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Geopolitical shocks and carbon pricing: Do clean energy assets act as a hedge?

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ABSTRACT

While the interaction between geopolitical events and emission trading system (ETS) is somewhat complex, very little is known about how geopolitical shocks impact global carbon prices. In this study, we extend this scant literature by exploring the linkage between geopolitical risk (GPR) and the Chinese carbon markets. Given that geopolitical shocks may influence the Chinese ETS in several ways, such linkage merits an empirical investigation. Methodologically, we combine the Markov regime switching (MRS) model with the vector autoregressive (VAR) process and apply it to the Shenzhen and Hubei carbon markets. The results suggest that while the standard VAR model fails to capture any connection between geopolitical shocks and carbon returns, employing the MRS-VAR process reveals that GPR in fact exerts significant effects on the Chinese carbon markets implying that such effects appear to be regime-dependent. More specifically, the impact of geopolitical shocks is negative in the high volatility regime, but statistically insignificant in the low volatility regime. Further investigations show that higher geopolitical risk leads to higher hedging costs and that clean energy equities could be a suitable hedge for the Chinese carbon markets amid the periods of high geopolitical uncertainties. These outcomes have key implications which would be crucial for reaching the net-zero goals.

1. Introduction

Global climate change is largely attributable to greenhouse gas (GHG) emission from fossil fuel consumption. This is also the case for the Chinese economy given that fossil fuels accounted for 82 % of primary energy consumption in China.[1] Tackling climate change thus requires a fundamental transition from nonrenewable to renewable energy sources. However, there is a huge gap between the current and required levels of investments, policy implementation, and governmental and institutional financing for a sustainable energy system with net zero carbon emissions. A major further complication in the renewable energy transition is the great deal of uncertainty surrounding the world economy and global energy markets. More specifically, geopolitical risk and thereby rising oil price uncertainty have recently increased substantially due to COVID-19 pandemic and Russian invasion of Ukraine. Such uncertainties might cause a significant delay in clean energy promotion in China, which is a key factor to reduce the amount of CO_2 released into the atmosphere.

To this end, the carbon emission trading system (ETS) could play a pivotal role in energy transition in China towards carbon neutrality. However, the Chinese emission market is still immature because of low carbon prices and poor liquidity [1,2]. Given that an efficient carbon trading market is essential for reducing the emissions from power generation, the Chinese government should adopt effective strategies to increase the influence of the ETS. An efficient carbon market is also important for accelerating the deployment of carbon capture, utilization and storage (CCUS) projects, which is also crucial for achieving the net-zero goals.

Given that the ETS has a key role to play in attaining carbon-neutrality, the empirical literature focusing on the volatility dynamics of Chinese emission market is growing substantially. Some recent contributions include Chun [3], Lin and Chen [4], Xu [5], Dutta et al. [6], Ma et al. [7]. Chun [3], for instance, examine the risk transmission linkage between the Chinese and EU carbon markets. Employing the bivariate GARCH model, Lin and Chen [4] find a time-varying association among the Beijing carbon market, the coal market and the Chinese

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[1] This piece of information is sourced from https://www.reuters.com/markets/commodities/china-india-struggle-curb-fossil-fuels-kemp-2023-10-19/

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clean energy equity market. Besides, Xu [5] show that the variation in Chinese carbon prices is sensitive to global energy market uncertainties. More recently, Dutta et al. [8] document that the emission prices in China are characterized by time-varying jumps. In addition, Ma et al. [7] find that the regional carbon markets in China influence the volatility of the firms operating in the corresponding emission trading region.

Note that although the volatility of Chinese carbon emission trading (CET) market has received considerable attention in recent empirical works, the literature is still scant. Since precise estimates of time-varying volatilities are essential for increasing the efficiency of carbon trading in China, it is crucial to identify the factors causing variations in emission prices. To this end, the current study aims to examine if increasing risks due to geopolitical conflicts are a key driver of the Chinese emission market volatility. Note that geopolitical risk (GPR) can impact carbon trading in China via several channels. Firstly, leading economies such as China and India have been purchasing cheap crude oil from Russia since the inception of the Russo-Ukrainian war, which has significant effects on the sustainable investment in these countries. As the Chinese economy is heavily dependent on overseas oil, purchasing cheap oil might help economic growth, but hamper the transition towards carbon-neutrality. Thus, green transition would probably be sluggish as a consequence of the ongoing war. Secondly, geopolitical shocks might have a substantial effect on energy supply chains by creating chaos in energy imports or generating uncertainty in crude oil sectors. This would increase China's dependency on coal or other fossil fuels, thereby raising CO_2 emissions and subsequently, ETS prices. Thirdly, global political equilibrium may impact the overseas investment in China's cleantech and alternative energy markets. If geopolitical shocks impede such financing, there might be a significant delay in the transition process, thus causing an upsurge in emission prices due to a lack of effective substitutes. Finally, due to the connectedness between global carbon markets, geopolitical shocks influencing other ETS may lead to a ripple effect. Thus, fluctuations in carbon policies or pricing in key economies could transmit to the Chinese emission markets, which in turn causes a variation in carbon prices. Overall, the interaction between geopolitical events and emission markets is somewhat complex, and therefore the Chinese carbon market being a new asset class could be highly vulnerable to geopolitical uncertainty. In sum, the linkage between GPR and the Chinese emission prices merits an empirical investigation.

Moreover, this paper also examines how we can hedge the downside risk of the Chinese emission trading markets when the geopolitical risk is relatively high. In doing so, we construct a two-asset portfolio comprising CET and crude oil. For comparison purposes, another portfolio is formed which includes CET and the iShares Global Clean Energy ETF (ICLN). Note that several recent studies [9–11] explore the hedging strategies among crude oil, clean energy assets and the Chinese carbon markets. However, these papers do not consider the hedging effectiveness of these assets when the GPR reaches a pick. Our study aims to fill this gap in the existing literature.

Methodologically, we employ the Markov regime-switching vector autoregression (MRS-VAR) model to inspect whether an upsurge in geopolitical risk impacts the Chinese emission prices across various regimes (e.g., low and high volatility states). The application of this process is beneficial as we can investigate if carbon prices tend to swap between different volatility states. Besides, this model helps us measure the impulse response functions which are useful for examining the direction, duration and strength of the effect of geopolitical risk across different volatility regimes.

Our findings indicate that while the standard VAR model fails to capture any linkage between geopolitical shocks and carbon returns, employing the MRS-VAR process reveals that GPR in fact exerts significant effects on the Chinese carbon markets suggesting that such effects appear to be regime-dependent. More specifically, the impact of geopolitical shocks is negative in the high volatility regime, but statistically insignificant in the low volatility regime. Further investigations reveal that higher geopolitical risk leads to higher hedging costs and that clean energy asset could be a suitable hedge for the Chinese carbon markets amid the periods of high geopolitical uncertainties. These findings of this empirical study could provide useful policy-relevant evidence for the governments. Besides, this research could be informational for environment-friendly investors who play a pivotal role in the reduction of CO_2 emissions.

Note that although geopolitical risk and green investments seem strongly intertwined [12], investigating the impact of GPR on carbon markets, which also belong to the sustainable finance ecosystem, is surprisingly ignored in the existing literature. While Lu et al. [13] examine the association between GPR and ETS, our study differs from this earlier work in several aspects. Firstly, we analyze the Chinese carbon markets, whereas Lu et al. [13] consider the EU market in their investigation. This is an important extension of earlier works given that while both the EU and Chinese carbon markets share the common objective of reducing greenhouse gas emissions, they differ significantly in terms of market structure, regulatory frameworks, allowance allocation methods, price stability, and long-term goals [6,14]. The EU carbon market, for example, has developed mechanisms aimed at price stability, such as the Market Stability Reserve (MSR), which adjusts the supply of allowances based on market conditions to prevent excessive volatility. The Chinese carbon market, on the other hand, lacks similar mechanisms like the MSR, which might contribute to abrupt price changes during periods of regulatory or market uncertainty. Besides, the latter also experiences significant price fluctuations due to lower trading volumes and a limited number of participants, leading to concerns about market stability and predictability. Moreover, while the EU market operates under a robust regulatory framework set by the European Commission, with clear rules for trading, monitoring, reporting, and verification of emissions, China's carbon market is still developing processes for transparency and enforcement even though it has frameworks for regulation and monitoring. Secondly, Lu et al. [13] employ the GARCH-MIDAS model, whereas we consider the application of MRS-VAR approach to examine if the impact of GPR on carbon trading varies across high and low volatility regimes. Thirdly, we explore how we can hedge the downside risk of the Chinese emission trading markets when the geopolitical risk is relatively high. To sum up, our analysis produces several novel findings, which have key implications for investors and policymakers.

This article is organized as follows: Section 2 briefly reviews the relevant literature. The datasets used are described in Section 3. We discuss the methods in Section 4. Empirical findings are discussed in Section 5. We check the robustness of our analysis in Section 6, while Section 7 summarizes the paper.

2. Literature review

2.1. Geopolitical risk and financial markets

The impact of GPR on different financial markets has received considerable attention in recent years. While it is now evident that GPR can predict the return and volatility of different assets, the literature is still growing due to the ongoing wars and other geopolitical issues (e.g., heightened tensions between the US and China). The objective of this section is to briefly review the relevant literature. We begin with Gkillas et al. [15] who document that GPR plays a pivotal role in predicting the volatility of Dow Jones Industrial Average (DJIA). Employing the quantile regression model, Jiang et al. [16] find that GPR exerts a negative effect on the stock prices of Chinese tourism companies. Kannadhasan and Das [17] also use a similar method to show that GPR is negatively related in the lower quantiles and positively related in the intermediate and upper quantiles for the Asian emerging stock markets. In addition, Dutta and Dutta [18] apply the Markov regime switching model to report that an increase in the GPR index raises (diminishes) the probability of being in the low (high) volatility regime for the renewable energy equity prices. More recently, Demiralay et al. [12] find that key geopolitical events (e.g., the Russo-Ukrainian war) lead to higher volatilities for the climate change stocks. Besides, Yilmazkuday [19] also show that global stock markets are highly sensitive to geopolitical conflicts including the Russo-Ukrainian war.

Another strand of literature examines the influence of GPR on exchange rates. Salisu et al. [20], for example, apply the GARCH-MIDAS model to the BRICS exchange rates and find that such economies are more exposed to global than domestic geopolitical shocks. The study also reveals that the BRICS exchange rates are less exposed to historical geopolitical shocks compared to recent ones. Using the quantile causality-in-means analysis and quantile-on-quantile regression model, Bossman et al. [21] conclude that the Russo-Ukrainian war has an asymmetric impact on the USD-denominated foreign exchange (FX) rates. In addition, a recent study by Hossain et al. [22] suggests that the Russian invasion of Ukraine has a negative effect on the FX markets. Employing a structural vector autoregression model, Yilmazkuday [23] examines the impact of GPR on the exchange rates of 35 countries. The findings indicate that shocks emanating from geopolitical tensions cause currency depreciations only in China, Israel, the Philippines and the United States, while they lead to currency appreciations mostly in South Africa, Brazil, Australia, and Iceland, among others.

Moreover, several recent studies explore how GPR impacts the cryptocurrency markets. Aysan et al. [24], for instance, apply the Bayesian Graphical Structural Vector Autoregressive (BSGVAR) method to show that the information on GPR is useful for predicting both return and volatility of Bitcoin market. The study further finds that this digital asset could be used to hedge global geopolitical risks. In addition, Będowska-Sójka et al. [25] find that GPR increases the correlation between cryptocurrency and other financial markets including stock and oil. Analyzing a number of cryptos such as Bitcoin, Ether, Ripple, Dash, and Tether, Alexakis et al. [26] conclude that trading in these cryptocurrency markets observes a growth due to recent geopolitical crises (e.g., the Russo-Ukrainian war). A recent study by Yilmazkuday [27] also finds a significant linage between geopolitical shocks and digital asset class. In particular, the results indicate that leading cryptos react negatively to GPR. Moreover, adopting the time-varying parameter vector autoregressive model, Chen et al. [28] document that the impact of GPR increases during the financial turmoil.

Another line of research is focused on the relationship between GPR and commodity markets. Most of the articles in this group investigate if geopolitical shocks are important for crude oil markets. Some recent contributions include Assaf et al. [29], Smales [30], Mignon and Saadaoui [31], Yilmazkuday [27] and Chowdhury et al. [32]. For example, Mignon and Saadaoui [31] investigate how US–China political relationships and geopolitical risks impact oil prices. Employing the structural VAR model, the authors show that these factors tend to raise oil prices during the turbulence periods. Chowdhury et al. [32] examine the role of GPR in forecasting energy market tail risk. Applications of several machine learning (ML) models suggest that GPRs contribute 19.15 % to the ML model's predictive power. Notably, some recent studies explore the association between GPR and other commodity markets including metal and agriculture. Baur and Smales [33], for instance, find that including precious metals in a diversified portfolio mitigates the effects of geopolitical risk. In particular, the findings suggest that in the face of extreme geopolitical risks, only gold and silver consistently exhibit safe haven features. A recent study by Devadoss and Ridley [34] document that Russian invasion of Ukraine leads to a significant disruption to international wheat markets, thereby increasing its prices by around 2 % globally. Applying the heterogeneous autoregressive (HAR) and LASSO models, Dutta et al. [6] also find that geopolitical shocks play a crucial role in predicting food price volatility.

2.2. *Uncertainties and carbon markets*

A number of recent studies are focused on the linkage between uncertainties and carbon price variations. Important examples include Liu et al. [14], Dong et al. [35], Jiang et al. [36], Kim et al. [37], Liu et al. [38], Lu et al. [13], Wang et al. [39], Cao et al. [40], Cheng et al. [41], Wang and Zhang [42] and Xiao et al. [43]. Liu et al. [14], for instance, show that economic policy uncertainty (EPU) exerts a substantial effect on the volatility levels of EU carbon market. Using the GARCH-MIDAS model, the study also shows that the information content of EPU is useful for predicting the future volatility of EU emission prices. Wang et al. [39] also find that EPU has a time-varying association with the Chinese carbon markets and that such relationship is asymmetric. Employing the TVP-VAR approach, Liu et al. [38] show that EPU increases the correlations between EU carbon and global crude oil prices, whereas GPR tends to reduce such associations. Moreover, Dong et al. [35] adopt the quantile vector autoregression (QVAR) model to confirm that EPU and climate policy uncertainty (CPU) have significant effects on China's carbon markets, which vary markedly in different time and frequency domains. Cao et al. [40] also document that higher CPU leads to lower carbon returns for the Chinese ETS, suggesting an inverse association. Another recent study by Wang and Zhang [42] reveals that EPU influences the linkage between carbon and stock markets in China. Applying the TVP-VAR model, Cheng et al. [41] also report that the relationship between carbon and energy markets is significantly driven by EPU, GPR and CPU.

As suggested by the existing literature, only a few studies have examined the association between GPR and carbon markets. More importantly, these papers are mainly focused on the EU carbon prices and the China's carbon markets are totally unnoticed. This is surprising given that geopolitical events seem to have a substantial influence on the Chinese carbon prices. For example, if geopolitical tensions lead to energy supply disruptions, China might accelerate its transition to renewable energy, influencing carbon prices. Besides, geopolitical instability can impact China's economic growth, which in turn affects demand for energy and emissions levels. A slowdown in economic activity may reduce carbon emissions, potentially lowering carbon prices. In addition, Changes in geopolitical conditions can influence foreign investment in China's green technologies and carbon markets. Positive sentiment around stability can attract investment, driving up carbon prices, while negative sentiment can deter investment, leading to lower prices.

Therefore, the purpose of this empirical study is to extend the prior literature by investigating the effect of GPR on China's carbon prices.

3. Data

Following the previous literature [44,4,5,45], we consider using the daily carbon emission prices from the Shenzhen and Hubei pilots as they have the highest trading volume. The aforementioned studies also argue that although there exist eight ETS pilots in China, the Shenzhen and Hubei pilots seem to be more active than the rest. Our sample includes the observations from June 2014 to November 2023 and this time period is dictated by data availability. We collect the emission trading data from the Carbon Pricing Dashboard in World Bank. Besides, the information on the daily geopolitical risk index, introduced by Caldara and Iacoviello [46], is retrieved from the website of economic policy uncertainty.

Fig. 1 portraying the Shenzhen and Hubei emission price series reveals several interesting facts. For instance, both price series experience a decline amid the 2014 oil market crisis and the COVID-19 pandemics. In addition, the Hubei index demonstrates some spikes in 2019 as well as in 2022, which are not the case for the Shenzhen CET market. Besides, unlike the Shenzhen index, Hubei emission market witnesses a huge decline in 2023.

Next, Fig. 2 depicts the geopolitical risk and this graph indicates that while the GPR index exhibits several spikes during the sample period, the most prominent one has been observed amid the ongoing Russo-Ukrainian War.

Table 1, displaying the summary statistics, reports that carbon

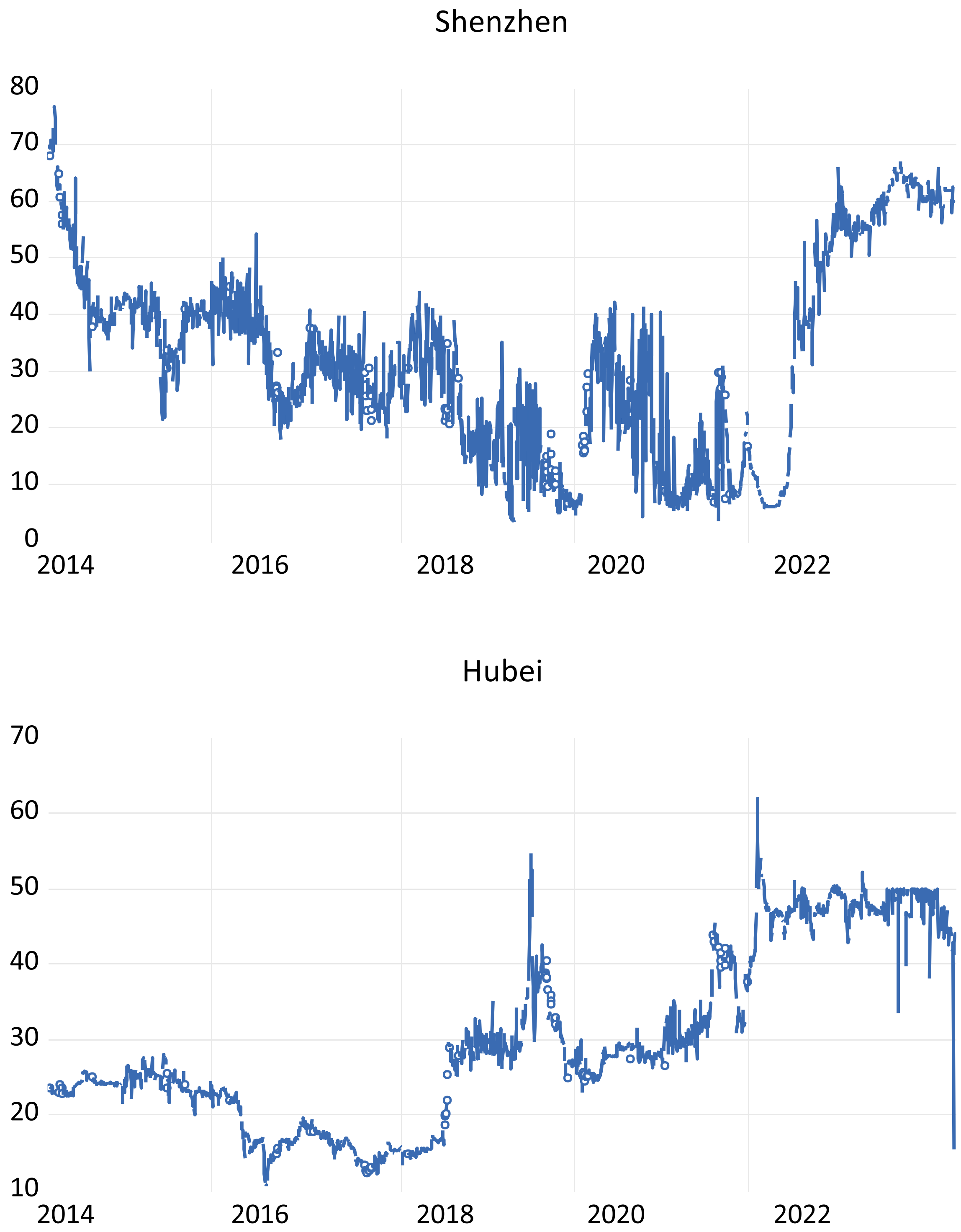

Fig. 1. Emission prices for the Shenzhen and Hubei markets.

returns are negative for the Shenzhen index and positive for the Hubei index. Of these two emission markets, the Shenzhen market is more volatile than the Hubei market. In addition, each of these carbon markets is negatively skewed, while the GPR index shows positive skewness. Besides, all the variables appear to be leptokurtic. The Jarque-Bera test also suggests that all these time series dissatisfy the normality condition.

Next, Table 2 shows the outcomes of different unit root tests: ADF, PP and KPSS. These tests suggest that each of the carbon return indexes is stationary and that GPR is non-stationary at levels when the KPSS test is applied. We, therefore, consider the first difference for the GPR index.

4. Methodology

4.1. VAR model

The VAR process has emerged as a suitable approach to modeling multivariate time series. A number of studies advocate this model given that it can successfully capture the dynamics of multiple variables and their interconnectedness [47,48]. A standard VAR process contains n linear models each consisting of n variables in which each variable depends on its own past values and the lagged values of the remaining $n-$

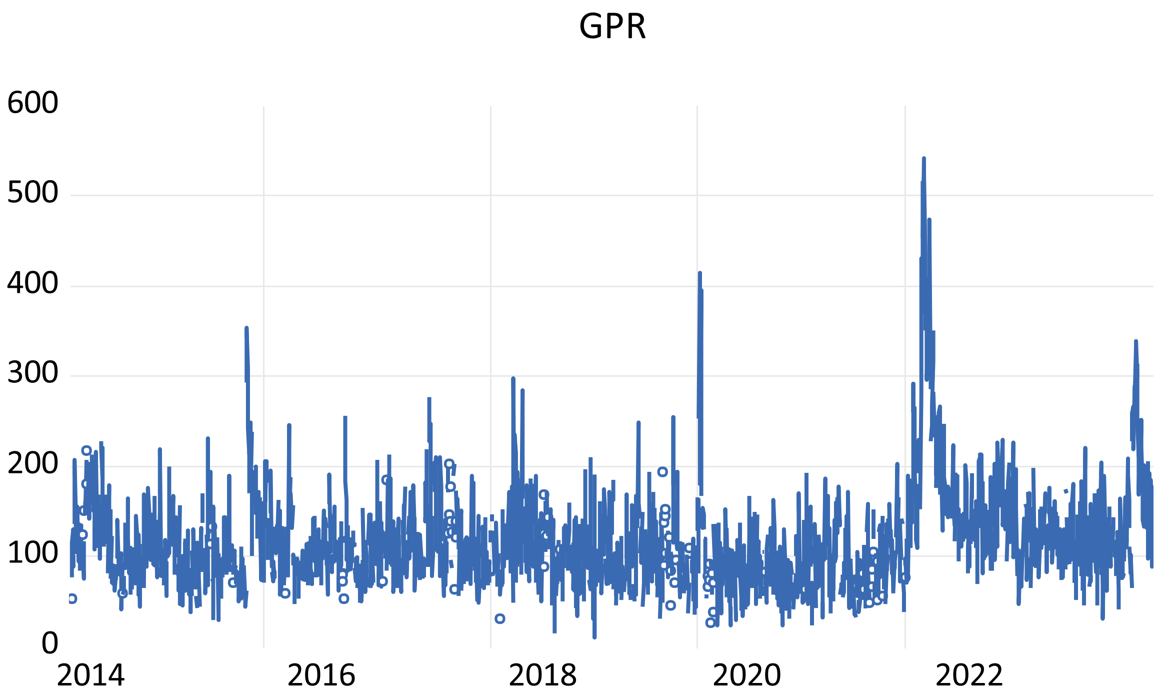

Fig. 2. Geopolitical risk index.

Table 1
Summary statistics.

	Shenzhen	Hubei	GPR
Mean	−0.0001	0.0003	116.68
Std. Dev.	0.2541	0.0515	54.98
Skewness	−0.0686	−0.3753	2.1584
Kurtosis	19.84	144.69	12.25
Jarque-Bera test	24,111.34***	170,653.20***	8867.99***

Notes: ***, ** and * denote significance at the 1 %, 5 % and 10 % levels, respectively.

Table 2
Results of unit root tests.

Unit root test	Shenzhen		Hubei		GPR	
	Level	Log-difference	Level	Log-difference	Level	1st difference
ADF	−2.53	−26.70***	−1.64	−33.26***	−7.66***	−21.79***
PP	−4.08***	−123.71***	−1.76	−82.05***	−30.73***	−323.31***
KPSS	0.95***	0.11	4.36***	0.09	1.52**	0.07

Notes: ***, ** and * denote significance at the 1 %, 5 % and 10 % levels, respectively.

1 variables.

In this study, we estimate the following VAR(2) process:

$$= \alpha_1 + \beta_1 R_{t-1} + \beta_2 R_{t-2} + \gamma_1 \Delta GPR_{t-1} + \gamma_2 \Delta GPR_{t-2} + \epsilon_{1t}(1)\ R_t \qquad (1)$$

$$\Delta GPR_t = \alpha_2 + \beta_3 R_{t-1} + \beta_4 R_{t-2} + \gamma_3 \Delta GPR_{t-1} + \gamma_4 \Delta GPR_{t-2} + \epsilon_{2t} \qquad (2)$$

where, R_t denotes the log-return for the Shenzhen and Hubei emission prices at time t and ΔGPR_t refers to the first-order difference for the GPR index at time t. In addition, ϵ_{1t} and ϵ_{2t} are white noise having mean 0. Notably, the lag length is chosen based on the Akaike Information Criterion (AIC), Hannan-Quinn Criterion (HQ) and Schwarz Criterion (SC).

In this paper, we first employ the traditional VAR process and then consider applying the MRS-VAR model, which is elaborated in the subsequent section.

4.2. *MRS-VAR model*

The MRS-VAR model, proposed by Hamilton [49] and Krolzig [50], integrates the MRS model with the VAR specification. This approach addresses the shortcomings of linear models while capturing asymmetries in financial time series [51–54]. Using this model is beneficial for our analysis as it enables us to examine the effects of increasing geopolitical risk on the Chinese emission prices in both low and high volatility regimes.[2] Furthermore, we can use the regime-dependent impulse-response functions to analyze how carbon returns respond to geopolitical shocks during periods of high and low volatility. Now, to explain the MRS-VAR model used in our analysis, let us define the following 2-dimensional time series vector:

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[2] Regime switching behavior is often observed in financial time series including carbon markets [67]. Variations in economic conditions, investor sentiment, or external shocks might cause a shift between high and low volatility regimes. In addition, climate policies (e.g., altering carbon pricing mechanisms or regulatory frameworks) can also lead abrupt shifts in market dynamics. For instance, if a government tightens emissions regulations, it may cause a sudden increase in carbon prices. Moreover, technological innovations in renewable energy or carbon capture and storage could cause a change in market fundamentals, leading to new regimes as the cost structures and competitive dynamics shift. Besides, key geopolitical events (e.g., wars, terrorist attacks) may lead to a shift in the economic landscape influencing the demand and supply in carbon markets, thereby causing structural breaks in the series.

$$y_t = (R_t,\ \Delta GPR_t)';\ t = 1, 2, \cdots, T$$

Now, let there be M states in the MRS-VAR model. Then this process is defined as:

$$y_t = v(S_t) + A_1(S_t)y_{t-1} + \ldots + A_p(S_t)y_{t-p} + e_t \tag{3}$$

where, v represents the intercept or mean for each regime, S_t refers to the regime variable ($S_t \in \{1, 2, \ldots, M\}$), $A_i(i = 1, 2, \ldots, p)$ is the regime-dependent matrix and $e_t \sim NID(0,\ \sum(S_t))$.

In the Markov regime switching regression, the variable S_t is assumed to be generated by the first order of the Markov chain and assuming that the state in period $t+1$ depends only on the state in period t, we can also calculate the transition probability between different states as follows:

$$p_{ij} = Pr(S_{t+1} = j | S_t = i),\ \sum_{j=1}^{M} p_{ij} = 1\ \forall i, j \in \{1, 2, \ldots, M\} \tag{4}$$

Note that the optimal model form appears to be MRS(2)-VAR(2) based on the AIC, HQ and SC values. Then the transition probability matrix takes the following form:

$$P = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix}$$

with $p_{i1} + p_{i2} = 1$ for any $i \in (1, 2)$

Consistent with Hamilton [49] and Krolzig [50], we estimate the parameters of our MRS-VAR process by using direct maximization of the log-likelihood function.

5. Empirical findings

Table 3 displays the outcomes of the standard VAR process. We report the results for both Shenzhen and Hubei markets, which reveal that the effect of geopolitical risk appears to be statistically insignificant. This finding is shocking given that China being a significant player in global carbon markets could be highly sensitive to geopolitical tensions or conflicts, which may lead to changes in government policies including stricter regulations and new carbon pricing mechanisms. However, this insignificant result could be attributed to the fact that there might be a regime-dependent linkage between these variables which is not detected by the typical VAR model which assumes that the responses of carbon returns to geopolitical shocks is not time-dependent. Under this circumstance, employing the MRS-VAR process could shed further light on the association between geopolitical risk and the Chinese carbon market returns.

The estimates of the MRS-VAR model are presented in Table 4, which indicates several interesting findings. Firstly, carbon returns are now significantly influenced by the variation in geopolitical risk. More importantly, the effect of GPR tends to vary across the regimes. For instance, while referring to the Shenzhen market (see Panel A), we notice that the impact of geopolitical shocks is statistically significant in regime 2. This is, however, not the case for regime 1. This result also holds for the Hubei market. Thus, our analysis confirms that the effect of geopolitical risk is regime-specific. Secondly, the results further show that regime 1 is less volatile than regime 2 as demonstrated by the regime-specific variances for both carbon markets. Hence, we can conclude that the effect of geopolitical risk is significant across the high volatility states only. The negative impact could be due to the fact that when geopolitical risk increases, it often affects overall economic sentiment [33]. For instance, concerns over potential economic slowdowns or disruptions in trade can lead to reduced industrial production. Since many industries in China are significant carbon emitters, a decline in output means lower demand for carbon allowances, which can drive prices down. Additionally, when the carbon market is volatile, investors typically become more risk-averse. They may prefer to liquidate carbon assets perceived as risky or uncertain. This selling pressure can result in a drop in carbon prices, as supply increases while demand diminishes. Overall, we find that the information on geopolitical risk could be valuable for understanding the dynamics of CET prices.

Table 3
Results of VAR model.

Dependent variable →	Carbon returns (Shenzhen)		Carbon returns (Hubei)	
	Estimate	Standard error	Estimate	Standard error
Constant	−0.0001	0.0048	0.0005	0.0010
R_{t-1}	−0.5594***	0.0217	−0.4118***	0.0221
R_{t-2}	−0.1875***	0.0218	−0.1274***	0.0220
ΔGPR_{t-1}	−0.0123	0.0126	0.0005	0.0027
ΔGPR_{t-2}	−0.0145	0.0125	0.0006	0.0027
Log-likelihood	193.14		1333.03	

Notes: This table reports the estimates of the VAR model for both carbon markets. ***, ** and * denote significance at the 1 %, 5 % and 10 % levels, respectively.

Table 4
Results of MRS-VAR model.

Dependent variable →	Carbon returns (Shenzhen)		Carbon returns (Hubei)	
	Estimate	Standard error	Estimate	Standard error
Panel A: Regime 1				
Constant	−0.1499***	0.0327	−0.1696***	0.0209
R_{t-1}	−0.0003	0.0059	−0.0002	0.0011
R_{t-2}	−0.0030	0.0058	0.0003	0.0011
ΔGPR_{t-1}	−0.0275	0.0201	0.0129	0.0106
ΔGPR_{t-2}	−0.0003	0.0020	−0.0003	0.0004
Sigma	0.0046***	0.0004	0.0002***	0.00001
Panel B: Regime 2				
Constant	−0.6317***	0.0418	−0.4981**	0.0440
R_{t-1}	−0.0245	0.0307	0.0010	0.0076
R_{t-2}	−0.0263	0.0312	0.0007	0.0078
ΔGPR_{t-1}	−0.2331***	0.0419	−0.2576***	0.0543
ΔGPR_{t-2}	−0.0025	0.0142	0.0014	0.0032
Sigma	0.1324***	0.0098	0.0066***	0.0005

Notes: This table reports the estimates of the MRS-VAR model for both carbon markets. ***, ** and * denote significance at the 1 %, 5 % and 10 % levels, respectively.

Next, Table 5 reports the transition probability between the low and high volatility states. Moving to the estimates for the Shenzhen market, we notice that the probability of being in Regime 1, which represents the low volatility regime, is 0.9549 while the likelihood of transition from regime 1 to regime 2 equals 0.0451. Likewise, the probability of being in Regime 2 is equal to 0.9083, while the likelihood of transition from regime 2 to regime 1 is 0.0917. This finding suggests that the probability of being in the high volatility state is lower than that of being in the low volatility state. These statistics further reveal that regime 1 and regime 2 tend to persist for about 3 weeks and 1.5 weeks, respectively. The estimates for the Hubei market can be explained in a similar way.

Summarizing, our findings suggest that while the standard VAR model fails to capture any linkage between geopolitical shocks and carbon returns, employing the MRS-VAR process reveals that GPR in fact

Table 5
Regime features.

CET ↓	p_{11}	p_{12}	p_{21}	p_{22}	DU1	DU2
Shenzhen	0.9549	0.0451	0.0917	0.9083	22.21	10.89
Hubei	0.8828	0.1172	0.2591	0.7409	8.52	3.85

Notes: This tables presents the probabilities of regime switching and the durations (DU) in each state.

exerts a significant effect on the Chinese carbon prices. In addition, the regime-specific linkage indicates a strong switching behavior for both carbon markets. Fig. 3a and 3b, plotting the filtered probabilities for these markets, also ensure the swapping behavior.

Notably, the outcome that geopolitical shocks exert significant effects on the CET returns when the Chinese carbon markets are highly volatile merits further explanations. This finding particularly suggests that policymakers and investors need not pay attention to geopolitical risk index when the carbon markets behave normally. However, such result does not necessarily imply that the information content of geopolitical risk is not important for predicting carbon returns during the low volatility periods. This is due to the fact that GPR could have an indirect effect on emission prices as well. For example, the Chinese emission markets are highly sensitive to crude oil volatility irrespective of the market states [5]. Given that energy market volatility is often driven by geopolitical shocks, GPR can influence carbon prices though

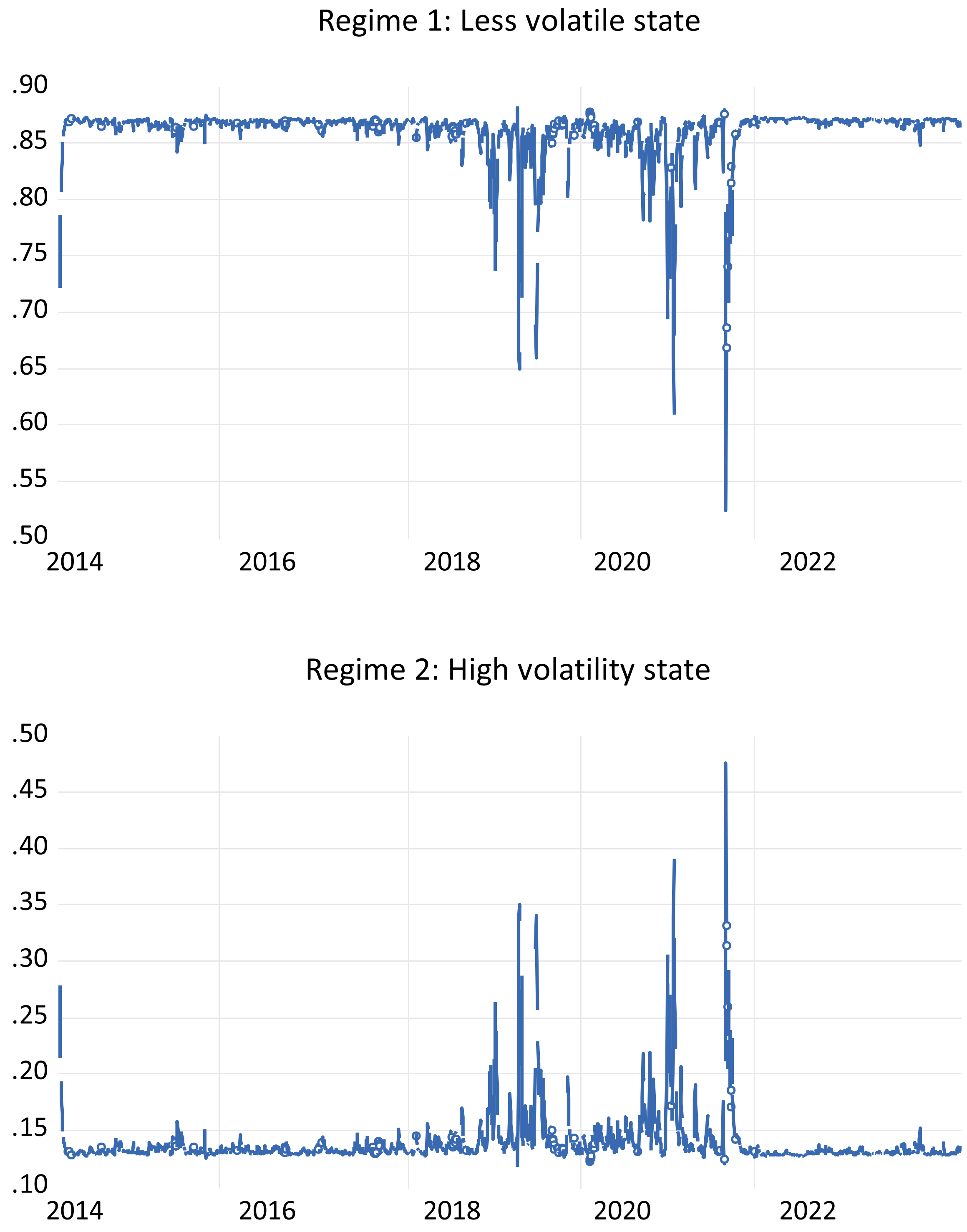


Fig. 3a. Filtered probabilities for the Shenzhen market.
Notes. The filtered probabilities are derived from the Markov regime switching regression. The probabilities refer to the likelihoods of remaining in the low volatility states for the Shenzhen market. The X-axis indicates the timeline, while the Y-axis shows the filtered probabilities.

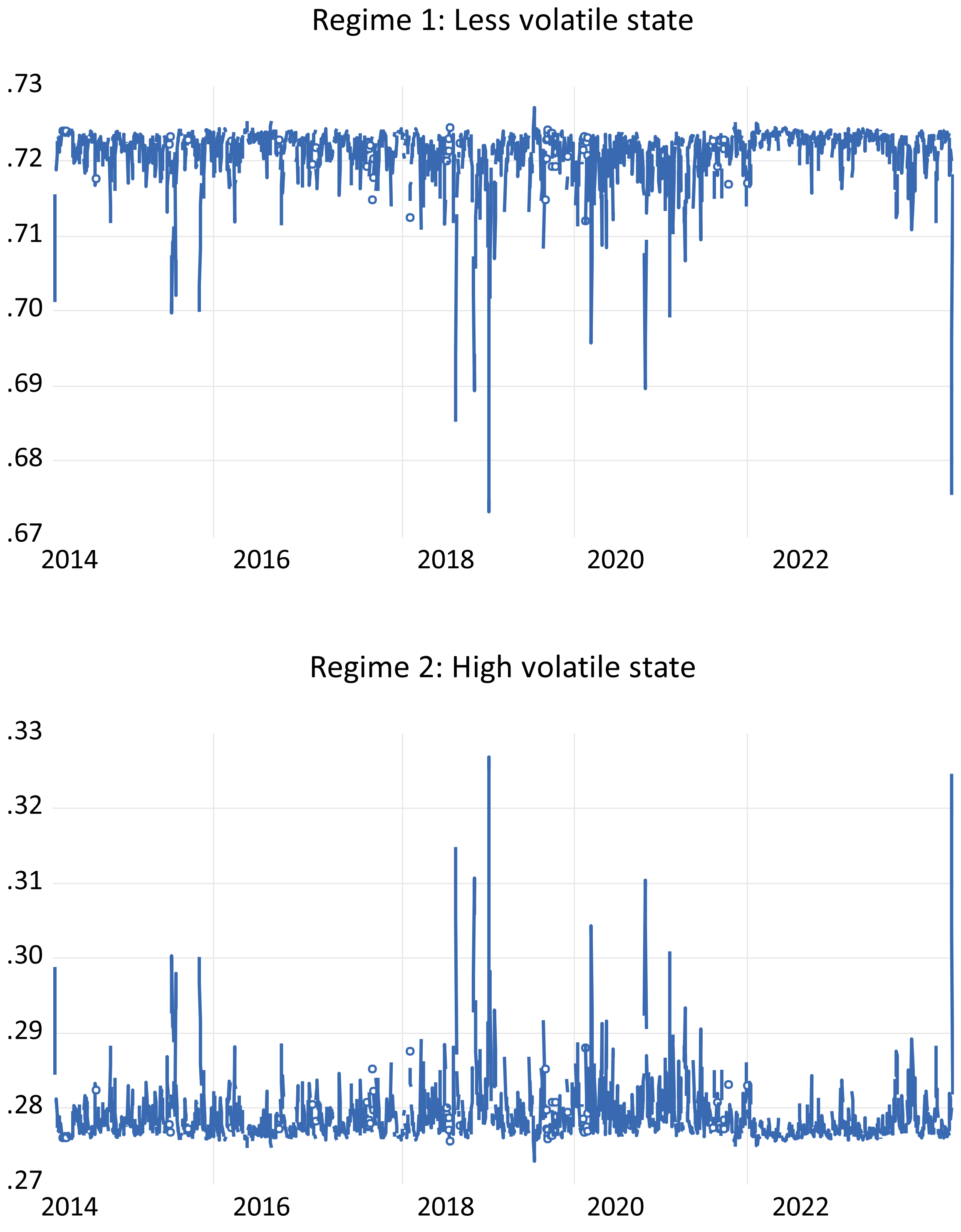


Fig. 3b. Filtered probabilities for the Hubei market.

Notes. The filtered probabilities are derived from the Markov regime switching regression. The probabilities refer to the likelihoods of remaining in the low volatility states for the Hubei market. The X-axis indicates the timeline, while the Y-axis shows the filtered probabilities.

this channel even when the market is relatively calm. For the high volatility state, on the other hand, the negative association between GPR and carbon returns also provides an important piece of information as such relationship indicates the necessity of finding proper hedging instrument when carbon prices experience large swings. In sum, the empirical results reveal that participants in the Chinese carbon markets should utilize appropriate financial tools to hedge the shocks emanating from significant geopolitical events amid the crisis periods.

5.1. *Regime-dependent impulse-response functions*

We will now focus on the regime-dependent cumulative impulse-response functions (IRFs) to discuss the direction, duration and strength of the effect of geopolitical shocks on the Chinese carbon markets across different regimes. Fig. 4a exhibits the IRFs for the Shenzhen carbon market. This diagram shows that in the low volatility state (i.e. regime 1), a shock to the GPR index causes a negative response in ETS returns which reaches an extreme value of −0.009 on day 2,

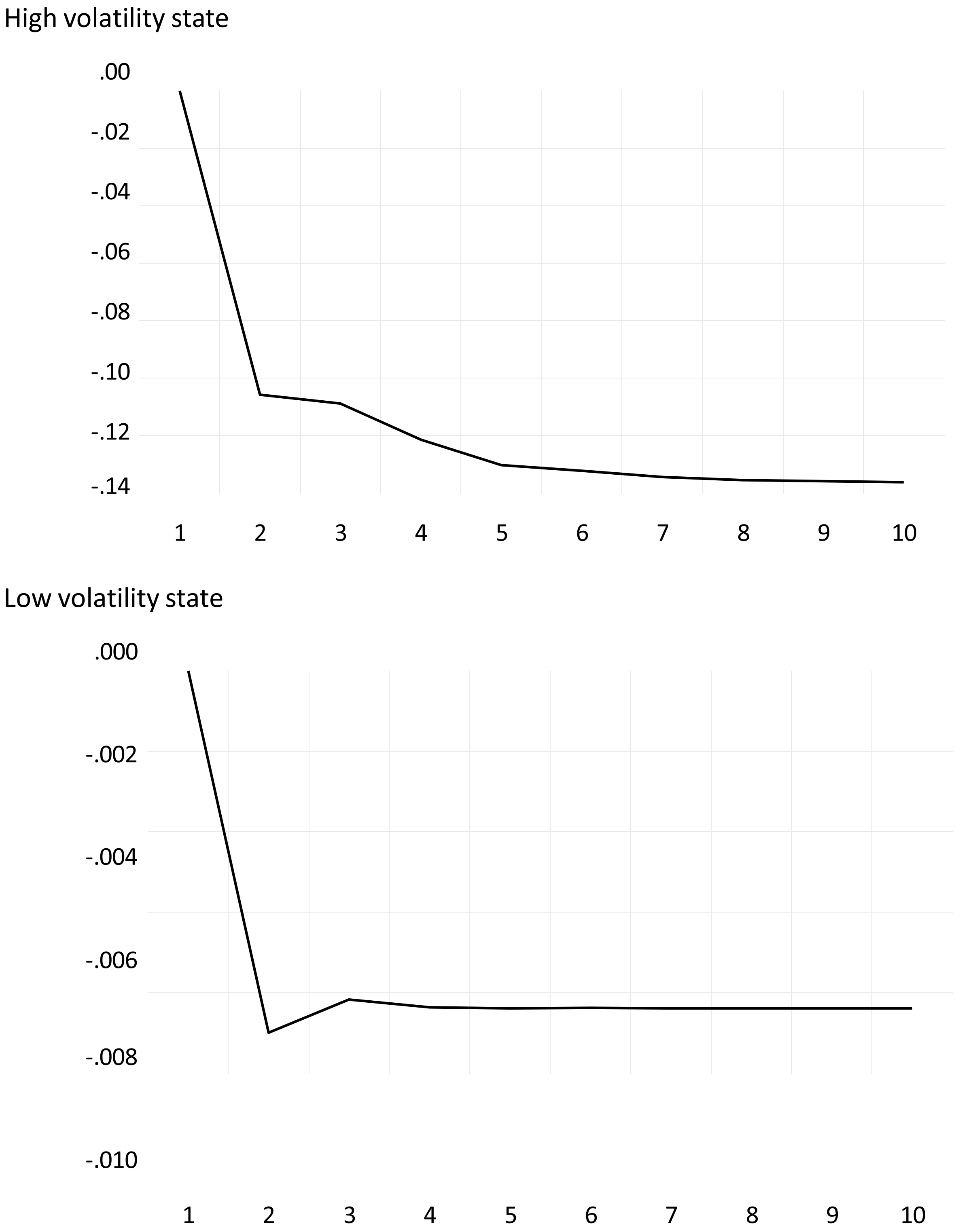
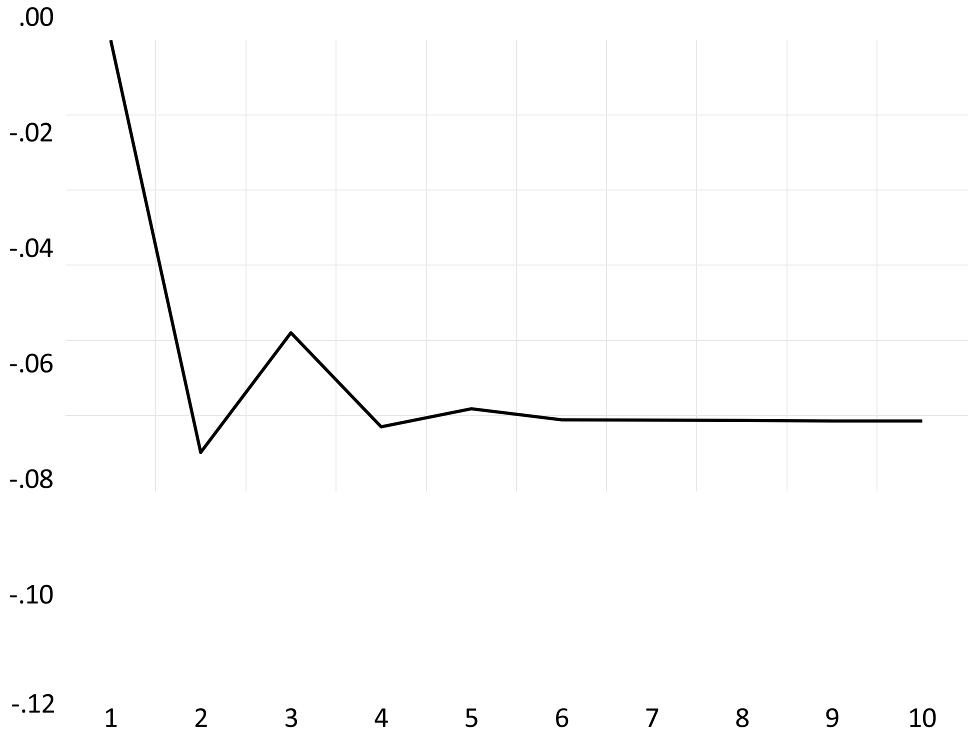


Fig. 4a. Cumulative response of Shenzhen market returns to GPR across various regimes.
Notes. In this graph, the x-axis indicates the time period proxied by the number of days ahead, while the y-axis shows the impulse responses of carbon returns to a one-unit shock in GPR.

implying that a 1-unit shock to GPR reduces carbon returns by 0.009 % on the second day. The response then slightly increases on day 3 and finally sets to be steady between −0.008 and −0.009. In regime 2, on the other hand, the response also indicates a negative trend and it approaches to the value of −0.11 on day 2. This means that 1-unit shock to GPR reduces carbon returns by 0.11 % on the second day. During the remaining periods, the cumulative responses tend to decrease gradually and equal the value of −0.14 on day 10.

Moving to Fig. 4b, which displays the IRFs for the Hubei market, we

High volatility state



Low volatility state

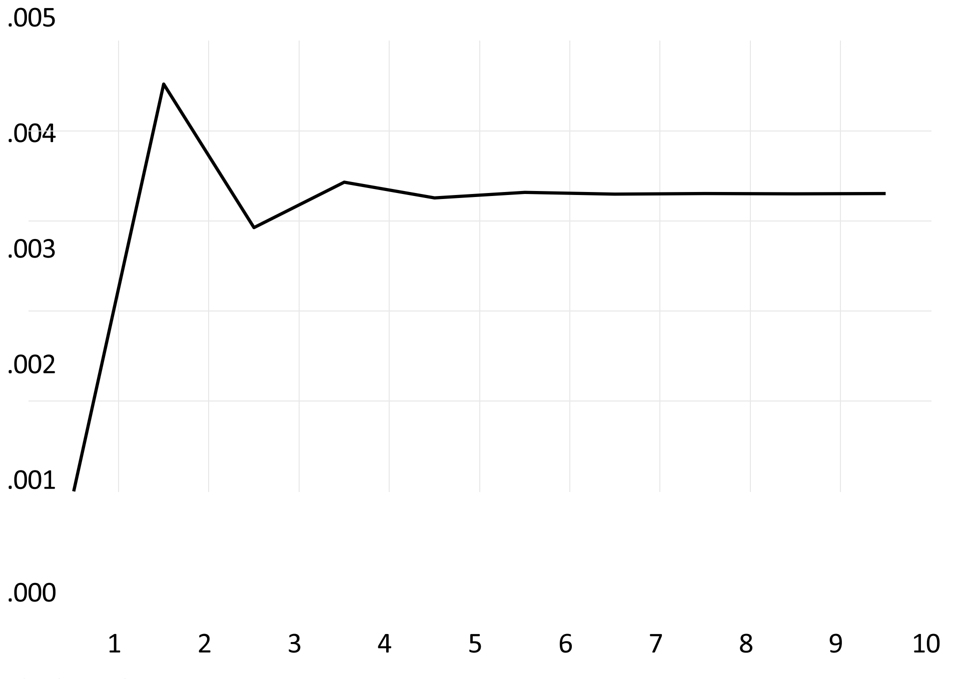


Fig. 4b. Cumulative response of Hubei market returns to GPR across various regimes.
Notes. In this graph, the x-axis indicates the time period proxied by the number of days ahead, while the y-axis shows the impulse responses of carbon returns to a one-unit shock in GPR.

observe that in the low volatility state (i.e., regime 1) carbon returns react positively to geopolitical shocks.[3] The response reaches a peak value of 0.0045 on day 2, indicating that 1-unit shock to GPR increases carbon returns by 0.0045 % on the second day. This response then decreases on day 3 and from day 4 it starts to increase again and remains steady for the remaining periods. For the high volatility regime, however, we notice a strong positive response like the Shenzhen market. Hence, these graphs plotting the impulse response functions suggest that the effects of geopolitical shocks on carbon returns are regime-specific. To put it another way, these impacts tend to vary under different market conditions. Thus, we can conclude that the influence of geopolitical risk is positive in the low volatility state and negative in the high volatility state when the Hubei market is taken into account.

5.2. Portfolio implications

To compute the hedge ratios, we employ the DCC-GARCH model proposed by Engle [55]. We now briefly discuss this process as follows:

$$r_t = \mu + \gamma r_{t-1} + \varepsilon_t \tag{5}$$

$$\varepsilon_t = H_t^{\frac{1}{2}} z_t \tag{6}$$

where, r_t denotes the return vector and H_t refers to the matrix of conditional volatilities defined as:

$$H_t = D_t R_t D_t \tag{7}$$

$$D_t = diag\left(\sqrt{h_t^{CET}}, \sqrt{h_t^{O}}\right) \tag{8}$$

$$R_t = diag(Q_t)^{-1} Q_t diag(Q_t)^{-1} \tag{9}$$

where, D_t and R_t indicate the matrices of dynamic conditional correlations and the time-varying conditional variances, respectively. In addition, h_t^{CET} and h_t^{O} are the conditional variances for the CET market and other asset (WTI/ICLN) returns.

Note that in a univariate GARCH(1,1) process, the components of H_t are defined as:

$$h_t = \omega + a\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{10}$$

Moreover, the time-varying covariance matrix, denoted as Q_t, is represented as:

$$Q_t = (1 - \theta_1 - \theta_2)\overline{Q} + \theta_1 z_{t-1} z'_{t-1} + \theta_2 Q_{t-1} \tag{11}$$

where θ_1 and θ_2 refer to the non-negative scalar parameters satisfying the condition $\theta_1 + \theta_2 < 1$, and $\overline{Q}$ denotes the unconditional matrix of standardized residuals z_t ($z_t = \varepsilon_t \ / \sqrt{h_t}$).

Then the hedge ratios can be computed as:

$$\delta_t = \frac{h_t^{CETO}}{h_t^{O}} \tag{12}$$

with h_t^{CETO} indicating the conditional covariance between CET and other asset returns.[4] Portfolios with lower hedge ratios are cheaper to be hedged [56].

Table 6 displays the average hedge ratios for the carbon and oil portfolios across the high and low geopolitical risk regimes. We define these two regimes as follows: for the high-risk regime GPR surpasses its mid-value, while for the low-risk regime GPR remains under the mid-value. Now looking at the Shenzhen/oil portfolio, we find that when geopolitical risk is high (low), a $100 long position in Shenzhen can be hedged with a $11.2 ($4.4) short position in oil. This finding implies that the Shenzhen CET is cheaper to hedge when geopolitical risk is at lower levels. This outcome also holds for the Hubei CET. We further observe that the Hubei CET is cheaper to hedge than the Shenzhen CET. Summarizing, we conclude that higher geopolitical risk leads to higher hedging costs.

5.3. Regime-dependent hedge ratios

Using the Markov switching DCC (MRS-DCC) model, extensively used in recent studies [57–60], we now estimate the regime-specific hedge ratios. More specifically, we examine if oil and clean energy equities can hedge the Chinese carbon market risk under different market conditions.

Following Lee [61], the time-varying covariance matrix for the MRS-DCC model can be written as:

$$Q_t = (1 - \theta_1(s_t) - \theta_2(s_t))\overline{Q} + \theta_1(s_t) z_{t-1} z'_{t-1} + \theta_2(s_t) Q_{t-1} \tag{13}$$

where, the regime variable, $s_t = 0, 1$ and is governed by the transition probabilities, $p_{ij} = Pr(s_{t+1} = j | s_t = i)$. In such case, the regimes are determined according to average levels of Q_t.

Table 7 reports these findings, which reveal that clean energy asset (ICLN) still offers better hedging opportunities than crude oil (WTI). The hedge ratios also confirm that these hedges perform better when the Chinese carbon markets remain in the low volatility regime.

5.4. Discussions

The significant impact of GPR on carbon trading can be elucidated through the lens of risk perception and investment theory. For instance, geopolitical shocks, such as armed conflicts, economic sanctions, or political instability, create uncertainty in global markets, which can influence investor confidence in carbon credit markets, leading to fluctuations in Chinese carbon prices. In addition, investors may become more risk-averse due to geopolitical tensions, potentially pulling out of carbon markets or delaying investments in green technologies. This can decrease liquidity in carbon trading markets and impact the overall functioning of carbon pricing mechanisms. Besides, in response to geopolitical events (like oil price spikes due to conflicts), the Chinese

Table 6
Optimal hedge ratios.

Portfolio	High geopolitical risk regime	Low geopolitical risk regime
Shenzhen/WTI	0.1122	0.0440
Hubei/WTI	0.0341	0.0112
Shenzhen /ICLN	0.0396	0.0284
Hubei/ICLN	0.0251	0.0209

Notes: This table reports the average hedge ratios for the carbon and oil/clean energy portfolios across the high and low geopolitical risk regimes.

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[3] In periods of low volatility state for the Hubei market, we find a positive association between GPR and carbon returns. This could be due to the fact that any perceived risk can lead to a disproportionate reaction in the market. In particular, if investors believe that geopolitical tensions will lead to stricter climate policies, they may invest more heavily in carbon markets, driving up prices. Besides, geopolitical risks can sometimes threaten the supply of fossil fuels, leading to higher prices for these commodities. Since carbon prices are often linked to fossil fuel prices (as they represent the cost of emitting carbon), higher fossil fuel prices can positively influence carbon prices, especially when there is low market volatility [13].

[4] The information on crude oil prices (WTI) and ICLN index is retrieved from the Bloomberg terminal.

Table 7
Regime-specific hedge ratios.

Portfolio	High volatility regime	Low volatility regime
Shenzhen/WTI	0.0987	0.0622
Hubei/WTI	0.0753	0.0509
Shenzhen /ICLN	0.0761	0.0479
Hubei/ICLN	0.0549	0.0383

Notes: This table reports the average hedge ratios for the carbon and oil/clean energy portfolios across the high and low volatility regimes for the Chinese emission markets.

government may prioritize energy security over environmental sustainability. This could lead to increased investments in fossil fuels rather than renewable energy sources, reducing demand for carbon credits generated from low-emission projects. Moreover, amid the rising geopolitical tensions, the government may also adjust environmental regulations, either tightening them to meet emission reduction goals or relaxing them to support struggling economies. Such policy changes can significantly influence carbon trading by altering the supply and demand dynamics for carbon credits.

Moreover, the effect of geopolitical shocks on carbon trading can be explained with the help of supply shock theory as well. In particular, geopolitical events can lead to disruptions in the production of goods or services associated with high carbon emissions. For example, if tensions lead to sanctions on a major industrial producer, the reduction in their output could decrease overall emissions, affecting the supply of carbon credits available in the market. Moreover, in response to geopolitical tensions, China may adopt stricter environmental regulations or, conversely, roll back existing regulations. Such changes can impact the supply of carbon credits in the market, either increasing their scarcity (if regulations tighten) or flooding the market (if they are loosened). Besides, a sudden decrease in the supply of carbon credits, due to a geopolitical shock, can lead to a sharp increase in prices. Specifically, if a major emitter reduces output due to geopolitical unrest, the remaining credits become more valuable. Conversely, if a shock increases available credits, prices may drop, potentially undermining the incentive to reduce emissions. Consistent supply disruptions may also deter long-term investment in clean technologies, as stakeholders view the market as prone to instability. This can hinder China's ability to meet its carbon neutrality goals.

Note that our analysis extends similar works such as Liu et al. [38], Lu et al. [13] and Cheng et al. [41] in various ways. For instance, we identify that the impact of GPR on the Chinese carbon markets is regime-dependent. This result simply indicates that the CET is exposed to significant risks stemming from geopolitical shocks and that GPR influences the CET differently under varied market conditions. This result has a number of policy implications. Firstly, given that geopolitical shocks could introduce volatility in carbon markets, affecting prices and trading behaviors, policymakers need to strengthen regulatory frameworks to ensure market stability, such as implementing price controls or stabilizing funds to mitigate severe fluctuations. Secondly, developing risk assessment and management strategies will also help market participants navigate uncertainties associated with geopolitical events, ensuring a more resilient carbon market. Moreover, geopolitical tensions may challenge energy security and influence energy supply chains. To this end, policymakers must balance climate goals with the need for secure and reliable energy sources, potentially leading to revisions in carbon policies that account for both emissions reductions and energy needs. Thirdly, to reduce vulnerability to geopolitical shocks, there is a need for policies promoting diversification in energy sources (e.g., increasing investments in renewables and domestic energy resources) while maintaining emissions reduction commitments. Fourthly, geopolitical factors may affect international energy prices and trade flows, necessitating adaptive pricing mechanisms. Hence, policymakers should consider allowing for periodic adjustments to carbon prices to reflect changes in external economic conditions. Finally, in response to external geopolitical pressures, China may need to prioritize investments in domestic clean technologies and industries, facilitating innovation and job creation within its carbon market framework. In particular, encouraging regional carbon trading schemes and localized renewable energy projects can help cultivate resilience and adaptability at the local level, providing flexibility amidst geopolitical shocks. To sum up, while geopolitical shocks present challenges, they also create policy space for strategic shifts such as investing in clean energy self-sufficiency (e.g., solar, nuclear), using the ETS to incentivize low-carbon innovation during crises, strengthening domestic green finance to buffer against global uncertainty. Thus, China could use geopolitical disruption as a catalyst to build a more resilient, self-sufficient, and effective carbon market.

Furthermore, unlike earlier studies, we show that higher geopolitical risk leads to higher hedging costs for the Chinese carbon market. Such outcome implying that diversification becomes less effective under extreme geopolitical risk needs special attention. Note that China's carbon market lacks liquid carbon futures, options, or swaps, which are necessary for hedging price risk. Therefore, when geopolitical shocks (e.g., energy crises or trade disruptions) create uncertainty, regulated entities in China have few tools to hedge carbon price risk. To this end, investors need to select suitable assets to hedge geopolitical risk. Some potential assets could be commodities, stocks or currencies. Our analysis also reveals that during the periods of high geopolitical tensions, oil and clean energy equites can be considered as potential hedges, although green assets offer better hedging opportunities than dirty assets. Moreover, in order to manage risk, investors could also shift to liquid hedging instruments, increase the use of options and employ proxy hedges (e.g., sector-specific ETFs). In sum, China's carbon market is still in its formative stage, and geopolitical shocks primarily affect policy expectations and compliance behavior, rather than sparking sophisticated financial hedging. To make carbon markets more efficient, the Chinese government could develop domestic carbon futures markets to manage energy and emissions risk, promote carbon finance innovation (e.g., green derivatives) and insulate the market from global carbon politics (e.g., US policy changes).

6. Robustness checks

In this section, we check the robustness of our MRS-VAR analysis by considering the application of quantile VAR (QVAR) process. In addition, we also examine the impact of other key uncertainty indicators such as crude oil volatility index (OVX) and the equity market VIX on the Chinese carbon prices.[5] Several recent studies conclude that these uncertainty measures exert significant effects on the variations in carbon prices [41,62] .[6]

Note that employing the QVAR model, proposed by Chatziantoniou et al. [63], is particularly useful for our analysis given that this model measures the effect on the conditional quantiles of the dependent variable due to its own and independent variables' past values within the system [64]. Besides, this quantile connectedness approach offers a thorough understanding of the connections among the variables, especially when asymmetry and heteroscedasticity are present. Moreover, applying the QVAR model also examines the association between different uncertainty indicators and carbon markets under varying market conditions, specifically at thresholds of 0.05 (downward:

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[5] The information on OVX and VIX is retrieved from the Bloomberg terminal.

[6] While earlier studies [35,42] show that economic policy uncertainty (EPU) can explain the variations in carbon prices, we do not consider the EPU index in our analysis as daily observations are not available for this uncertainty measure.

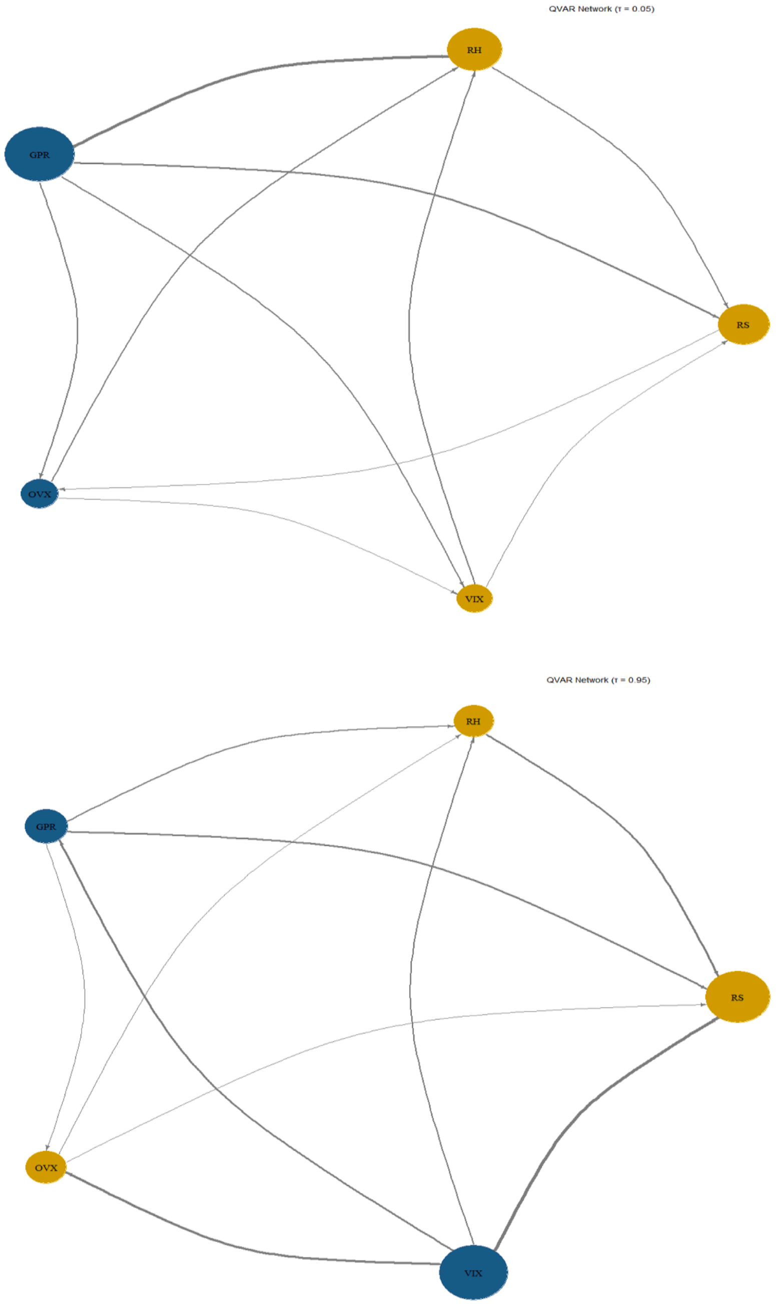

Fig. 5. Network plots on major quantiles ($\tau = 0.05, \ \tau = 0.95$).
Notes. RH and RS indicate the returns for the Shenzhen and Hubei carbon markets, respectively.

bearish), 0.50 (normal), and 0.95 (upward: bullish) .[7]

Fig. 5 plots the output of our QVAR analysis. This graph displays the connectedness of the variables over the extreme quantiles (i.e., $\tau = 0.05$, $\tau = 0.95$), with yellow (blue) representing the net receiver (transmitter) of shocks to the system. We notice that for the extreme lower quantile ($\tau = 0.05$), carbon returns (i.e., RH and RS) are the net receivers and GPR as well as OVX are the net transmitters of shocks. However, the connection between GPR and Shenzhen market is stronger than that between GPR and Hubei market, since we do not find any direct transmission of shocks from GPR to Hubei returns. But GPR could have an indirect impact on the Hubei market as the former exerts a substantial effect on OVX. Moreover, while VIX plays the role of a net receiver, it transmits shocks to both Shenzhen and Hubei markets.

Proceeding further, we find that for the extreme upper quantile ($\tau = 0.95$), OVX is no longer a net receiver, whereas VIX now acts as the net transmitter. The diagram also indicates a very robust association between geopolitical shocks and carbon returns as we witness a direct transmission of shocks from GPR to both Shenzhen and Hubei markets. In addition, OVX and VIX also play a crucial role in explaining the variations in carbon prices. The results of the QVAR model are in line with the MRS-VAR analysis given that applying both models indicates that the impact of GPR on China's carbon markets is regime-specific.

To sum up, our findings extend the prior works [41,38,13] by showing that geopolitical shocks not only impact the EU carbon prices, but also plays a crucial role in predicting the variations in the Chinese carbon prices. Given that the EU and Chinese carbon markets are linked

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[7] For the sake of brevity, the QVAR network approach has not been elaborated here, but it can be found in a number of recent studies [68–70].

to each other [65,66], increasing geopolitical tensions can affect the energy supply and prices in both Europe and China. This, in turn, influences global carbon prices. Besides, geopolitical climates can affect public sentiment towards climate policies in China and Europe. Heightened awareness of climate change and environmental issues among the public can pressure governments to take actions, which might influence the carbon pricing mechanisms in both regions. In addition, geopolitical competition can spur innovation and technology transfer between regions. For instance, advancements in carbon capture and storage technology in Europe or China could influence carbon prices if such technologies become adopted widely and reduce the overall demand for carbon allowances.

7. Conclusions

Although the interplay between geopolitical events and emission trading system is somewhat complex, very little is known about how geopolitical shocks impact global carbon prices. In this study, fill this vacuum in the exiting literature by studying the linkage between geopolitical risk and the Chinese carbon markets. Given that geopolitical shocks may influence the Chinese ETS in several ways, such linkage merits an empirical investigation. Methodologically, we combine the Markov regime switching model with the vector autoregressive process and apply it to the Shenzhen and Hubei carbon markets. The results suggest that while the standard VAR model fails to capture any linkage between geopolitical shocks and carbon returns, employing the MRS-VAR process reveals that GPR in fact exerts significant effects on the Chinese carbon markets suggesting that such effects appear to be regime-dependent. More specifically, the impact of geopolitical shocks is negative in the high volatility regime, but statistically insignificant in the low volatility regime. Further investigations reveal that higher geopolitical risk leads to higher hedging costs and that clean energy asset could be a suitable hedge for the Chinese carbon markets amid the periods of high geopolitical uncertainties.

Policymakers could use the results of our analysis to understand the economic consequences of geopolitical risk while determining the proper plan of action to minimize the CO_2 emissions in China. As the Chinese economy is a leading importer of foreign oil, high uncertainty in global crude oil markets due to rising geopolitical risk could influence investor sentiment and trading decisions, thereby hampering the advancement of sustainable technologies in China. Policymakers should, therefore, formulate appropriate strategies such as lifting carbon taxes and promoting clean energies in order to mitigate the adverse impact of geopolitical conflicts and energy market uncertainty.

Moreover, the government should also develop the monitoring system for the carbon futures market for stabilizing the risk linked to emission trading. An improved futures markets would then attract more eco-friendly investors which is important for increasing its liquidity. However, if the volatility of emission trading remains extremely sensitive to geopolitical uncertainty, then the investors might lose their interests in the Chinese ETS. Hence, the government fails to take active measure to lessen the impact of geopolitical risk on the Chinese carbon market. Otherwise, the energy transitions process would be hindered.

Our analysis offers important implications to investors as well. For instance, participants in the Chinese carbon market need to adjust their portfolio during the periods of high geopolitical tensions and our analysis could help them find appropriate financial instruments (e.g., clean energy equites) for hedging the downside risk of their investments. Besides, participants in China's carbon markets should be aware of how different sources of uncertainties can affect the risks associated with it. Given that carbon prices in China are significantly influenced by uncertainties in the international energy and financial markets, investors should consider not only the supply and demand dynamics but also the fluctuations occurring in global equity and oil markets.

In future, researchers could investigate how geopolitical shocks impact the linkage between global carbon markets. In addition, empirical research could be conducted to examine the effects of geopolitical shocks on the higher order moments such as kurtosis. Besides, event study methodology can be employed to check the influence of various geopolitical events on carbon prices. Such spillover analyses would be useful for risk management and portfolio optimization.

CRediT authorship contribution statement

Anupam Dutta: Writing – review & editing, Writing – original draft, Supervision, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sourav Mukharjee:** Writing – review & editing, Writing – original draft, Software, Investigation, Data curation. **Gazi Salah Uddin:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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