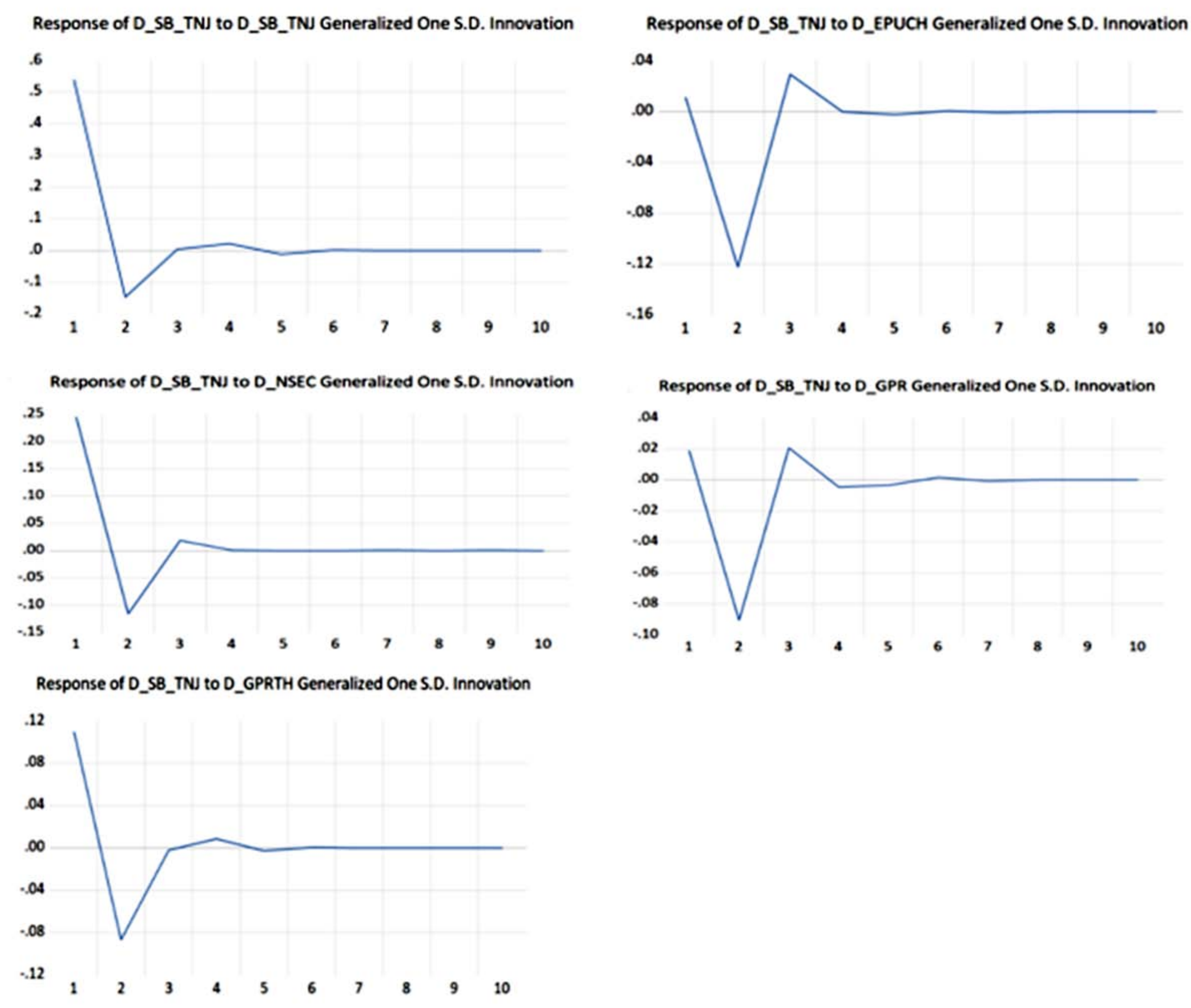

Figure 1 Regime no.1 for the trading route from Sabine Pass to Tianjin.

Note: The upper left diagram denotes the response to a shock on freight rates; the upper right diagram on EPU; the middle left on national security; the middle right on GPR; the bottom left on GPR (acts); the bottom right on GPR (threats).

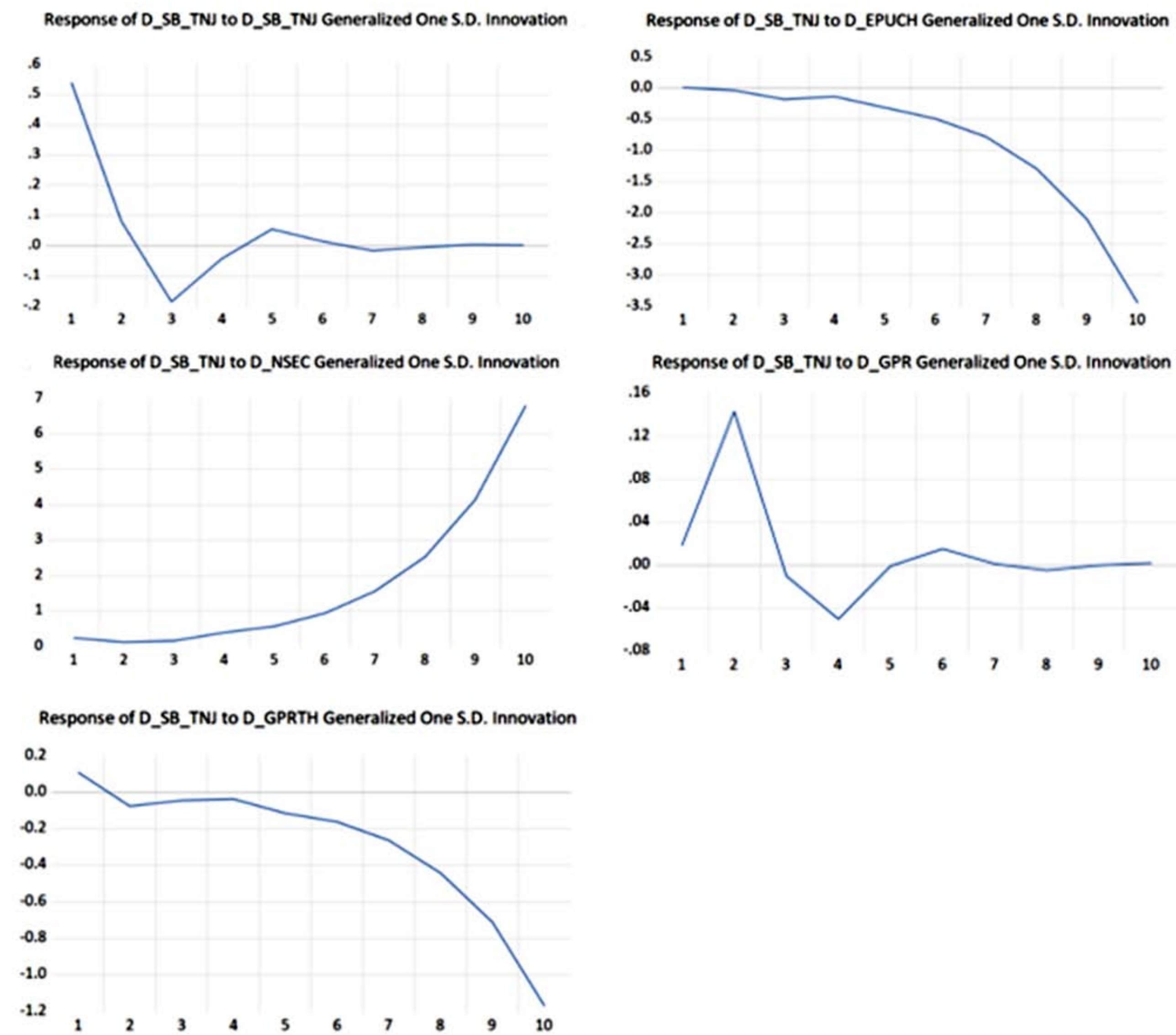

Figure 2 Regime no.2 for the trading route from Sabine Pass to Tianjin.

Note: The diagrams follow the Figure 1 pattern.

impact dies out after the 5th month. The effect of a shock on EPU is completely different. It appears after the 5th month and impacts around -3.5%. This negative impact is rationale and denotes that a slow down in Chinese economy, and its industrial sector, reduces the demand for LNG transportation services. In contrast, a shock on national security increases the freights up to 7% after the 4th month. As the national security index is measured globally, and China is not threatened by existing war conflicts, we attribute this finding to the competition for the available fleet in other routes. This competition increases the freight rates for all vessels regardless the route in which they operate, as it might be more profitable to reroute a vessel to another destination port. Lastly, a shock on geopolitical indices, increases the freight rates and this effect dies out after the 3rd month. These impacts are more intense compared to the 1st regime.

Figure 3 depicts the freight rates' response to a given shock of one standard deviation on all other variable, for the route from USA to Europe, under the bullish market sentiment. As in the USA-China route, the freight rates respond positively to their shocks but within a narrower range. A shock on EPU and National security index, presents the same results with the previous route, but the effects of EPU are more pronounced. The impact of a shock on GPR is also greater in the USA-Europe trading route denoting the vulnerability of Euro-

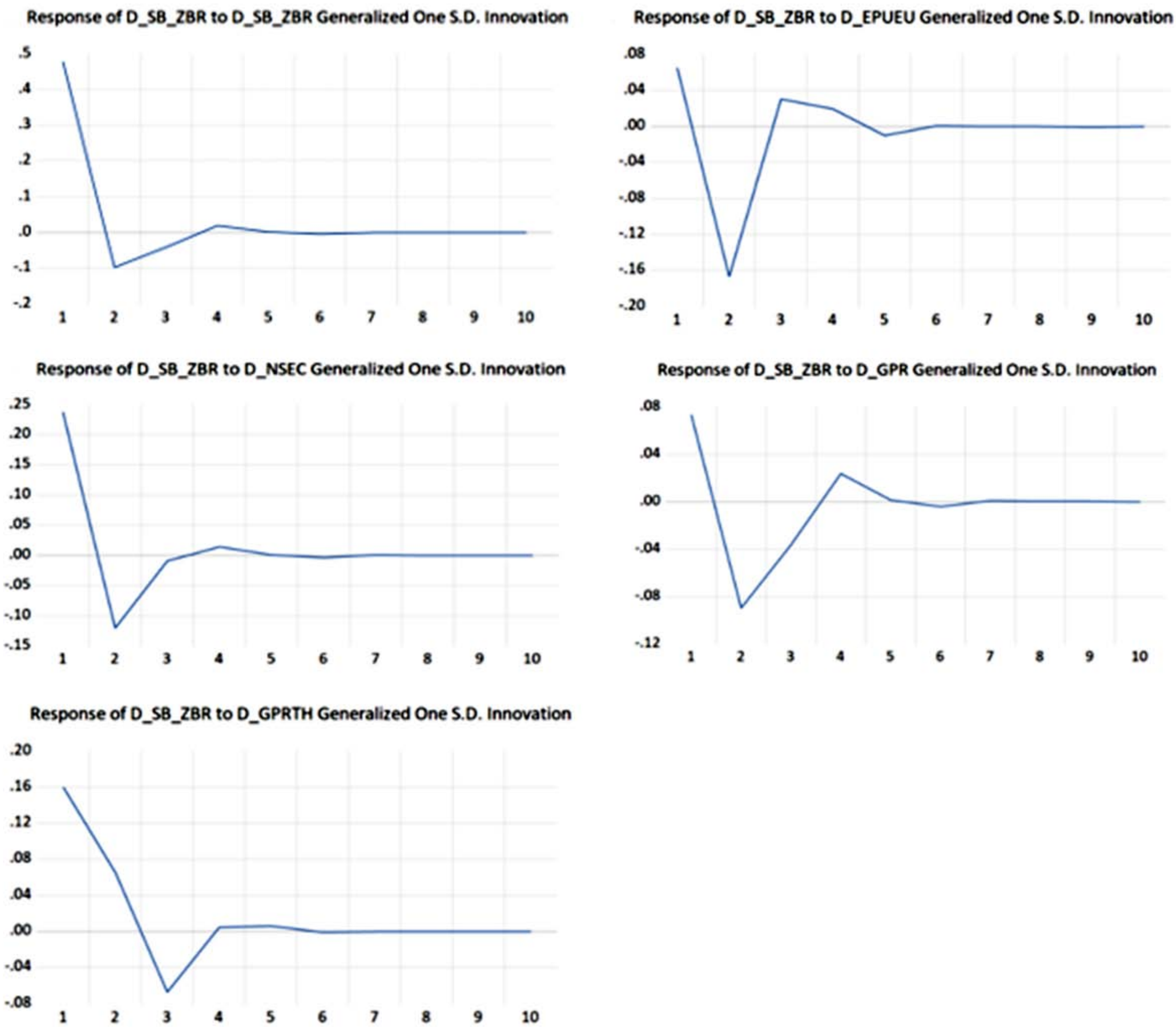

Figure 3 Regime no.1 for the trading route from Sabine Pass to Zeebrugge.

Note: The diagrams follow the Figure 1 pattern.

pean natural gas market to geopolitical events. More specifically, the magnitude of a shock on GPR and GPR with respect to threats is 0,08% and 0,16% respectively while the corresponding magnitude in the USA – China route is 0,02% and 0,12%. We also notice that the effects of the shocks on the freight rates are absorbed after a 4-month period. Hence, we conclude that the freight rates, in both routes, respond with the same pattern to shocks in the freight rates, geopolitical indices and EPU, but with different magnitude.

Figure 4 provide information regarding the freight rates' response to a shock on the variables, under bearish market conditions, for the route from Sabine Pass to Zeebrugge. Firstly, we notice that there are different patterns in the responses compared to the bullish market conditions. Freight rates respond positively to their own shock. Namely there is an increase by 1% which increases by time, denoting the change in the market sentiment. Similarly, a shock on EPU and National security index, affects the freight rates, persisting for a long period. On the other hand, the impact of the shock on GPR and GPR with respect to threats, is 0,05% and 0,16% respectively. These responses are slightly less intense compared to bullish market conditions. We attribute this finding both the mechanism of freight rates' formation in this route, as well as to the importance of geopolitics, energy dependence, energy mix, and economic fundamentals in Europe.

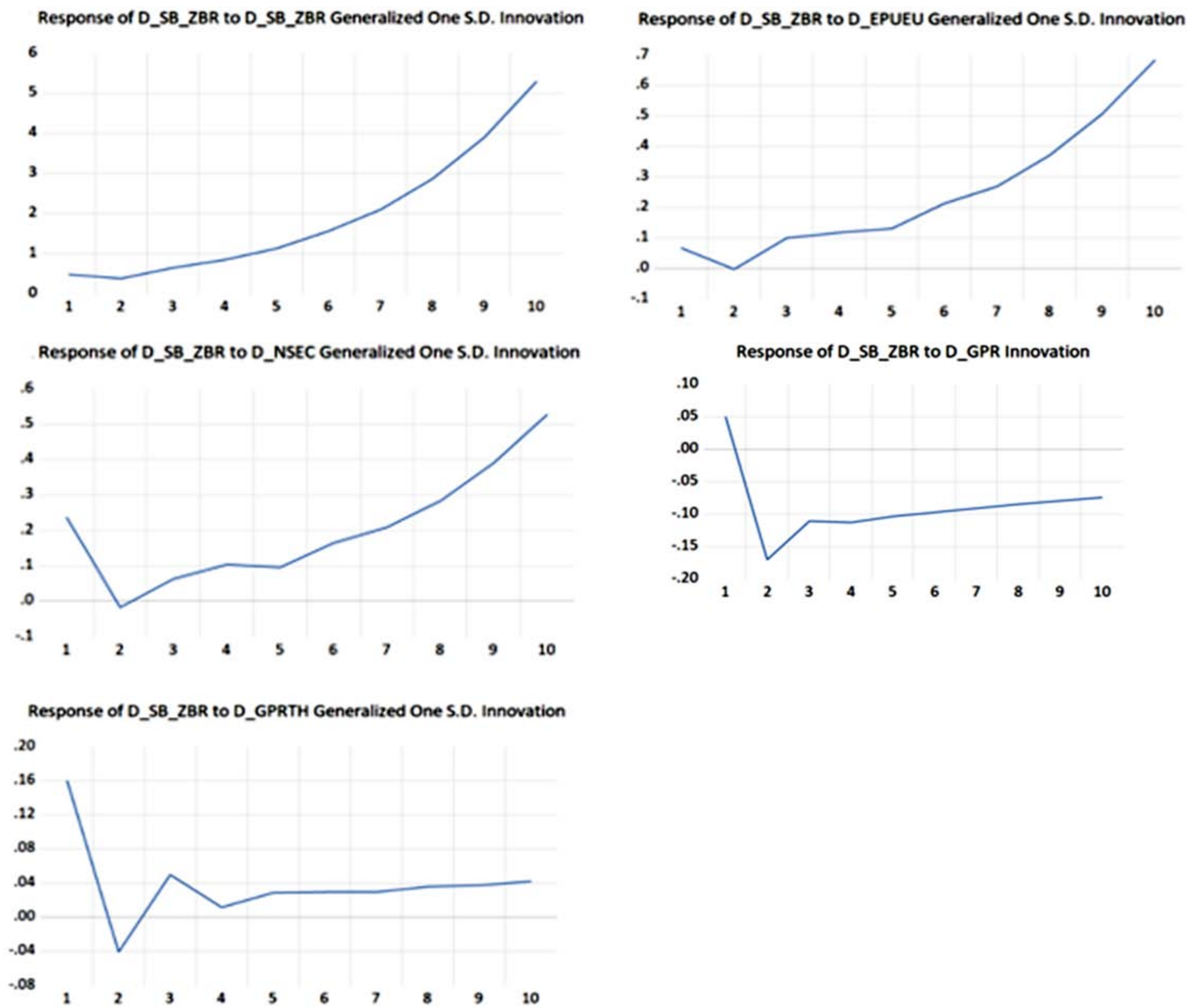

Figure 4 Regime no.2 for the trading route from Sabine Pass to Zeebrugge.

Note: The diagrams follow the Figure 1 pattern.

4 Discussion

Our results suggest that the economic policy uncertainty and geopolitical effects on the LNG vessels sectors vary across regions based on the market sentiment. Regarding the economic policy uncertainty, we observe differences on a shock's impact across the Sabine Pass – Tianjin route between the two regimes. When the market is upward, a shock leads to an immediate negative response of -0.12%, while when the market is downward the same shock leads to more permanent negative impact reaching -3.5% after a 10-month period. We attribute these findings to the role of natural gas, and especially of LNG, in the industrial activity in the Chinese economy. Hence, a slowdown in the industrial processes might lead to lower demand for LNG transport. Turning to Sabine Pass – Zeebrugge route, when the market is in the positive state, a shock of one standard deviation on EPU cause an increase of freight rates by 0.8% which turns negative the next month, and then is absorbed. On the negative state of freight market, the freights react to the shock by an increase which is accumulated by the months reaching up to 0.7%. We notice that in both routes, when the market is upward, the reaction follows the same pattern. We attribute this difference to. Lastly, we observe a different reaction to the same when the market is downward. This finding makes sense due to the robustness of Chinese economy, which is less vulnerable to economic uncertainty. The Chinese industry can also switch from gas to coal its energy consumption when gas prices are high. without considering the environmental aspect to the same extent as the Europeans. Hence, the Chinese industry is less dependent to natural gas in comparison with the European. The findings related to USA-China trading route, are in accordance with Drobetz et al. [11]

Turning to the shock on the National Security index, both routes react similarly and to the same extend, under both regimes. When the market is up, there is an immediate increase in freight rates around 0.25% which is absorbed after the 3rd month. On the other hand, when the market is down, the freight rates increase in both routes, but in the USA-Europe, the increase is more pronounced from the beginning of the shock, while in the route USA-China, the increase becomes clearer after the 5th month. These findings are the expected ones as during the period that covers data sample. Europe has been more susceptible to national security concerns contrary to China who is not threatened by existing war conflicts. In contrast, European countries have experienced such conflicts like the Russian invasion to Ukraine, that led to natural gas flow disruption from Russia to Europe. Given the energy dependence of Europe from Russia, the European economies rely on LNG to meet their natural gas needs. This results in a significant increase in the demand for LNG vessels, which in turn leads to higher freight rates.

Lastly, regarding the geopolitical risk indices, we notice similar reaction patterns in both routes when the market is bullish. There is an expected initial increase of the freight rates, which more pronounced in the USA-Europe trading route, denoting the geopolitical weakness of Europe, during the examined period. Namely, the impact of GPR and GPR threats, is 0.02% and 0.12% for the Chinese trading route, while the respective impacts for the European trading route is 0.08% and 0.16%. Except from the different magnitude of the shocks, we also observe that the shock of geopolitical threats dies out with a slower pace. When the market sentiment is downward, the freight rates react differently in the two trading routes. In the Chinese route, there is an increase up to 0.15% in the 2nd month and is absorbed by the 5th month, while the react to threats is an immediate increase of 0.2% which turns negative after a month and continues a downward trend. This can be attributed to the alternatives to LNG of the Chinese energy mix. When the market is bearish, the freight rates react different across the trading routes. In the Sabine Pass – Tianjin route, there is an initial increase of 0.04% continuing up to 0.15% and then the shock is absorbed. When the shock refers to threats, there is an initial increase which is gradually reduced. However, in the European route the respective shock persists after the initial 0.15% around 0.05%. Despite our results are in accordance with Michail et al. [12] we notice a slightly different magnitude of the shocks' impact. We attribute this difference to the different data sample, as this paper include both the Russian – Ukraine conflict as well as the beginning of the tensions in the Middle East which affected Europe to greater extent than China.

As the LNG shipping market is a niche area of study, further research should be conducted when data for other trading routes become available. Another research question should refer to the topic but with higher frequency data, as well as, with alternative geopolitical sentiment indices.

5 Conclusion

This paper discusses the impact of a shock on economic policy uncertainty index, and on geopolitical risk index on LNG freight rates, in two trading routes, from USA to China, and from USA to Europe. The analysis is conducted to a sample period spanning from January 2018 to December 2023, with monthly observations. This timeframe covers the Rusia – Ukraine conflict and the beginning of the tensions in the Middle East. It also covers the period of the pandemic Covid-19 and the following economic activity slowdown.

We employed a Markov – switching Vector Autoregressive, with switching mean. The endogenous variables for each route are the freight rates, the economic policy uncertainty index, the national security index and the geopolitical risk index. As exogenous variables, we employed the industrial production and the price premium.

As the energy commodities are particularly susceptible to geopolitical events, the vessels involved in their transportation are particularly vulnerable. The academic research has been primarily focused on geopolitical impacts on oil and gas prices, rather than on the effects on shipping sector. Our result indicates that the freight rates react differently under different market sentiment and across the trading routes.

A shock on the economic policy uncertainty index impacts in a negative way the freight rates in the USA-China trading route, contrary to the USA – Europe trading route in which increases the freights despite the market conditions. The effect of a shock on National security index is more pronounced at the USA-Europe route. A shock on Geopolitical indices creates an upward trend in the freight rates for both routes under bullish market conditions, which is more intense in the USA-Europe trading route denoting the vulnerability of Europe to geopolitics.

Our results are of great importance to both shipowners and charterers. Both have the ability to adjust their chartering policy in response to geopolitical events. Additionally. they have the ability to assess the market cycle by region and consider their strategy.

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