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Article

Do geopolitical risks affect stock market returns and volatilities: an analysis based on the TVP-VAR model

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Abstract. This study examines the effects of geopolitical risk (GPR) shocks on stock market returns and volatility across G7, BRICS, and Gulf countries, using a time-varying parameter vector autoregression (TVP-VAR) model. By analyzing responses over short, medium, and long-term horizons, our findings reveal significant variations in how geopolitical risks impact stock markets across different countries and timelines. We observe that GPR-related impacts on stock returns weaken over time, while volatility effects tend to strengthen, suggesting persistent risks for investors in these markets. These insights provide new perspectives for portfolio management and investment strategies during times of geopolitical uncertainty.

Keywords: geopolitical risks; G7 countries; BRICS countries; Gulf countries; stock market returns, volatility; TVP-VAR model
JEL classification: G11 ; G17

1. Introduction

War and border disputes have a harmful effect on financial markets (Kumari et al., 2023). The start of the Russian-Ukrainian conflict on February 24, 2022, caused a sharp increase in geopolitical risk facing regional and international financial markets. Intuitively, this risk harms financial markets directly and indirectly (Umar et al., 2022). Indeed, the factors influencing the dynamics of financial markets are not limited to economic and financial factors. They also include shocks induced by uncertainty (Antonakakis et al., 2017). Among these shocks is geopolitical risk, which covers geopolitical tensions, war risk, terrorist attacks, and military threats (Alqahtani et al., 2020).

Geopolitical risk is defined by Caldara and Iacoviello (2022) as "the risks associated with wars, acts of terrorism, and tensions between states that affect the normal and peaceful course of international relations". This risk is a key determinant of stock market dynamics and investment decisions (Caldara and Iacoviello, 2022, Baur and Smales, 2020). Effectively, the unpredictable disclosure of geopolitical events will harm investor sentiment (Drakos, 2010). It delays the decision-making process of market players (Salisu et al., 2022) by pushing them to postpone or divest their equity investments (Antonakakis et al., 2017). This can cause a massive sell-off of stocks by investors seeking a stable future characterized by safer financial instruments (Apergis and Apergis, 2016). This situation causes large variations in stock volatility and a decrease in stock returns (Drakos, 2010, Jeribi et al., 2015, Wang et al., 2020).

Numerous studies in the literature have examined the effects of geopolitical events, including terrorist attacks (Corbet et al., 2018; Papakyriakou et al., 2019), wars, and political tensions (Omar et al., 2017; Hudson and Urquhart, 2015) on stock markets.

Following the Russian-Ukrainian conflict, governments, investors and academics are more concerned with examining the impact of the sharply rising GPR on financial markets. Our study aims to extend the existing literature by investigating the impact of GPR geopolitical risk on stock market returns and volatility during a period marked by global financial crises, including the health crisis and the Russian-Ukrainian conflict, leading to significant changes and sudden geopolitical risks.

The remaining paper is organized as follows. Section 2 details the literature review. The data and methodology are presented in Section 3. Section 4 presents empirical results and analysis. The discussion is presented in Section 5. The last section presents concluding remarks.

2. Literature review

Based on the GPR index developed by Caldara and Iacoviello (2022), studies are conducted to examine the relationships between GPRs and financial market dynamics. Bourras et al. (2019) study the role of GPR on the volatility of 18 emerging markets and find that GPR has a significant impact on the volatility of emerging stock markets. Examining the link between GPR and stock market volatility in emerging economies, Salisu et al. (2022) find that emerging market volatility responds positively to GPR. Based on the GARCH-MIDAS approach, Ndako et al. (2021) show that the GPR would increase the volatility of Islamic stocks in Indonesia and Malaysia. Other studies find that GPR has a significant impact on the commodity market (Cunado et al., 2020; Plakandaras et al., 2019; Gkillas et al., 2020). Aysan et al. (2019) demonstrate that GPR induces negative returns for Bitcoin and positive price volatility.

Following the Russian-Ukrainian conflict, recent literature is more concerned with examining the impact of the GPR on financial markets. Boungou and Yatié (2022) reveal that the Russian-Ukrainian war had a negative impact on the stock market, especially for the countries bordering these warring nations. In studying the impact of the Russian-Ukrainian conflict on global stock markets, Boubaker et al. (2022) find that the war had a negative impact on developed economies compared to emerging countries. Zhang et al. (2023) use the bias-corrected LSDV estimator to study the effect of GPR on stock market volatility for 32 countries and regions. They claim that GPR has a significant positive effect on stock market volatility. By applying the wavelet coherence approach, Będowska-Sojka et al. (2022) analyze the impact of geopolitical risk on different types of securities. They argue that different asset classes can provide the best hedge against geopolitical risk. Boungou et al. (2022) analyze the dynamic connectivity between Russia, Europe, the United States, and global commodity markets to see the impact of the Russian-Ukrainian war on global financial markets. By providing insight into the vulnerability of the constituent companies of the main stock market indices of the G7 countries to war events, Abbassi et al. (2022) show that stock prices are fragile in the face of GPR geopolitical risk and create negative abnormal returns.

Although a significant number of studies have examined the effects of GPR geopolitical risk on financial market dynamics, there are limitations to be explored. First, previous studies assumed that the relationship between GPRs and financial market dynamics was time-invariant and used the event study approach, VAR, SVAR, or GARCH. However, in reality, following spikes linked to major geopolitical events such as the invasion of Iraq, the Gulf War and the Russian-Ukrainian crisis, GPRs evolve over time (Caldara and Iacoviello, 2022). The responses of stock markets to variations in the GPR are, therefore, heterogeneous over time. Secondly, most studies focus on the study of the GPR influence on a specific area and over a short period, which does not allow conclusions and comparisons to be made between the impact of different peaks linked to geopolitical events on the different stock markets.

The contributions of our article are multiple: First, we focus on the time-varying responses of the stock indices of the G7, BRICS and GOLF countries to GPR shocks by distinguishing between the transitory and persistent effects of the crisis in several important respects. Second, we analyze the GPRs' dynamic effects on stock markets at different times and time horizons through the construction of TVP-VAR models. Third, our estimation sample covers a longer period than previous studies and is marked by global financial crises, including the health crisis and the Russian-Ukrainian conflict, leading to significant and sudden changes in geopolitical risk.

To the best of our knowledge, this is the first attempt to study in depth the impact of multiple PBR shocks on the dynamics of different stock markets using the TVP-VAR model. The lack of empirical studies may be mainly due to the absence of major geopolitical events that characterize past periods and, consequently, to a lack of data. In our case, the period under study is essentially characterized by the Russian-Ukrainian conflict, which can be considered a major geopolitical event. A second possible explanation is that prior to this study, the database lacked indicators to measure the importance of geopolitical events. The creation of this type of indicator made our task easier.

3. Data and methodology

3.1 Data specifications

Our research provides a monthly dataset of the Geopolitical Risk Index (GPR). This risk is represented using the daily GPR index of Caldara and Iacoviello (2022). This GPR Index reflects various risks resulting from changes in government, civil unrest, threats of war, military conflicts, terrorist attacks, and any tension between states and political actors that affect the peaceful course of international relations. According to Caldara and Iacoviello (2022), the GPR index is constructed by counting the number of articles mentioning words related to geopolitical tensions in 11 major national and international newspapers (share of the total number of press articles). GPR index data are obtained from the Caldara and Iacoviello webpage (https://www.matteoiacoviello.com/gpr.htm).

We also consider monthly frequency data for stock index prices in the G7 countries (USA, UK, Germany, France, Japan, Italy, Canada), the BRICS countries (Brazil, Russia, India, China, South Africa) and the Gulf States (KSA, Oman, Qatar, Kuwait, Bahrain, UAE). The stock index price data are obtained from Datastream. We have chosen the SP500, FTSE, Nikkei, DAX40, CAC40, FTSE MIB and

S&P/TSX indices to represent the US, UK, Japanese, German, French, Italian, and Canadian stock markets, respectively. For BRICS countries, China's SSE, Russia's RTSI, India's BSE 30, Brazil's BVSP and South Africa's JTOPI indices are used. For the Gulf States, the Bahraini, Omani, Qatari, Saudi and UAE stock markets are represented respectively by the BAX, MSM30, QEAS, TASI and ADX indices.

We believe that these indices provide a very good representation of stock market trends in the countries in question, and we can be confident in the results found with this data. In addition, we have chosen this group of countries (G7, BRICS and Gulf) because we believe it covers a large part of the current political scene and that these countries are most affected by the geopolitical events under consideration.

We calculate monthly returns by considering the difference in the logarithmic values of two consecutive prices

$$r_{i,t}= \ln (P_{i,t}/P_{i,t-1}) \times 100,$$

where $r_{i,t}$ represents the monthly percentage returns for index i at time t, while $P_{i,t}$ represents the price of index i at time t .These monthly r turns were then annualized.

Moreover, the volatility series are not directly observable and must be estimated. The GARCH(1,1) model is the simplest version of the GARCH models, where the autoregressive and ARCH components are both of order one. This model assumes that past squared error and past volatility also influence current volatility. The parameters of the GARCH(1,1) model are estimated using maximum likelihood. Although simple, the GARCH (1,1) model can adequately capture the dynamics of volatility in many financial time series. What's more, the GARCH(1,1) model is preferred by many economists over other stochastic volatility models because of its relative ease of implementation. In fact, because this model is given by discrete-time stochastic difference equations, the likelihood function is easier to manipulate and consequently, the estimates are more accurate than continuous-time models. And since financial data is generally collected at discrete intervals, GARCH models are the most appropriate models for representing volatility in financial markets. Indeed, despite its simplicity, we believe that the GARCH (1,1) model is optimal for predicting the volatility of stock market index returns for the countries selected in our sample. We apply this model to determine the conditional variance of each index i as follows:

$$\begin{cases} r_{i,t} = a_{i,0} + \varepsilon_{i,t} \\ \varepsilon_{i,t} \rightarrow N\left(0, \sigma_{i,t}^2\right) \\ \sigma_{i,t}^2 = C_{i,0} + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2 \end{cases} \quad [1]$$

where σ_t^2 is the conditional variance of the residuals with the conditions α. β≥0 and α+β<1.

The study period extends from January 2016 to April 2023. Our data sampling period is marked by unexpected events such as the COVID-19 pandemic crisis and the Russian-Ukrainian conflict.

3.2 Methodology

The methodology used in this study is time-varying parameter vector autoregression (TVP-VAR). It is an innovation of the traditional VAR framework, which assumes that all model parameters are constant over time (Antonakakis and Gabauer, 2017[27]). The TVP-VAR approach, as a statistical technique used to estimate a vector autoregressive (VAR) model with time-varying parameters, eliminates the need to define an arbitrary window length for the estimation. In effect, it contributes to individual point estimates for each of the periods of the study instead of a single average point estimate for the whole period of the sample. Which can capture the dynamic behavior of variables more accurately. This method is useful primarily in modeling economic and financial time series data, where relationships between variables may change over time.

The TVP-VAR model developed by Primiceri (2005) is defined by

$$y_t = B_{0,t} + B_{1,t} y_{t-1} + \ldots\ldots + B_{p,t} y_{t-p} + u_t = X_t^{'} \Theta_t + u_t \qquad [2]$$

$$X_t^{'} = \left[1, y'_{t-1}, \ldots\ldots, y'_{t-p}.\right] \qquad [3]$$

where yt is a vector (n × 1) of observed dependent variables and $B_{0,t}$...$B_{p,t}$ are matrices of time-varying coefficients (n × n) translated into the form of a matrix Θ_t. X_t is the (n×k) matrix, including the ordinates and offsets of the endogenous variables. ut is the independent structural shock with dimension (n × 1) assumed to be a normally distributed heteroscedastic disturbance term with zero mean and a time-varying variance-covariance matrix Ωt. This matrix can be broken down as follows:

$$\Omega_t = A_{t-1} H_t \left(A_{t-1}\right)^{'}$$

where At is a lower triangular matrix, Ht is a diagonal matrix.

$$A_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 & 0 & 0 \\ \alpha_{31,t} & \alpha_{32,t} & 1 & 0 & 0 \\ \alpha_{41,t} & \alpha_{42,t} & \alpha_{43,t} & 1 & 0 \\ \alpha_{51,t} & \alpha_{52,t} & \alpha_{53,t} & \alpha_{54,t} & 1 \end{bmatrix}$$

$$H_t = \begin{bmatrix} h_{1,t} & 0 & 0 & 0 & 0 \\ 0 & h_{2,t} & 0 & 0 & 0 \\ 0 & 0 & h_{3,t} & 0 & 0 \\ 0 & 0 & 0 & h_{4,t} & 0 \\ 0 & 0 & 0 & 0 & h_{5,t} \end{bmatrix}$$

Following Primiceri (2005) (equations [5]-[7]) the time-varying parameters are assumed to depend on the following random walk process as:

$$\Theta_t = \Theta_{t-1} + v_t \qquad v_t \rightarrow N(0,Q) \qquad [5]$$

$$\alpha_t = \alpha_{t-1} + \tau_t \qquad \tau_t \rightarrow N(0,S) \qquad [6]$$

$$\ln(h_{i,t}) = \ln(h_{i,t-1}) + \sigma_i \eta_{i,t} \qquad \eta_{i,t} \rightarrow N(0,1) \qquad [7]$$

According to Primiceri (2005), it is assumed that the coefficients of contemporaneous relationships between variables evolve independently in each order of the equation to simplify inference and increase estimation efficiency. Thus, the error terms of the measurement equation and the transition equations (the parameters of the At matrix) are independent. Given stochastic volatility, parameters must be defined with maximum likelihood estimation. Markov Chain Monte Carlo (MCMC) based on Bayesian inference was also used to simulate sampling.

Technically, the TVP-VAR model has two main advantages. First, random volatility is taken into account in the estimation of the model, which significantly improves the quality of parameter estimation and avoids the problem of heteroskedasticity. Second, the TVP-VAR model allows us to identify in a meaningful way whether the influence of exogenous factors on endogenous variables shows a structural change. Indeed, in a TVP-VAR model as proposed by Primiceri (2005), the coefficients evolve with structural changes. Therefore, in order to test for time-varying effects between variables, the TVP-VAR model is considered as a flexible and powerful approach. It also provides a novel dynamic way of looking at the evolution of the relationship by identifying differences in the influence of various events.

4. Empirical results and discussion

4.1 Preliminary analyses

Table 1 shows the descriptive statistics for the GPR index, the monthly returns (panel A) and the conditional variance series (Panel B) of the G7, BRICS and Gulf stock market indices. As shown in Table 1, all the stock market indices studied show similar behavior in terms of returns, and the range of variation in these returns is small. Indeed, the BVSP index (flagship index of Brazil's São Paulo Stock Exchange) has the highest average return, followed by the BSE (Indian Stock Exchange index) and the Abu Dhabi Stock Exchange (UAE) index. On the other hand, only the Oman stock market index posted a negative average return over the study period. The Chinese index had the lowest positive average return.

In terms of standard deviation, investment in the Bahrain stock market can be considered the safest, while investment in the Russian stock market is very risky. The latter can be explained by the Russian invasion of Ukraine. Skewness values are low but negative for all return series. Kurtosis values are greater than three for virtually all return series (with the exception of Japan, South Africa, KSA, and Qatar). These results indicate that the probability distribution of returns in the sample (with the exception of Japan, South Africa, KSA, and Qatar) is asymmetric and leptokurtic and rejects the normality confirmed by Jarque-Bera (J.-B.) statistics.

Table 1. Descriptive Statistics.

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	JB	Obs
GPR	102.8013	325.4400	60.60164	35.82020	3.300504	19.43118	1149.709	88
Panel A: Indices returns								
G7 stock market indices								
USA	0.094314	1.357056	-1.518952	0.552216	-0.565972	3.751062	6.766434	88
UK	0.034732	1.386537	-1.688554	0.432372	-0.773560	6.122911	44.53588	88
Germany	0.056387	1.664915	-2.040667	0.589801	-0.461879	4.193598	8.352693	88
Japan	0.059130	1.668301	-1.264153	0.544833	-0.338623	3.429915	2.359461	88
France	0.068117	2.182283	-2.146030	0.573665	-0.189864	5.939288	32.20655	88
Italy	0.037416	2.459574	-2.887717	0.718877	-0.470959	6.086181	38.17632	88
Canada	0.060512	1.170430	-2.218500	0.459590	-1.376000	9.187664	168.1559	88
BRICS stock market indices								
China	0.002973	1.699654	-2.335511	0.555897	-0.486206	5.993300	36.31991	88
Russia	0.031388	2.189547	-6.509287	1.129673	-2.499401	14.80033	602.1975	88
India	0.110502	1.530670	-2.977927	0.593425	-1.354873	9.943830	203.7182	88
Brasil	0.114218	1.756908	-4.037607	0.810932	-1.529734	9.365449	182.8907	88
South Africa	0.065096	1.510438	-1.343617	0.532145	0.130942	3.304914	0.592371	88
Gulf stock market indices								
Bahraïn	0.062394	1.019529	-1.957794	0.389424	-1.484343	10.44053	235.3070	88
Kuwait	0.061857	1.393309	-2.530908	0.526312	-1.534887	8.832443	159.2833	88
Oman	-0.017718	1.127539	-1.915278	0.404916	-0.649262	7.736067	88.42715	88
Qatar	0.027650	1.644088	-1.282169	0.556983	-0.102878	2.845795	0.242420	88
KSA	0.064957	1.728884	-1.848417	0.653920	-0.427031	3.342267	3.104079	88
Panel B: Indices volatility								
G7 stock market indices								
USA	0.349883	1.195069	0.056675	0.270802	0.922936	3.028674	12.49625	88
UK	0.194598	1.697595	0.019423	0.223137	4.866163	29.22011	2868.112	88
Germany	0.339060	1.575335	0.198275	0.188541	4.120157	24.23298	1902.054	88
Japan	0.288312	0.534708	0.266000	0.036826	4.547489	27.36638	2480.278	88
France	0.369096	3.516855	0.114625	0.483547	5.080932	30.89545	3231.873	88
Italy	0.512339	0.826530	0.076468	0.111342	-1.404599	6.664227	78.16656	88
Canada	0.266981	4.430728	0.056621	0.526840	6.121145	46.50111	7488.141	88
BRICS stock market indices								
China	0.285438	1.888137	0.206153	0.229790	5.592734	35.57790	4350.259	88
Russia	1.647087	43.11977	0.302961	4.704396	8.027124	70.44637	17624.76	88
India	0.390518	7.259795	0.080986	0.768153	8.281832	74.38137	19688.74	88
Brasil	0.674802	6.796237	0.411888	0.701214	7.726937	67.57642	16166.10	88
South Africa	0.277656	0.859246	0.077403	0.127576	2.699911	11.33494	361.6410	88
Gulf stock market indices								
Bahraïn	0.180558	1.910986	0.071991	0.230610	5.495450	38.72667	5123.048	88
Kuwait	0.289881	2.777954	1.72E-07	0.300635	6.754604	54.97319	10573.61	88
Oman	0.150564	0.260339	0.073515	0.019824	1.689719	16.89985	750.2970	88
Qatar	0.307896	0.856196	0.181924	0.131581	1.870552	6.776140	103.6020	88
KSA	0.416821	1.307038	0.308581	0.166302	3.346162	15.98800	782.7428	88
UAE	0.263502	2.432828	0.115890	0.248337	7.767309	67.80945	16285.83	88

The descriptive statistics of the conditional variance series obtained by the GARCH (1,1) model are presented in Panel B of Table 1. This panel shows that the highest average conditional variance for the G7 countries is observed for the Italian stock market index (0.512339). The highest average conditional variances for the BRICS and Gulf countries are obtained for the Russian (1.647087) and Saudi (0.416821) markets, respectively. Furthermore, the Jarque-Bera test shows that the null hypothesis of normality is rejected for all return and volatility series examined.

In addition, the Augmented Dickey-Fuller (ADF) and Phillips and Perron (PP) tests were used to examine the stationarity of the variables. Table 2 shows that all variables (both yields and volatilities) are stationary in terms of levels at the 1% significance level for both the ADF and PP tests. Consequently, the level data were used for the following empirical study.

Table 2. Unit root tests

Variables	**ADF test**		**PP test**	
GPR	-3.876951***		-3.931328***	
	Return	***Volatility***	***Return***	***Volatility***
G7 stock market indices				
USA	-10.98700***	-2.951146**	-11.16284***	-2.948086**
UK	-9.082738***	-6.105537***	-9.096397***	-5.798166***
Germany	-9.991293***	-7.520084***	-9.991293***	-7.453225***
Japan	-10.28373***	-12.08317***	-10.30959***	-12.08317***
France	-9.811079***	-7.931754***	-9.813727***	-7.898927***
Italy	-10.59588***	-4.062610***	-10.60848***	-4.089589***
Canada	-10.55670***	-5.784601***	-10.56286***	-5.674474***
BRICS stock market indices				
China	-10.62961***	-19.01510***	-10.97546***	-22.73520***
Russia	-9.694159***	-9.037548***	-9.804686***	-9.037548***
India	-9.988251***	-8.736843***	-10.01856***	-8.736843***
Brasil	-8.420072***	-7.516881***	-8.639780***	-7.520713***
South Africa	-9.653704***	-5.180757***	-9.656024***	-5.271113***
Gulf stock market indices				
Bahraïn	-6.375853***	-5.371185***	-5.984285***	-5.380160***
Kuwait	-8.097271***	-8.997574***	-8.207790***	-8.992385***
Oman	-9.997543***	-6.857102***	-10.03244***	-6.911374***
Qatar	-9.372080***	-4.796342***	-9.372080***	-4.647228***
KSA	-9.644327***	-7.207502***	-9.642112***	-8.064956***
UAE	-9.576446***	-8.066089***	-9.575057***	-8.035662***

***. ** and * denote significance at 1%. 5% and 10% level respectively.

4.2 Causality test results

We begin our analysis with the Granger linear causality test. This test will answer our research question: does geopolitical risk affect the returns and volatility of stock markets in G7, BRICS and Gulf countries? Table 3 presents the results of this test. By considering the geopolitical risk index GPR as the causal variable, the results show that the null hypothesis of Granger non-causality cannot be rejected in a relatively large number of cases. Indeed, for the G7 countries, geopolitical risk only affects the returns of the American and Canadian markets in the Granger sense. For BRICS countries, only Chinese and Indian stock market returns are strongly influenced by geopolitical risk. On the other hand, the null hypothesis of non-causality in the Granger sense is rejected in the case of returns on all Gulf markets.

Regarding stock market volatility, the linear causality test reveals a single significant causal relationship between the GPR index and stock market investment risk (extracted via a GARCH model). Otherwise, the alternative hypothesis of the Granger test is only accepted in the case of Russia. This result can be attributed to the Russian-Ukrainian war.

However, the Granger causality test is a linear test that gives a general and aggregate view of the nature of the relationship between two variables. This link is constant over the entire period and only superficially characterizes the causality between markets. Additionally, as we pointed out in the statistical description, streaks are associated with fat tails, excessive kurtosis, and nonnormality. Given this evidence, it is imperative to further study the dynamic relationships between the GPR index and different stock markets. The non-linear TVP-VAR model, therefore, constitutes the appropriate model for studying the time-varying and continuous effect of geopolitical risks on the different stock markets of the G7, BRICS, and Gulf countries.

Table 3. Linear causality test results: GPR as the causal variable

	Return		***Volatility***	
	F-stat.	***Prob.***	***F-stat.***	***Prob.***
H_0 : GPR does not Granger cause G7 market				
USA	4.29701**	0.0168	2.08703	0.1307
UK	1.10224	0.3371	0.49736	0.6100
Germany	0.80586	0.4503	0.16012	0.8523
Japan	0.49740	0.6100	0.51507	0.5994
France	1.19582	0.3077	0.15965	0.8527
Italy	1.66218	0.1961	0.46223	0.6315
Canada	2.99262*	0.0557	0.13545	0.8735
H_0 : GPR does not Granger cause BRICS stock market				
China	2.37190*	0.0926	0.52163	0.5955
Russia	0.43239	0.6504	11.8990***	3.E-05
India	3.18673**	0.0465	0.34763	0.7074
Brasil	1.13239	0.3273	0.15544	0.8563
South Africa	0.94908	0.3914	2.08703	0.1307
H_0 : GPR does not Granger cause Gulf stock market				
Bahraïn	6.51155***	0.0024	0.16510	0.8481
Kuwait	4.03717**	0.0213	0.06123	0.9407
Oman	2.32776*	0.0960	0.10609	0.8995
Qatar	5.76246***	0.0046	0.16517	0.8480
KSA	2.87802*	0.0620	0.47725	0.6222
UAE	2.32736*	0.0944	0.21362	0.8081

***. ** and * denote the rejection of the nullhypothesis of Granger-non-causality at 1%. 5% and 10% significance level respectively.

4.3 Time-varying effects of the GPR index on stock market returns and volatilities

We used the MCMC method based on the Bayesian framework to estimate the TVP-VAR model (Primiceri 2005, Kang et al. 2015, Degiannakis et al. 2018 and Toparlı et al. 2019). Table 4 shows the results of the parameters estimating selected in the TVP-VAR model. For all the zones considered (G7, BRICS, Golf) and for both returns and volatilities, the mean of the estimated parameters lies within the confidence interval. What's more, the inefficiency factors are relatively low, and the Geweke statistics show that the parameter converges to the posterior distribution. We can therefore conclude that the MCMC algorithm efficiently draws the posterior distribution.

Table 4. Estimation results of the main parameters in the TVP-VAR model

Parameter	Mean	Std. Dev.	95% confidence interval	Geweke	Inef.
Estimation for the set (GPR, G7 stock market indices return)					
(Σβ)1	0.0023	0.0003	[0.0018, 0.0029]	0.259	6.06
(Σβ)2	0.0023	0.0003	[0.0018, 0.0028]	0.216	6.08
(Σα)1	0.0047	0.0010	[0.0031, 0.0072]	0.055	19.26
(Σh)1	0.0058	0.0018	[0.0034, 0.0102]	0.004	32.37
(Σh)2	0.0055	0.0016	[0.0034, 0.0096]	0.692	28.82
Estimation for the set (GPR, G7 stock market indices volatility)					
(Σβ)1	0.0023	0.0003	[0.0018, 0.0029]	0.862	6.06
(Σβ)2	0.0023	0.0003	[0.0018, 0.0029]	0.695	4.21
(Σα)1	0.0055	0.0044	[0.0032, 0.0105]	0.000	20.89
(Σh)1	0.0058	0.0021	[0.0034, 0.0110]	0.014	32.73
(Σh)2	0.3027	0.1423	[0.0042, 0.4594]	0.000	340.07
Estimation for the set (GPR, BRICS stock market indices return)					
(Σβ)1	0.0023	0.0003	[0.0018, 0.0029]	0.975	4.60
(Σβ)2	0.0023	0.0003	[0.0018, 0.0029]	0.786	4.52
(Σα)1	0.0046	0.0010	[0.0031, 0.0070]	0.294	14.97
(Σh)1	0.0056	0.0016	[0.0034, 0.0099]	0.728	29.56
(Σh)2	0.0056	0.0019	[0.0034, 0.0102]	0.611	31.86
Estimation for the set (GPR, BRICS stock market indices volatility)					
(Σβ)1	0.6693	0.2087	[0.4614, 1.2824]	0.000	307.79
(Σβ)2	0.0023	0.0003	[0.0018, 0.0029]	0.320	5.15
(Σα)1	2.1744	2.1985	[0.0026, 6.8471]	0.000	341.56
(Σh)1	0.1476	0.3499	[0.0036, 1.1731]	0.000	322.95
(Σh)2	0.0059	0.0046	[0.0033, 0.0112]	0.501	25.21
Estimation for the set (GPR, Gulf stock market indices return)					
(Σβ)1	0.0102	0.0564	[0.0018, 0.0054]	0.220	167.39
(Σβ)2	0.0023	0.0003	[0.0018, 0.0029]	0.370	4.40
(Σα)1	0.0046	0.0010	[0.0031, 0.0069]	0.0031	25.37
(Σh)1	0.0058	0.0021	[0.0035, 0.0114]	0.166	26.40
(Σh)2	0.0056	0.0016	[0.0034, 0.0098]	0.063	32.71
Estimation for the set (GPR, Gulf stock market indices volatility)					
(Σβ)1	0.0023	0.0003	[0.0018, 0.0029]	0.020	6.85
(Σβ)2	0.0023	0.0003	[0.0018, 0.0028]	0.186	5.27
(Σα)1	0.0060	0.0141	[0.0033, 0.0072]	0.168	15.71
(Σh)1	0.0056	0.0017	[0.0034, 0.0099]	0.299	22.34
(Σh)2	0.0071	0.0098	[0.0034, 0.0233]	0.007	36.23

4.3.1 Time-varying effects of the GPR index on G7 stock market returns

Figure 1 shows the responses of stock index returns in the G7 countries to geopolitical risk shocks (GPR index) at different time horizons. We have analyzed impulse responses over the short (1 month), medium (6 months), and long term (12 months). Interval analysis of impulse responses enables us to simulate impulse responses more effectively and reveal differences between different terms. In general, responses vary over time. As shown in Figure 1, over a 1-month time horizon, geopolitical risks mainly exert positive effects on the returns of virtually all G7 stock market indices. Otherwise, a shock to the GPR index mainly triggers short-term increases in returns in the G7 countries. In the case of the USA and the UK, the GPR has a negative effect on returns from mid-2020, resulting in lower returns for the stock market indices of these two countries. In the medium term, however, yield responses in the G7 countries are weak. They are mostly negative, with temporary positive responses. Over the 12-month horizon, responses are small and almost non-existent. On the other hand, the largest positive effects are seen in the period between mid-2017 and mid-2020, and the largest negative impacts occur around early 2020 and late 2022. We also find that yield responses to geopolitical risk are strongest in the short term, much weaker in the medium-term lag, and negligible in the long term. We can therefore conclude that the effect of the GPR index on the returns of the G7 country indices is seen more in the short term. It is interesting to note that G7 country index returns react to the GPR with little difference over the entire study period and for all three time horizons. Our findings are in line with the article by Salisu et al. (2022), which illustrates that GPR is an important predictor of stock returns in advanced economies and that their markets are adversely affected by GPR threats (such as threats of war and terrorism).

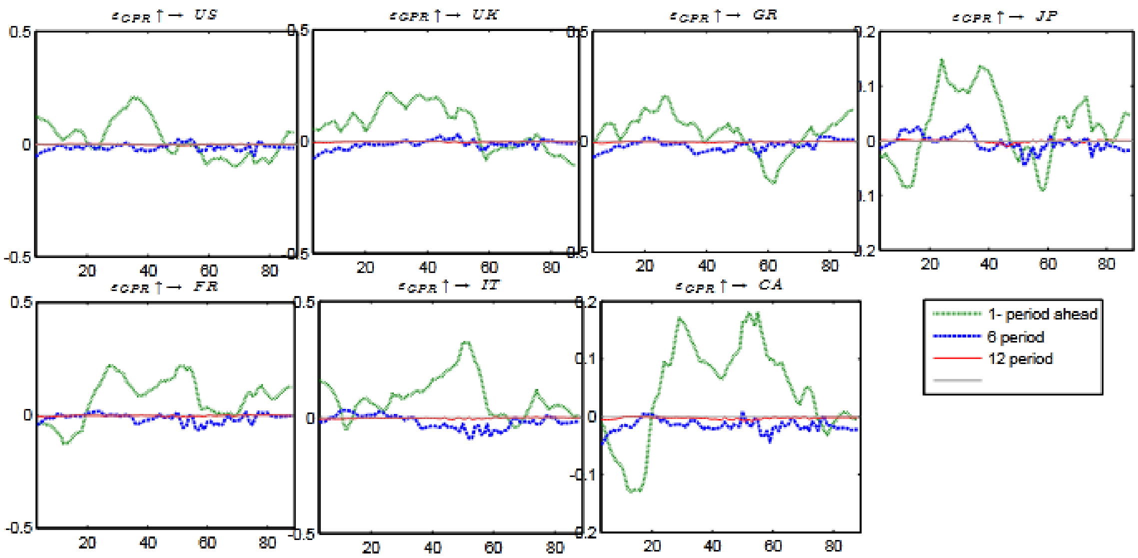

Figure 1. Time-varying responses of G7 country indices returns to the GPR at different time horizons. *Note*: GPR refers to the GPR benchmark. US, UK, GR, JP, FR, IT and CA refer to the returns of the benchmark equity indices in the USA, UK, Germany, Japan, France, Italy and Canada, respectively.

Our results show that the impulse responses of stock index returns following a shock to the GPR index vary over time. To deepen this analysis, we propose to study the dynamic effect of geopolitical risk on specific dates. Our study period (2016-2023) is not characterized by significant geopolitical events, and even the evolution of the GPR index registers only one peak in 2022 with the Russian invasion of Ukraine. We propose three dates: January 2017, January 2020, and February 2022. These three periods correspond to the election of Donald Trump as President of the United States, the first wave of the health crisis, and the war between Russia and Ukraine, respectively.

As shown in Figure 2, G7 return responses are highly volatile, frequently shifting from positive to negative at all three predefined dates. As a result, we can say that the effects of the GPR index on G7 stock market returns have no regular direction during specific geopolitical events. Indeed, in the face of unpredictable and significant geopolitical risks, investors' behavior towards stock market investments can go either way, depending on their expectations and risk aversion. Some investors choose to buy stocks, and others choose to sell based on their expectations for the future, triggering a corresponding rise or fall in stock returns.

In addition, the biggest return reactions were seen during the health crisis and the Russian invasion of Ukraine. During the health crisis and the war between Russia and Ukraine, the return responses of the G7 stock indices (except Japan) are similar, passing through a negative-positive-negative alteration process. In the case of Japan, the effect of the GPR index on NIKKEI returns is always positive during the COVID-19 crisis and negative during the Russian invasion of Ukraine. This result is in line with the study by Abbasi et al. (2022), which shows that the stock prices of G7 countries are fragile in the face of war events, creating negative abnormal returns.

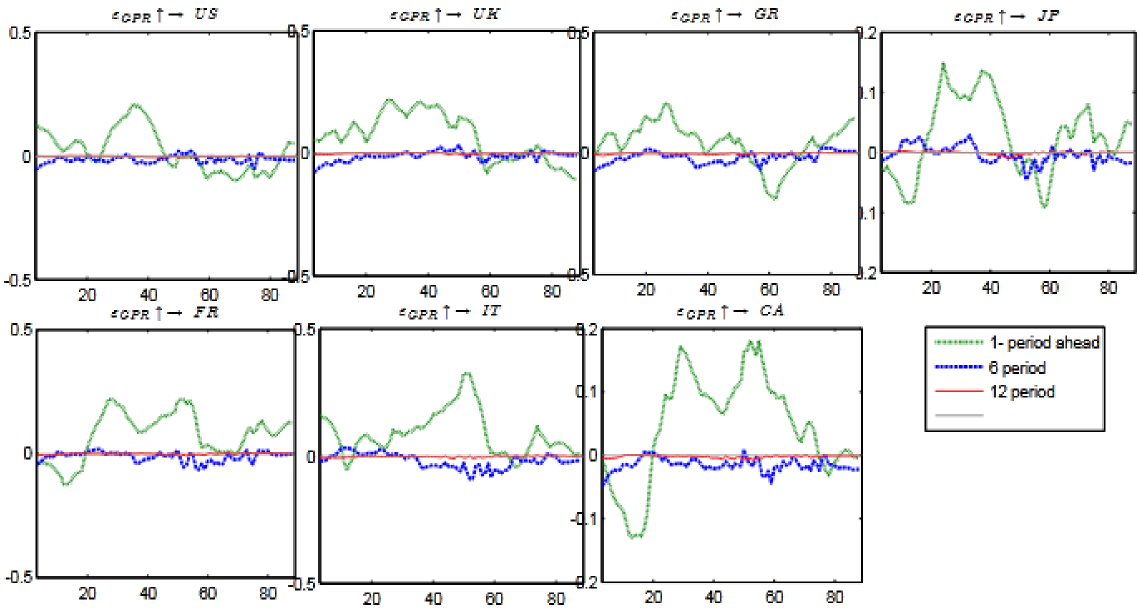

Figure 2. Time-varyingresponses of G7 country indices returns to the GPR at differentdates. *Note*: GPR refers to the GPR benchmark.US, UK, GR, JP, FR, IT and CA refer to the returns of the benchmark equity indices in the USA, UK, Germany, Japan, France, Italy and Canada, respectively.

4.3.2 Time-varying effects of the GPR index on G7 stock market volatilities

In addition to studying the effect of political risk on stock returns, we also propose to analyze the effect of the GPR index on stock market volatility. As already mentioned, these volatilities have been extracted using GARCH models. Figure 3 shows the impulse responses of G7 stock index return volatilities to short-, medium- and long-term GPR index shocks. As in the case of returns, volatility responses are dynamic and change over time. As shown in Figure 3, in the short, medium and long term, geopolitical risks mainly exert positive effects on the volatilities of almost all G7 stock market indices and over the entire study period (except for the UK and Italy). For these two countries, we observe mainly positive reactions, with temporary negative reactions for the period mid-2019 and end of 2020. Overall, we can conclude that the GPR index has a positive effect on the volatility of stock market indices in the G7 countries, which translates into higher risks for this type of investment. This finding confirms the conclusions of Balcilar et al. (2018), Bouras et al. (2019) and Das et al. (2019), who also found positive GPR effects on stock volatility. We also note that, unlike returns, volatility responses to geopolitical risk are strongest in the long term, much weaker in the medium term and negligible in the short term. We can therefore conclude that the effect of the GPR index on the volatilities of the G7 indices is more pronounced in the long term. There is therefore some persistence in the effect of GPR indice on volatilities.

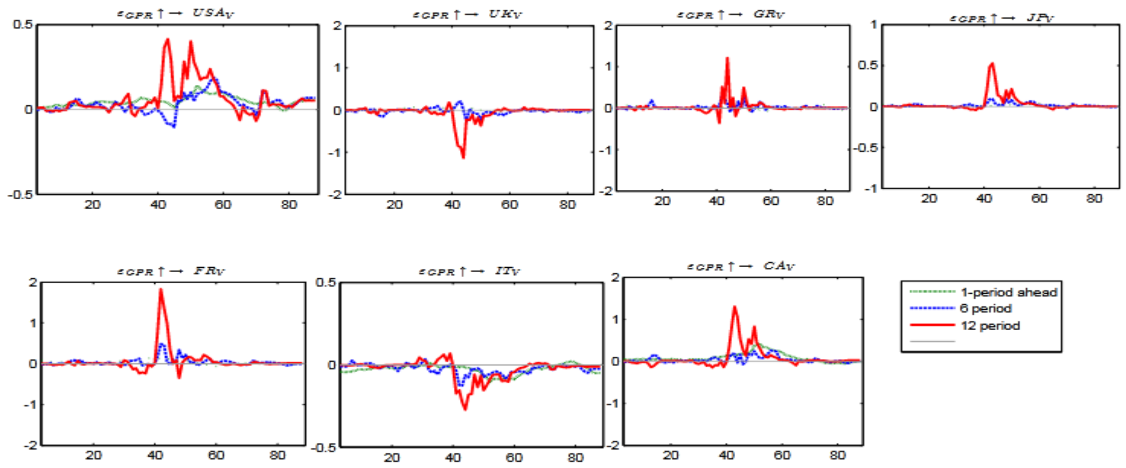

Figure 3. Time-varying responses of G7 country indices volatilities to the GPR at different time horizons. *Note*: GPR refers to the GPR benchmark. US_V, UK_V, GR_V, JP_V, FR_V, IT_V and CA_V refer to the volatilities of the benchmark equity indices in the USA, UK, Germany, Japan, France, Italy and Canada, respectively.

As shown in Figure 4, the reactions of G7 volatilities are, in the majority of cases, positive on all three predefined dates. Consequently, we can say that geopolitical risk increases the risk of investing in G7 stock markets. In addition, the strongest reactions were observed in 2022, corresponding to the Russian invasion of Ukraine. During the war between Russia and Ukraine, the volatility of the G7 stock indices (with the exception of Italy) reacted largely positively to the GPR index shock.

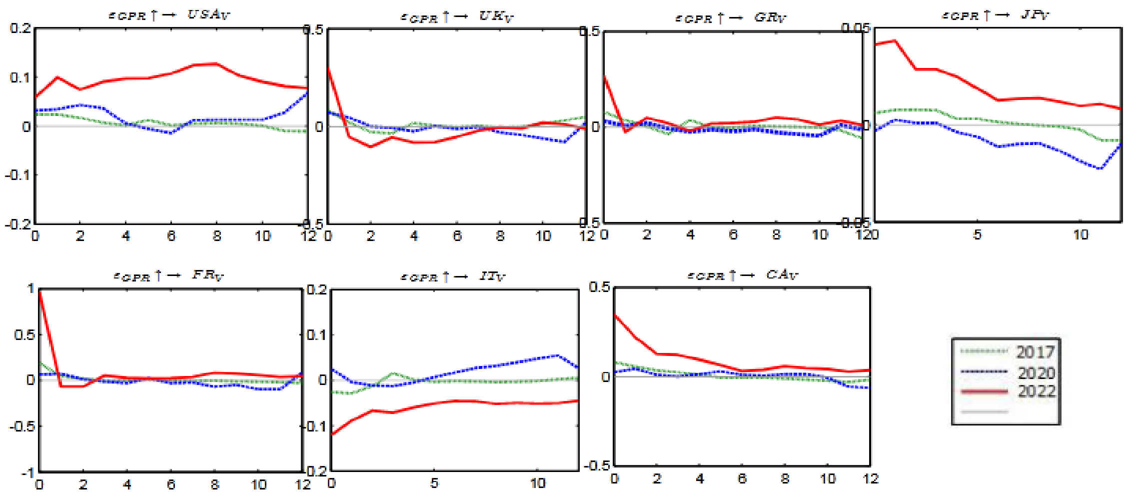

Figure 4. Time-varying responses of G7 country indices volatilities to the GPR at different dates. *Note*: GPR refers to the GPR benchmark. US_V, UK_V, GR_V, JP_V, FR_V, IT_V and CA_V refer to the volatilities of the benchmark equity indices in the USA, UK, Germany, Japan, France, Italy and Canada, respectively.

4.3.3 Time-varying effects of the GPR index on BRICS stock market returns

The impulse responses of BRICS stock index returns to geopolitical risk shocks (GPR index) at different time horizons are plotted in Figure 5. As shown in Figure 5, at a one-month horizon, geopolitical risks mainly affect returns in different ways across countries. In the case of China, a shock to the GPR index mainly triggers short-term declines in stock index returns. In contrast, the GPR index has a positive impact on the Indian stock index. In the case of Russia, the GPR has had a negative impact on returns since mid-2020, leading to falling stock index returns for both countries. In the medium term, however, the return responses in the G7 countries are weak. They are mostly negative, with temporary positive reactions. Over the 12-month horizon, the reactions are weak and almost non-existent. Moreover, the largest positive effects are observed between mid-2017 and mid-2020, and the largest negative effects occur between early 2020 and late 2022. We also find that yield responses to geopolitical risk are strongest in the short term, much weaker in the medium term, and negligible in the long term. We can therefore conclude that the effect of the GPR index on BRICS country index returns is most pronounced in the short run. It is interesting to note that BRICS index returns react to the GPR with little difference over the entire period studied and for all three time horizons.

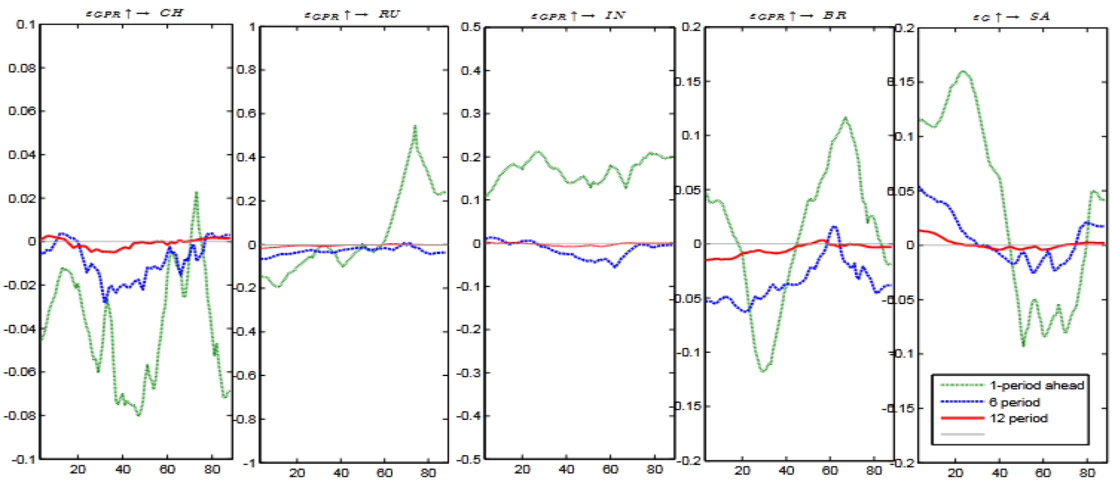

Figure 5. Time-varying responses of BRICS country indices returns to the GPR at different time horizons. *Note*: GPR refers to the GPR benchmark.CH, RU, IN, BR, and SA refer to the returns of the benchmark equity indices in China, Russia, India, Brazil, and South Africa, respectively.

Figure 6 shows that the return reactions of the BRICS countries are highly volatile, frequently changing from positive to negative on the three predefined dates. As a result, the impact of the GPR index on BRICS stock returns does not have a regular direction during specific geopolitical events. Our results are in line with the study of Balcilar et al. (2018), who studied the effect of geopolitical uncertainty on the return and volatility dynamics of BRICS stock markets and asserted that the geopolitical risks (GPR) effect is heterogeneous on stock markets and does not affect the returns dynamics in these markets in a uniform manner.

In fact, the largest return reactions were observed during the Russian invasion of Ukraine. In this sense, the return reactions were consistently negative. The Russian invasion of Ukraine negatively affected stock returns in the BRICS countries. Similarly, during the health crisis, the reactions of stock index returns in China, Russia, and India were similar. They are sometimes negative and sometimes positive. The effect of the GRP index on stock market returns is always negative in the case of Brazil and positive in the case of South Africa.

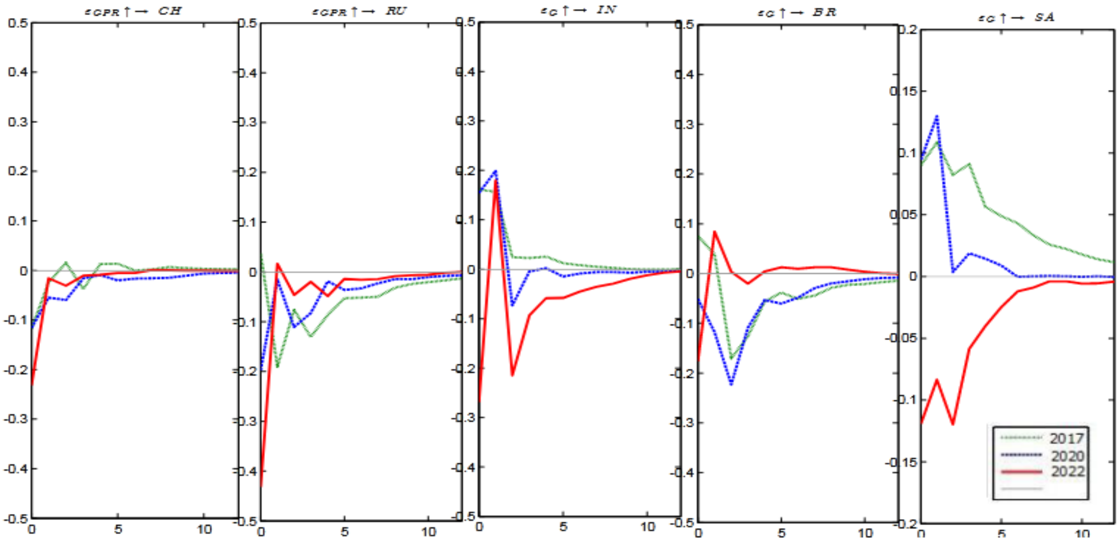

Figure 6. Time-varying responses of BRICS country indices returns to the GPR at different dates. *Note*: GPR refers to the GPR benchmark.CH, RU, IN, BR, and SA refer to the returns of the benchmark equity indices in China, Russia, India, Brazil, and South Africa, respectively.

4.3.4 Time-varying effects of the GPR index on BRICS stock market volatilities

As shown in Fig. 7, the impulse responses of BRICS stock index volatilities to shocks linked to geopolitical risks (GPR index) at different time horizons are positive overall, with some temporary negativities (with the exception of China). This finding is similar to the results found in the case of G7 countries. In addition, the strongest positive effects are observed between late-2020 and mid-2022, a period characterized mainly by the health crisis and the Russian-Ukrainian conflict. In the case of China, volatility reactions following a shock to the GPR index are negative for all horizons studied. We also note that, as in the case of volatilities in the G7 countries, volatility reactions to geopolitical risk are strongest in the long term, much weaker in the medium term and negligible in the short term. We can therefore conclude that the effect of the GPR index on BRICS country index volatilities is most pronounced in the long term. We can conclude that there is a persistence of GPR index shocks, which explains the greater long-term effect on volatility.

As shown in Figure 8, the volatility responses of BRICS stock indices are broadly positive at all three predefined dates. This result confirms the findings of Salisu et al. (2022), who assert that the stock market volatility of these countries reacts more positively to geopolitical risks.

The effects of geopolitical risk increase the risks of investing in BRICS stock markets. Furthermore, the strongest reactions were observed in 2020, a year characterized primarily by the first wave of the COVID-19 pandemic. The greatest impact of this crisis was seen in China. This result seems logical, given that the Coronavirus was first detected in Wuhan. In addition, during the Russian invasion of Ukraine, the volatility of the BRICS stock indices also reacted positively to a shock to the GPR index. The magnitude of this effect, however, was smaller than that of the health crisis.

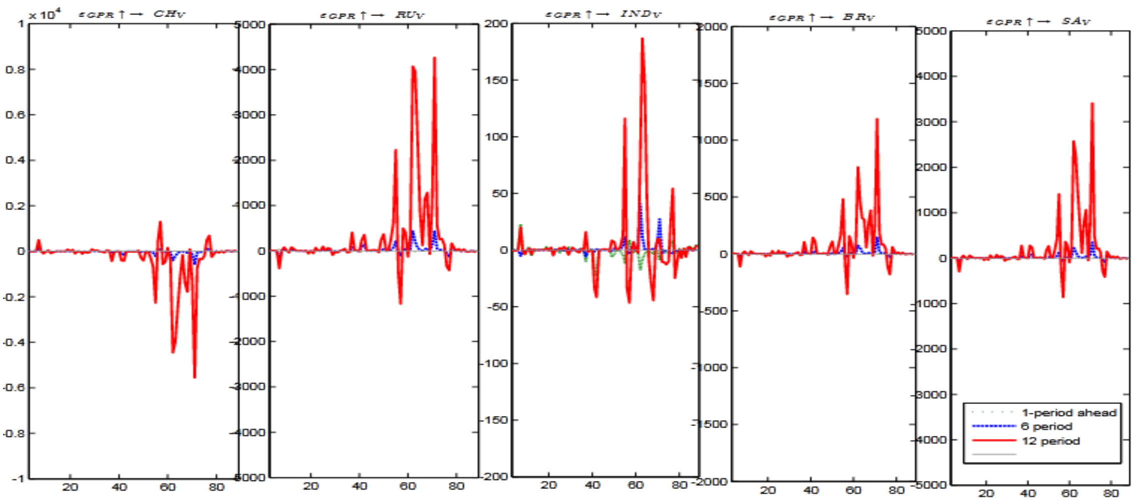

Figure 7. Time-varying responses of BRICS country indices volatilities to the GPR at different time horizons. *Note*: GPR refers to the GPR benchmark.CH_V, RU_V, IN_V, BR_V, and SA_V refer to the volatilities of the benchmark equity indices in China, Russia, India, Brazil, and South Africa, respectively.

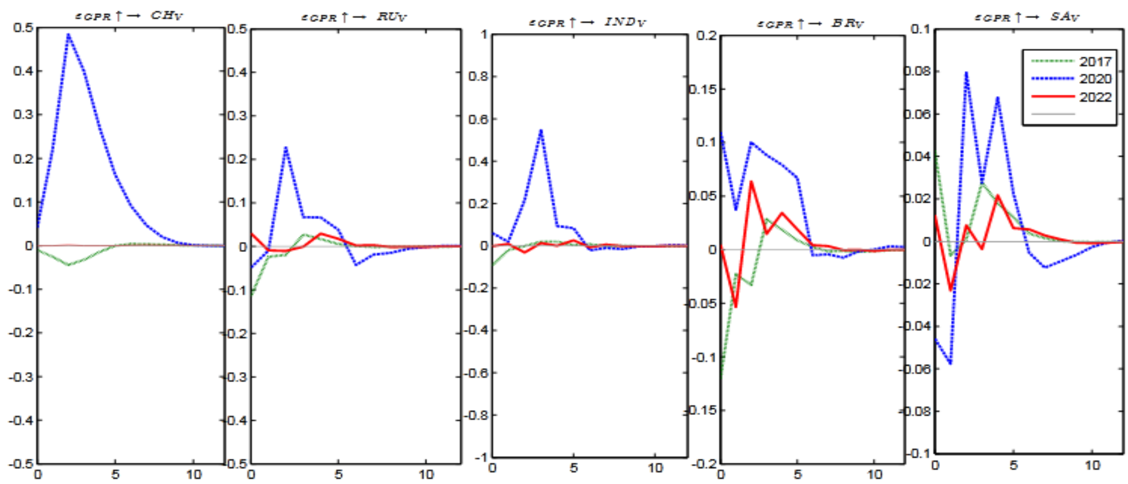

Figure 8. Time-varying responses of BRICS country indices volatilities to the GPR at different dates. Note: GPR refers to the GPR benchmark. CH_V, RU_V, IN_V, BR_V, and SA_V refer to the volatilities of the benchmark equity indices in China, Russia, India, Brazil, and South Africa, respectively.

4.3.5 Time-varying effects of the GPR index on Gulf stock market returns

As shown in Figure 9, the impulse responses of Gulf yields are heterogeneous across time horizons. At the one-month horizon, the responses are generally positive. Thus, when geopolitical events occur, investors in the Gulf countries choose to buy rather than sell stocks, leading to higher stock index returns. At the eight-month horizon, the responses are mostly negative. Gulf investors tend to sell stocks on the stock exchanges, leading to lower stock index returns. However, at the 12-month horizon, the responses oscillate between positive and negative at low levels. The functional strength of the responses also varies over time. The most significant responses occur in the short term, and the least significant effects occur in the long term. As in the case of the G7 and BRICS countries, the effects of the GPR index on Gulf returns weaken over time.

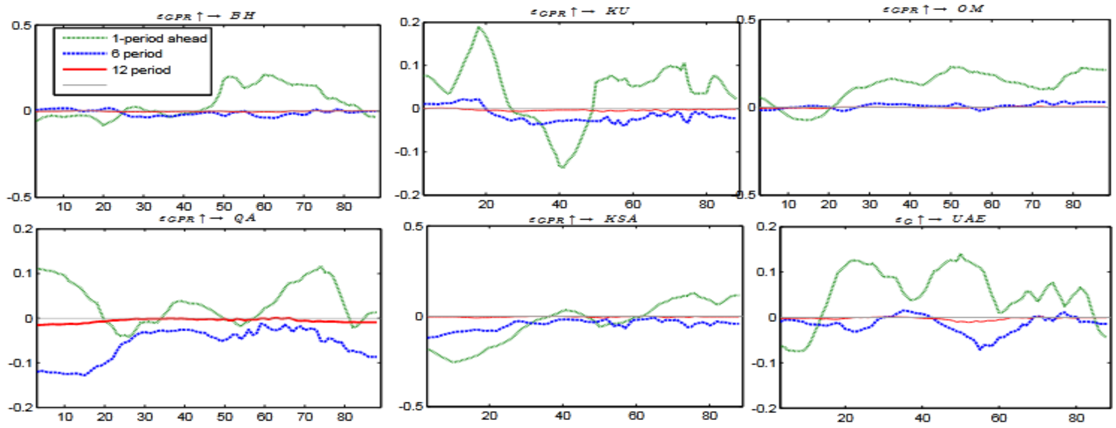

Figure 9. Time-varying responses of Gulf country indices returns to the GPR at different time horizons. *Note*: GPR refers to the GPR benchmark.BH, KU, OM, QA, KSA, and UAE refer to the returns of the benchmark equity indices in the Bahrain, Kuwait, Oman, Qatar, KSA, UAE, respectively.

As in the case of the G7 and BRICS countries, the feedback from the Gulf countries is very volatile, often swinging from positive to negative on the three predefined dates (Figure 10). Therefore, there is no regular direction for the impact of the GPR index on Gulf stock returns during specific geopolitical events. Our results do not coincide with the study by Alqahtani et al. (2022), which asserts that the time-varying conditional correlation between Gulf stock market returns and geopolitical risk is systematically negative.

During the health crisis, the reactions of the Gulf stock index returns were similar. They are initially negative, then positive, and then close to zero. During the Russian-Ukrainian conflict, the responses alternated between positive and negative, but the negative responses are more significant and have larger amplitudes. Figure 10 also shows that, in contrast to the G7 and BRICS countries, returns generally reacted positively to Donald Trump's victory in the US election.

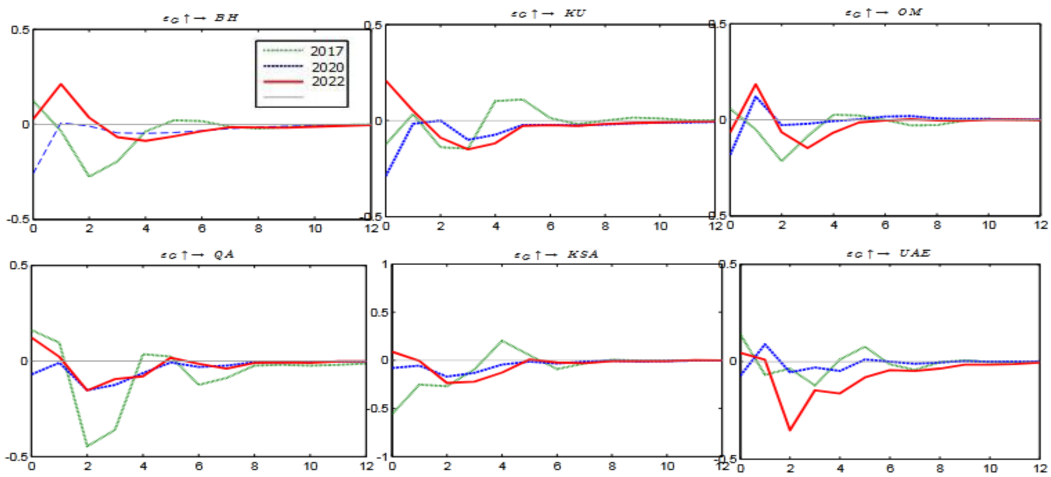

Figure 10. Time-varying responses of Gulf country indices returns to the GPR at different dates. *Note*: GPR refers to the GPR benchmark.BH, KU, OM, QA, KSA, and UAE refer to the returns of the benchmark equity indices in the Bahrain, Kuwait, Oman, Qatar, KSA, UAE, respectively.

4.3.6 Time-varying effects of the GPR index on Gulf stock market volatilities

As shown in Figure 11, the impulse responses of return volatilities in the Gulf region are very volatile, frequently changing from positive to negative in all three time horizons. Indeed, in the face of unpredictable and significant geopolitical risks, investors' behavior with respect to stock market investments may vary according to their expectations and risk aversion. Some investors may choose to buy stocks, while others may choose to sell based on their expectations for the future, leading to higher or lower stock market risk. As in the case of the G7 and BRICS, the GPR index impact on Gulf returns diminishes over time. We also find that, as in the case of G7 and BRICS volatilities, the volatility responses to the GPR index shocks increase with time horizons. They are strongest in the long term, much weaker in the medium term, and negligible in the short term. This more pronounced effect on long-term volatility can be attributed to the persistence of shocks in the GPR index.

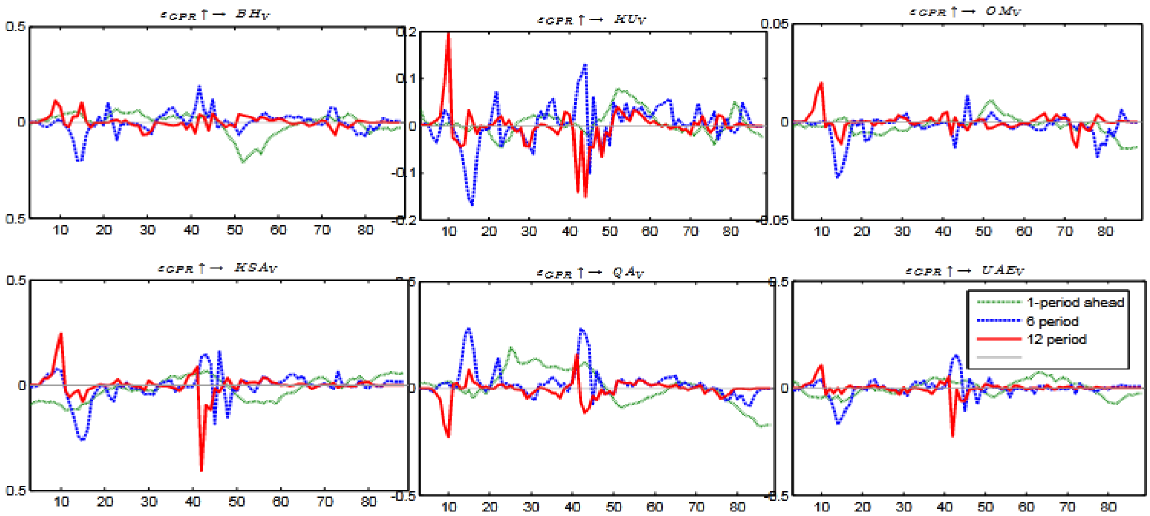

Figure 11. Time-varying responses of Gulf country indices volatilities to the GPR at different time horizons. *Note*: GPR refers to the GPR benchmark.BH_V, KU_V, OM_V, QA_V, KSA_V, and UAE_V refer to the volatilities of the benchmark equity indices in the Bahrïn, Kuwait, Oman, Qatar, KSA, UAE, respectively.

The Gulf indices volatility reactions are similar on the three predefined dates (Figure 12). During a health crisis, the reactions are first positive and then negative. For the Russian-Ukrainian conflict, the GPR index has a negative effect on the volatility, then the reaction is reversed. On the other hand, the effect of the GPR index during the 2017 US elections on the stock market volatilities of the Gulf countries does not have a regular direction and often goes from positive to negative.

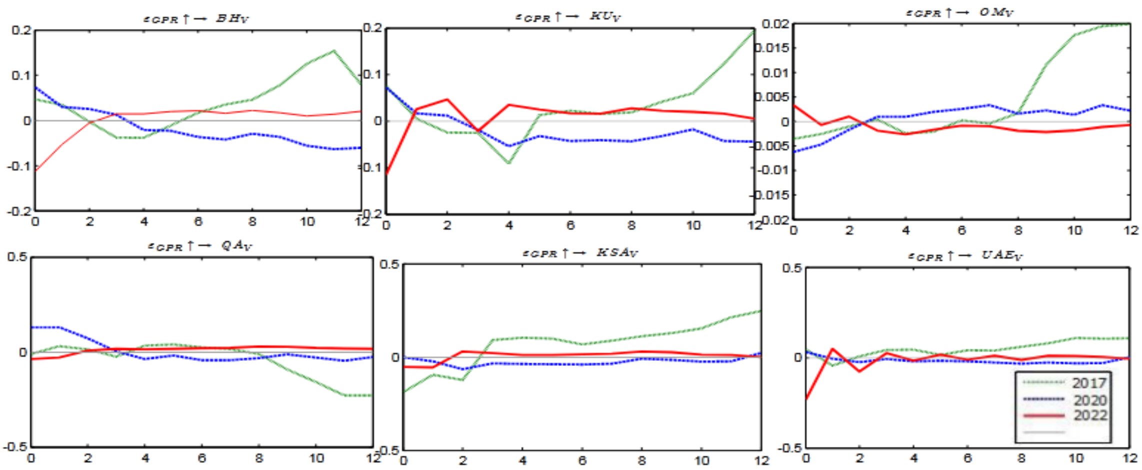

Figure 12. Time-varyingresponses of Gulf country indices volatilities to the GPR at differentdates. *Note*: GPR refers to the GPR benchmark.BHv, KUv, OMv, QAv,, KSAv, and UAEvrefer to thevolatilities of the benchmark equity indices in the Bahrïn, Kuwait, Oman, Qatar, KSA,UAE, respectively.

5. Discussion

This paper uses a time-varying parameter vector autoregression (TVP-VAR) model to examine the impact of the GPR index shock, which measures geopolitical risk, on stock index returns and volatility in G7, BRICS, and Gulf countries at three time horizons and three points in time.

The results of this study show that the impact of geopolitical risk on stock index returns in G7 and BRICS countries is significant but greater in the short run, which is consistent with Salisu et al. (20-22). Moreover, geopolitical risk has a positive impact on the volatility of G7 and BRICS stock markets. In other words, investing in these markets becomes riskier during periods characterized by a high GPR index, which is consistent with Balcilar et al. (2018), Bouras et al. (2019), and Das et al. (2019). In contrast to returns, the effect of the GPR index on the volatility of the G7 and BRICS stock indices was stronger in the long run. Thus, there seems to be some persistence in the way the GPR index affects volatility. Furthermore, we find that returns and volatility of G7 stock indices are more sensitive to geopolitical risk during the Russia-Ukraine war, which is consistent with the study by Abbasi et al. (2022). For the BRICS countries, on the other hand, the impact of geopolitical risk was greater during the COVID-19 pandemic. As with the G7 and BRICS stock indices, the impact of geopolitical risk on Gulf returns decreases over time, and the volatility response to geopolitical risk shocks is more pronounced in the long run. This more significant effect on long-term volatility is due to the persistence of the shocks.

The results of this study will certainly have an impact on financial investment strategies. Indeed, the addition of precious metals (especially gold) and cryptocurrencies to a portfolio of stock market indices can provide investors with an advantage in terms of diversification or hedging during geopolitical crises.

6. Conclusions and policy implications

From a global perspective, this paper explores the GPR index shock effects on the stock market indices returns and volatilities in three different country groupings (G7, BRICS, and Gulf countries) at three time horizons and three points in time. This study is based on the TVP-VAR models. The three-time horizons refer to lags of 1 month (short term), 6 months (medium term), and 12 months (long term), and the three time periods include 2017, 2020, and 2022 (corresponding to Donald Trump's victory in the US election, the first wave of covid-19 and the Russian invasion of Ukrania). From this study, we can conclude that, first, the GPR index effects on stock index returns vary over time and differ across countries, different lag periods, and different times. In addition, the effect of the GPR index on the returns of the G7, BRICS, and Gulf indices weakens over time. It is more pronounced in the short run. Moreover, stock market returns show a high vulnerability to geopolitical events, in particular, the Russian invasion of Ukraine.

Second, our study shows that the GPR index effects on the stock market indices volatility are generally positive for the different countries, lag periods and different dates chosen. Geopolitical risks increase the risk of investing in financial markets. We also find that this effect increases with time horizons for virtually all countries. In other words, the main impulse responses to shocks to the GPR index are observed in the long run. We can therefore conclude that there is a persistence of the GPR index shocks. Furthermore, it is clear that the Russian-Ukrainian war has the most significant impact on stock market risk.

The empirical findings of this study have policy implications and provide insightful information for portfolio managers and investors. Given that stock markets are affected by global geopolitical events such as the Russian-Ukrainian crisis, we suggest that investors diversify their portfolios by adding stocks that have proven their effectiveness in terms of hedging and risk reduction. These assets can be seen as safe havens, providing investors with hedging and diversification benefits. In that sense, investors turn to these assets as a hedge against risk in times of geopolitical crisis, particularly Russia's evasion of Ukraine. Adding precious metals and cryptocurrencies to a stock portfolio may help diversify during times of crisis.

The policy implications of this research are as follows. The establishment of a dynamic warning platform is necessary due to the unpredictability and complexity of crises. Furthermore, an information-sharing mechanism should be implemented to mitigate blind decisions due to information asymmetry. This will prevent speculators from taking advantage of the uneven distribution of information and allow investors to receive timely information on changes caused by crises. In addition, encouraging the participation of major investment institutions is crucial to enhancing investor confidence and thereby ensuring financial market stability. To mitigate the consequences of crises such as the COVID-19 health crisis or the Russian-Ukrainian crisis, we also recommend international cooperation.

Several lines of research can be considered to refine this work. First, we examine the impact of the Russian-Ukrainian war on stock, bond, and commodity markets using alternative methods such as the quantile connection approach or copulas. In addition, given the growing interest in digital assets, including cryptocurrencies, NFTs, and DeFi, we may examine the impact of geopolitical risk on these digital assets. In this context, it is interesting to compare the diversification benefits offered by commodities with those offered by digital assets.

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