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Research article

Asymmetric impacts of geopolitical risk on stock markets: A comparative analysis of the E7 and G7 equities during the Russian-Ukrainian conflict

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ABSTRACT

In a nonparametric quantile-on-quantile regression model, we analyze the asymmetric financial impact of the Russian-Ukrainian conflict-induced geopolitical risk (GPR) on the top-seven emerging (E7) and developed (G7) stock markets. Our findings indicate that the impact of GPR on stock markets is not only market-specific but also asymmetric. Except for Russia and China, all E7 and G7 stocks respond positively to GPR in normal conditions. Among the E7 (G7) countries, stock markets from Brazil, China, Russia, and Turkey (France, Japan, and the US) are resilient to GPR in bearish stages. The portfolio and policy implications of our findings have been highlighted.

1. Introduction

The gradual economic recovery from the systemic shocks of the still ongoing COVID-19 health crisis with the apogee in March 2020 [1], has been constrained by Russia's invasion of Ukraine on 24-Feb-2022.[1] This invasion has culminated in a heated geopolitical conflict whose repercussion has spilt over different markets and economies worldwide [2–6]. Due to their intensity, the consequences of the Russian-Ukrainian conflict have been likened to war events.[2] Theoretically, wars, military, and geopolitical conflicts exacerbate investors' uncertainty concerning the profitability of firms, leading to stock price volatility [7–9]. Market participants – such as investors, regulators, and practitioners – are particularly concerned about how stock markets are affected by geopolitical conflicts of military origin, which may be analyzed through the prism of geopolitical risk (GPR).

Although it is natural to expect that rising levels of geopolitical risk lead to plummeting stock prices, the heterogeneous character of markets – in terms of geographical location and economic class—renders some more resilient than others [10–12]. Similarly, as markets undergo varying states of calm, stressed, and bullish periods, the impacts of GPR on various stock markets are expected to be uneven [13]. In crisis periods, the intensity of effects experienced by developing markets is expected to be lesser than their developed counterparts due to under-developed monetary and economic systems that are a characteristic of developing economies [14,15]. Their exceptional growth prospect in recent periods has amplified the rate at which investors from the developed markets complement their

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[1] https://www.bbc.com/news/world-europe-60506682.
[2] https://www.theguardian.com/world/2022/mar/06/ukraine-fastest-growing-refugee-crisis-since-second-world-war.

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seemingly high-risk investments with assets from developing countries [1,16–20]. Given the link between these markets, analyzing the response of various representatives from each economic class towards geopolitical risk is important for asset allocation, risk management, and policy management.

Motivated by the above, we aim to present an early assessment of the asymmetric financial effects of the Russian-Ukrainian geopolitical conflict on emerging and developed stock markets, focusing on their influence on risk management strategies and policy actions. We proxy geopolitical risk with the geopolitical risk index developed by Ref. [21] and employ the quantile-on-quantile regression (QQR) approach of Sim and Zhou [22]. We sample the top-seven emerging markets (i.e., E7 comprising Brazil, China, India, Indonesia, Mexico, Russia, and Turkey) and the group of top-seven developed markets (i.e., G7 including Canada, France, Germany, Italy, Japan, the UK, and the US). From the QQR analysis, we find that, among the E7, the stocks from Brazil, China, Russia, and Turkey, and among the G7, stocks from Canada, France, Germany, Italy, and the US exhibit opposing dynamics to rising levels of GPR during bearish market conditions, thereby evidencing them as hedges and safe-havens against the downside risk of GPR. In a robustness measure, we confirm these findings for all those belonging to the E7 and the US only for the G7 in a spillover connectedness based on time-varying parameter vector autoregressions.

Our main contributions are twofold. First, as far as the discussion on the Russian-Ukrainian conflict is concerned, we undertake a comparative assessment of its asymmetric effects on the E7 and G7 markets. This timely provided new empirical evidence from a set of major emerging and developed stock markets is pivotal for portfolio management in the era of the conflict. Second, we employ the advanced nonparametric econometric technique—the QQR approach—that is not only robust to distributional outliers but also appropriate for nonlinearly distributed data, giving us the chance to observe how stock markets respond to GPR across different conditions of both stock prices and GPR levels. Note that although other quantile-based techniques, such as the quantile-connectedness approach (as employed by Refs. [23–25]) and the quantile-VAR technique [26], tail-event-network [15], etc., may be relevant in their domains, their application in this study will not help us analyze the relationship between the dependent and independent variables across different quantiles of both variables. Analyzing the relationship between the variables across the quantiles of both the dependent and the independent variables is important because the dynamics portrayed by the dependent variable are almost always different from the independent variable such that the dependent variable, in this case, a named stock market, could be in a bullish condition while the independent variable, in this case, GPR, may be in either a normal or bearish condition. Hence, for effective asset allocation and risk management, knowing how the variables behave across various dynamics of bullish, bearish, and normal conditions is relevant. To the best of our knowledge, such an assessment of the GPR impact on E7 and G7 stock markets during the military Russia-Ukraine military conflict has not been yet reported in the literature. Through the QQR approach, our research fills this void by providing the respective analysis, qualitative insights, and quantitative outcomes, which are capable of benefiting the risk management of equity-based portfolios under different bearish, bullish, and normal market conditions during the ongoing geopolitical conflict.

We proceed as follows. A review of related studies is presented in Section 2. In Section 3, we present the data and methodology. Section 4 discusses the QQR-based results. We ascertain the robustness of the findings in Section 5 and conclude in Section 6.

2. Literature review

The attention of academics and practitioners towards assessing the extreme financial effects of market crises has risen in recent periods because of the COVID-19 pandemic crisis, where various financial markets' reactions and overall economic recovery have been investigated widely (see, e.g., Refs. [1,15,20,24,25,27–34]). Meanwhile, discussions on the effects of geopolitical and military actions on financial markets are relatively scanty, particularly in the ongoing military tensions between Russia and Ukraine. Among the existing works, two earlier strands are worth discussing.

The initial strand of works covers studies that proxied geopolitical risk using terror and wars. From this literature strand, Frey and Kucher's [35,36] works document the negative effect of wars on the prices of government bonds from war nations. Choudhry [8] advances that war activities from 1939 to 1945 led to significant breaks in the structure of returns and volatility for US stocks. Meanwhile, Hudson and Urquhart [37] document a weak impact of war events on stocks from the UK.

The emergence of the second strand of literature was triggered by the introduction of Caldara and Iacoviello's [21] geopolitical risk index (GPR), which is based on computerized text searches. This GPR index has been employed in examining the influence of geopolitical risk on different asset types, both conventional and unconventional [38–42]. Choi [43] documents significant and strong power comovements between the volatilities of North-East Asian stocks and GPR. Among emerging markets, Zaremba et al. [44] test the predictability of GPR changes on stock returns and divulge that future returns from emerging market equities are significantly predicted by one-monthly lagged GPR changes.

Thus, specifically, in this study, we extend two major strands of works in academic research. First, we add to the vibrant literature that examines the place of geopolitical risk in financial markets. Earlier works highlight the detrimental effects of wartime actions on stock markets volatilities [7,8,45] and bond prices [35,36] when geopolitical risk is proxied by major war events or diplomatic conflicts [46]. The development of the electronic search-induced geopolitical risk index (GPR) by Caldara and Iacoviell [21] represented a natural advance in the state-of-the-art further impulse to a sub-strand of literature dedicated to the GPR's impact on varied assets including stocks [43,44], commodities [42,47], cryptocurrencies [38], green investments [48], among others.

Second, we extend the nascent literature focused on assessing the 2022 Russian-Ukrainian conflict's[3] impact on asset prices. From this strand of literature, Alam et al. [2] analyze the effect of the invasion on commodity markets and stocks from the BRIC and G7 markets. Boungou and Yatié [49] document adverse returns for global stocks following Russia's invasion of Ukraine. Boubaker et al. [50] conclude that the invasion has less (greatly) impacted emerging (developed) markets' equities. Sun et al. [51] report that the intensity of the effects resulting from the Russian-Ukrainian conflict is chiefly based on the degree of involvement by sectors and markets, stressing that EU countries and the manufacturing sector of the EU have suffered the most negative impacts of the ongoing conflict. This is consistent with Ahmed et al. [52], who report a negative relationship between geopolitical risk and European stocks. Yousaf et al. [9], in an event study, find that the timing of the impact of the Russian-Ukrainian conflict is non-homogeneous across equity markets. An important common conclusion of these works is that the GPR impact is market and/or condition specific, as cemented by Bedowska-Sojka et al. [11], Khalfaoui [53], and Adekoya et al. [54]. However, further to documenting the heterogeneity of the GPR influence, the asymmetries of the invasion-driven impacts are yet to be empirically examined during further research. The literature on this subject is rather scarce, being the only exception known to us, the work of Umar et al. [13], which reports asymmetric impacts of the Russian-Ukrainian conflict on various asset classes and Bossman et al. [12], who focus on major how currencies are asymmetrically affected by the GPR.

Continuing and extending the afore-discussed strands of literature, our paper provides evidence of how geopolitical risk influences the major emerging and developed equities markets, exploring chances of diversification and hedging prospects in various stock markets.

3. Data and methodology

3.1. Data

In addition to the daily geopolitical risk index (GPR) of Caldara and Iacoviell [21], we employ daily stock market 'close' prices (in US$) for E7 (namely, Brazil, China, India, Indonesia, Mexico, Russia, and Turkey) and G7 (Canada, France, Germany, Italy, Japan, the UK, and the US) stock markets over the period 24-Feb-2022 to 25-Jul-2022. The stock market data were supplied by EquityRT. To maintain comparison, the natural log transformation of all series is computed and used in estimations. This is in line with Adebayo et al. [55], Agyei [56], Alsubaie et al. [57], and Khan et al. [58]. Prior to the main analysis, we assess whether the data series is stationary and also examine whether the series are linearly or nonlinearly distributed. For this purpose, we employ two stationarity tests—the Augmented Dickey-Fuller and the Phillips-Perron tests—and the Broock-Dechert-Scheinkman (BDS) test [59].

The statistical properties and stationarity tests of the data are summarized in Table 1.

The stationarity of all the data series was confirmed by both the ADF and PP unit root tests at first difference. All the series rejected the normality hypothesis in the Jarque-Bera test; an indication that the data are non-normally distributed. Note that the QQR approach works well on nonlinear data series [33,55].

3.2. Methodology: the quantile-on-quantile regression (QQR) model

Developed by Sim and Zhou [22], the QQR model is a combination of nonparametric steps with the quantile regression (QR) model, while the QR of Koenker and Bassett [60] just extends the classical linear regression model by revealing the impact of an independent variable on the conditioned distributions of the dependent variable. Thus, the QQR model aids in assessing the overall relationship between the intended variables across the distributions of both the dependent and independent variables, rendering an all-encompassing view of the interrelations between them.

As stock markets evolve, different states—bearish, bullish, and normal—are observed from what the state of geopolitical risk may be at any given point. Hence, rather than using conventional approaches like simple linear regression and QR, a combination of the two models will provide a comprehensive understanding of the central interrelations between the geopolitical risk index (GPR) and stock prices. Therefore, we employ the nonparametric quantile regression approach to estimate the effect of various GPR quantiles on diverse quantiles of E7 and G7 stock prices.

The QQR model is expressed as:

$$SP_t = \beta^{\theta}(GPR_t) + u_t^{\theta} \tag{1}$$

where SP_t and GPR_t are stock price and geopolitical risk index, respectively at period t; $\beta^{\theta}(\bullet)$ is an unknown parameter determined as the estimated slope coefficient between the observed values of SP_t and GPR_t; θ is the θth quantile of the stock price's conditional distribution, and u_t^{θ} is the quantile residue, which is assumed to have a zero conditional θth quantile.

In this nonparametric approach, the right specification of the bandwidth (h) is essential. The wider the bandwidth, the larger the bias surrounding an estimate and the smaller the bandwidth, the larger the estimate's variance. To maintain a balance between bias and variance in this study, we maintain Sim and Zhou's [22] recommended bandwidth value of $h = 0.05$.

[3] It is noteworthy that the tensions between Russia and Ukraine could also be traced back to 2014, which influenced the initial study by Johannesson and Clowes [73] on energy resources and markets.

Table 1
Descriptive statistics and tests of stationarity of geopolitical risk, and E7 and G7 stocks.

Panel A: E7 stocks	Min	Max	Median	Mean	Std. dev	Skewness	Kurtosis	Normtest.W	Normtest.p	ΔADF	ΔADF.p	ΔPP	ΔPP.p
Brazil	9.7766	10.1761	9.9933	9.9801	0.1092	−0.1923	−1.1109	0.9502	0.0007	−6.8889	0.0000	−6.9258	0.0000
China	6.0894	6.3148	6.2017	6.1987	0.0519	0.0339	−0.2905	0.9729	0.0343	−9.6246	0.0000	−9.6186	0.0000
India	6.4889	6.6877	6.5674	6.5717	0.0510	0.2953	−1.0172	0.9579	0.0024	−9.1535	0.0000	−9.1549	0.0000
Indonesia	−2.4978	−2.3107	−2.3810	−2.3929	0.0490	−0.6340	−0.6184	0.9316	0.0001	−10.9406	0.0000	−10.8548	0.0000
Mexico	4.0020	4.2347	4.1229	4.1148	0.0613	0.0436	−1.0174	0.9578	0.0021	−8.3944	0.0000	−8.4029	0.0000
Russia	−0.0581	0.5262	0.3339	0.3088	0.1296	−0.6956	0.2242	0.9593	0.0090	−6.7552	0.0000	−6.6373	0.0000
Turkey	4.8682	5.1614	5.0016	5.0163	0.0660	0.4515	−0.7521	0.9505	0.0008	−9.8778	0.0000	−9.8504	0.0000
Panel B: G7 stocks													
Canada	9.5433	9.7815	9.6972	9.6836	0.0680	−0.2985	−1.2204	0.9296	0.0000	−8.2194	0.0000	−8.1829	0.0000
France	8.6858	8.9324	8.8280	8.8155	0.0645	−0.2006	−1.1270	0.9602	0.0029	−9.8883	0.0000	−9.8878	0.0000
Germany	9.4356	9.7068	9.6077	9.5947	0.0676	−0.4859	−0.8486	0.9474	0.0004	−9.5753	0.0000	−9.5753	0.0000
Italy	7.0464	7.3873	7.2714	7.2442	0.0823	−0.6505	−0.7282	0.9210	0.0000	−9.4808	0.0000	−9.4808	0.0000
Japan	2.4227	2.6241	2.5119	2.5147	0.0556	0.2263	−1.0633	0.9503	0.0008	−9.8018	0.0000	−9.8002	0.0000
UK	7.1378	7.3380	7.2657	7.2566	0.0565	−0.2365	−1.2275	0.9353	0.0001	−9.4208	0.0000	−9.4232	0.0000
US	9.5537	9.7418	9.6615	9.6539	0.0535	−0.1702	−1.2846	0.9401	0.0001	−9.8768	0.0000	−9.8767	0.0000
Panel C: Geopolitical risk index													
GPR	4.2914	6.2674	5.1589	5.2274	0.4274	0.3954	−0.3545	0.9765	0.0637	−10.9709	0.0000	−25.6422	0.0001

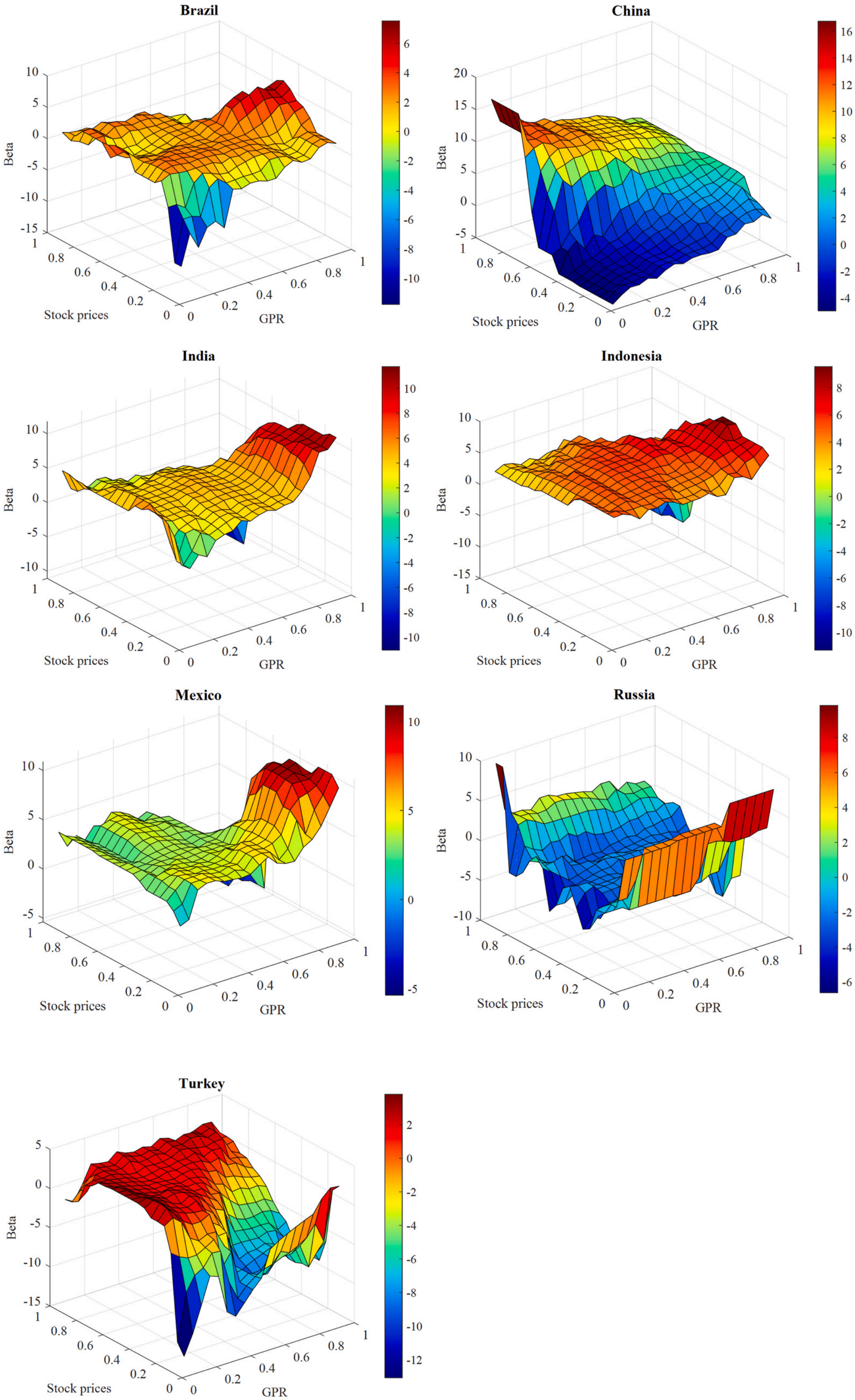
Notes: This table presents the statistical properties of the sample. The sample includes the stock prices of emerging seven (E7) stock markets namely Brazil, China, India, Indonesia, Mexico, Russia, and Turkey; the group of seven (G7) developed markets namely, Japan, Italy, Canada, the UK, Germany, the US, and France, and daily geopolitical risk index (GPR). The sample period starts from 24-Feb-2022 to 25-Jul-2022. Panel A, B, and C hold the statistical properties for E7, G7, and GPR, respectively. ΔADF and ΔPP are the tests of stationarity of the change in natural log transformation of the individual series using Augmented Dickey-Fuller and Phillips-Perron approaches, respectively. The estimates' probabilities are respectively depicted as ADF.p and PP.p. The test of normality of the series is denoted by Normtest.W and the accompanying probabilities by Normtest.p.

Table 2
BDS test of nonlinearity for E7 and G7stocks and GPR index.

Panel A: E7					Panel B: G7				
Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.	Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
Brazil					Canada				
2	0.17071	0.00461	37.05244	0.00000	2	0.16893	0.00463	36.47946	0.00000
3	0.28248	0.00735	38.45173	0.00000	3	0.28335	0.00737	38.47174	0.00000
4	0.35570	0.00877	40.54822	0.00000	4	0.35958	0.00877	40.99084	0.00000
5	0.40234	0.00917	43.89319	0.00000	5	0.40792	0.00914	44.61484	0.00000
6	0.43004	0.00886	48.53142	0.00000	6	0.43560	0.00882	49.40794	0.00000
China					France				
2	0.16616	0.00713	23.30820	0.00000	2	0.15634	0.00430	36.33347	0.00000
3	0.28347	0.01139	24.89641	0.00000	3	0.26343	0.00684	38.52575	0.00000
4	0.36393	0.01362	26.71128	0.00000	4	0.32990	0.00814	40.54258	0.00000
5	0.41458	0.01427	29.05539	0.00000	5	0.37054	0.00847	43.72776	0.00000
6	0.44433	0.01383	32.13676	0.00000	6	0.39412	0.00816	48.27827	0.00000
India					Germany				
2	0.16152	0.00446	36.24307	0.00000	2	0.15787	0.00510	30.97681	0.00000
3	0.27553	0.00711	38.76006	0.00000	3	0.26432	0.00813	32.50466	0.00000
4	0.34985	0.00849	41.20141	0.00000	4	0.33447	0.00972	34.41962	0.00000
5	0.39175	0.00888	44.13599	0.00000	5	0.37861	0.01016	37.25646	0.00000
6	0.41203	0.00858	48.00405	0.00000	6	0.40428	0.00983	41.11881	0.00000
Indonesia					Italy				
2	0.16644	0.00662	25.15192	0.00000	2	0.16584	0.00587	28.24151	0.00000
3	0.28015	0.01059	26.46635	0.00000	3	0.27726	0.00937	29.59766	0.00000
4	0.35674	0.01268	28.12632	0.00000	4	0.35193	0.01119	31.44137	0.00000
5	0.40651	0.01330	30.56188	0.00000	5	0.40241	0.01171	34.37809	0.00000
6	0.43417	0.01291	33.64226	0.00000	6	0.43691	0.01133	38.57950	0.00000
Mexico					Japan				
2	0.15437	0.00447	34.52721	0.00000	2	0.16853	0.00455	37.01487	0.00000
3	0.25717	0.00709	36.25594	0.00000	3	0.28687	0.00722	39.73153	0.00000
4	0.32331	0.00843	38.36320	0.00000	4	0.36448	0.00858	42.50635	0.00000
5	0.36483	0.00876	41.63841	0.00000	5	0.41564	0.00891	46.64303	0.00000
6	0.38766	0.00843	45.99786	0.00000	6	0.44508	0.00857	51.95148	0.00000
Russia					UK				
2	0.15948	0.00756	21.10603	0.00000	2	0.16016	0.00439	36.51361	0.00000
3	0.26688	0.01207	22.11162	0.00000	3	0.26910	0.00697	38.60746	0.00000
4	0.34223	0.01444	23.69533	0.00000	4	0.33704	0.00830	40.63395	0.00000
5	0.38793	0.01513	25.64428	0.00000	5	0.37934	0.00864	43.91801	0.00000
6	0.41318	0.01466	28.18503	0.00000	6	0.40366	0.00832	48.51080	0.00000
Turkey					US				
2	0.17468	0.00563	31.03032	0.00000	2	0.15834	0.00419	37.75590	0.00000
3	0.29322	0.00899	32.61347	0.00000	3	0.26722	0.00666	40.09985	0.00000
4	0.37107	0.01076	34.50232	0.00000	4	0.33978	0.00793	42.85040	0.00000
5	0.41879	0.01126	37.19667	0.00000	5	0.38469	0.00826	46.59298	0.00000
6	0.44354	0.01091	40.67439	0.00000	6	0.40998	0.00795	51.54949	0.00000

Panel C: GPR				
Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.12297	0.00624	19.72261	0.00000
3	0.21310	0.00994	21.43345	0.00000
4	0.27114	0.01188	22.83023	0.00000
5	0.30640	0.01242	24.67820	0.00000
6	0.32636	0.01201	27.17723	0.00000

Notes: This table presents the Broock-Dechert-Scheinkman (BDS) test of independence to scrutinise the linearity of the data series. Panels A, B, and C detail the results for the stock prices of emerging seven (E7) stock markets namely Brazil, China, India, Indonesia, Mexico, Russia, and Turkey; the group of seven (G7) developed markets namely Japan, Italy, Canada, the UK, Germany, the US, and France, and daily geopolitical risk index (GPR). The sample period starts from 24-Feb-2022 to 25-Jul-2022.



(caption on next page)

Fig. 1. QQR analysis: stock prices for E7 countries and GPR. *Notes:* This figure presents the quantile-on-quantile regression (QQR) estimates for the relationship between the geopolitical risk index (GPR) and stock prices of the emerging seven (E7) markets. The colour bar shows the coefficients. The x-, y-, and z-axes show GPR, stock prices, and the beta estimate, respectively across quantiles (0.05–0.95).

4. Results

4.1. BDS test of linearity

In this section, we undertake a quick preliminary assessment of the suitability of the QQR analysis, as employed in this study. The BDS test is used for this purpose. Results from the BDS test are reported in Table 2. The BDS test advanced by Broock et al. [59] holds that the observed variables are linearly distributed. A rejection of the null hypothesis suggests that the observed variables are nonlinear. From our results, all test statistics are rejected at the 1% significance level. Hence, we note that stock prices and the GPR index are nonlinearly distributed, substantiating the use of the QQR approach, which is particularly appropriate for this data type [57, 61–63].

4.2. QQR analysis

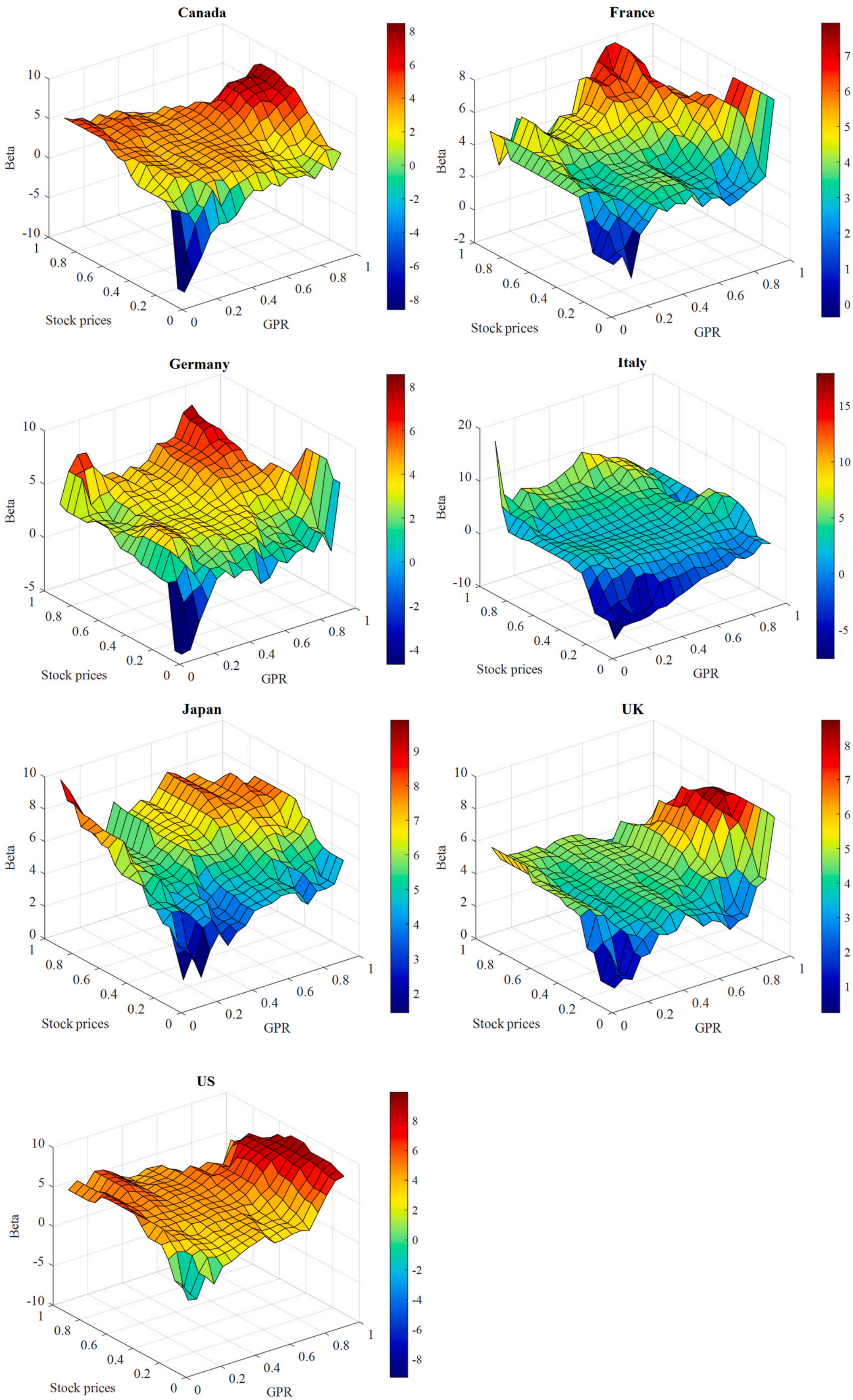
This section presents our main findings based on the QQR analysis. We ascertain how various GPR quantiles influence the varied distributions of stock prices in the E7 and G7 markets. For brevity, we present our findings in three-dimensional (3D) plots in Figs. 1 and 2 in respect of the E7 and G7 stock markets. For each plot in each Figure, the estimated slope coefficients $\beta_1(\theta, \tau)$ are plotted on the z-axis against the quantiles of stock prices on the y-axis (θ) and the GPR quantiles on the x-axis (τ). It is worth noting that based on θ, the estimated slope coefficient $\beta^{\theta}(\bullet)$ could differ with τ.

Fig. 1 shows the 3D plots for the E7 stock markets. Our main results are summarized as follows. First, among the E7 stock markets, particularly Brazil, China, and Turkey, we find a negative impact of GPR on the stock prices at bearish stages (i.e., across the quantile range 0.05–0.10) of both the stock prices and GPR. However, in the case of China, this negative impact extends across the medium quantiles (0.15–0.75) of stock prices and all quantiles of GPR. Second, common to Brazil, India, Indonesia, and Mexico, GPR negatively affects the stock prices across the upper quantiles (0.75–0.95) of both the stock prices and GPR. Third, we find a positive impact of GPR on the stock prices across the median quantiles (0.35–0.70) of both stock prices and GPR for all E7 stock markets except Russia. It is worth noting that in the case of China, some median quantiles of stock prices and GPR also show a negative impact of GPR. This suggests that among the E7 markets, Russian and Chinese stocks are most affected even in normal market conditions by either stock prices or GPR. Given the direct involvement of Russia and the relative indirect involvement of China in the ongoing geopolitical conflict, this observation is consistent with Sun et al.*'s* [51] conclusion that the intensity of the GPR effect in the era of the Russian-Ukrainian conflict is chiefly based on the degree of involvement. Notwithstanding, the fact that the relationship between GPR and stock prices is negative signals some diversification prospects. This finding lends support to Umar et al.*'s* [13] result that states that in the 2022 Russia-Ukraine geopolitical conflict, Russian equities are a hedge against GPR. Fourth, therefore, we note that among the E7 stock markets, the Brazilian, Chinese, Russian, and Turkish stocks could hedge against GPR in bearish stages, suggesting their potential as safe-havens.

Fig. 2 presents the 3D plots for the G7 stock markets. Our main findings are summarized as follows. First, similar to some of the E7 stock markets, we also find a negative impact of GPR on the stock prices across the lower quantiles (0.05–0.10) of both the stock prices and GPR for some of the G7 stock markets, particularly, Canada, Germany, Italy, and the US. Second, across the median and upper quantiles (0.30–0.95) of both stock prices and GPR, we document a positive impact of GPR on all G7 stock markets. However, it is important to note that in the case of Canada, the upper-most quantiles of both stock prices and GPR reveal a negative impact of GPR, as found in some emerging markets (i.e., Brazil, India, Indonesia, and Mexico). Third, our results show that among the G7 stock markets, the Canadian, French, German, Italian, and American stocks demonstrate counter dynamics to GPR in bearish stages, suggesting their potential hedging (safe-haven) attribute. Note that, in terms of the stocks from Brazil, China, and the US being hedges, we provide findings that are commensurate with those of Alam et al. [2], who analyzed the connectedness between commodities, the BRICS, and the G7 stock markets in the Russia-Ukraine era.

5. Robustness

To test whether the findings are robust to other estimation techniques, the overall, directional, and net connectedness between E7 and G7 markets amid the GPR are analyzed. For this purpose, we employ the time-varying parameter vector autoregression (TVP-



(caption on next page)

Fig. 2. QQR analysis: stock prices for G7 countries and GPR. *Notes:* This figure presents the quantile-on-quantile regression (QQR) estimates for the relationship between the geopolitical risk index (GPR) and stock prices of the emerging seven (E7) markets. The colour bar shows the coefficients. The x-, y-, and z-axes show GPR, stock prices, and the beta estimate, respectively across quantiles (0.05–0.95). Panel A: Full sample. Panel B: Sub-sample.

VAR)-induced spillover connectedness measure advanced by Antonakakis et al. [64]. With Koop and Korobilis' [65] Kalman filter approach with forgetting factors, the TVP-VAR connectedness methodology allows the variance-covariance matrix to vary in such a manner that arbitrary specification of rolling window size and missing observations, which are limitations of connectedness metrics like those of Diebold and Yilmaz [66] and Baruník and Křehlík [67], are overcome. With the aforementioned advantages, among others, the TVP-VAR connectedness approach has been utilized in recent works for either their principal or robustness analysis [68–72].

As part of the robustness checks, in this study, we first resort to the average and dynamic connectedness—based on two main samples (i.e., a one-year period covering July 2021 to July 2022, named as the full sample, and nearly a half-year period covering February to July 2022, named as the sub-sample, and represents the actual and apogee of the geopolitical conflict period)—to test whether the GPR amplified the overall connectedness between the analyzed stock markets. In addition, to test the risk reduction attributes of the individual markets, we analyze the net spillovers between these markets.

5.1. Averaged connectedness

The TVP-VAR spillover matrix that portrays the averaged connectedness among the E7 and G7 markets amid GPR is presented in Table 3. As per Akhtaruzzaman et al. [70], we base our estimations on a lag length of order one and a 10-step-ahead generalized forecast error variance decomposition.

The results from Panel A of Table 3 reveal that, in the presence of GPR, the overall connectedness between E7 and G7 markets, expressed by the total connectedness index, was 63.08% from July 2021 to July 2022. Therefore, more than two-thirds of the variations in one of either the E7 or G7 markets are contributed by the variations in all other E7 and G7 markets and GPR. From Panel B of Table 3, we show that owing to the geopolitical conflict between Russia and Ukraine, which amplified geopolitical risk, the connectedness index increased to 66.47%. This is consistent with Umar et al. [4], who found that Russia's invasion of Ukraine triggered an increase in the overall connectedness between various asset classes including Russian equities and bonds, European equities and bonds, and commodities such as oil, natural gas, gold, and wheat alongside Bitcoin and investor sentiment (VIX).

Based on the spillover matrix, the essential outputs that need to be emphasized, per the focus of the present study, are the net spillovers, which can be found in the last row of each panel. From the full sample, i.e., Panel A, the last row "NET" shows that Indonesia (−24.14%), Brazil (−22.66%), China (−21.03%), Russia (−20.27%), and Turkey (−19.16%) are all net recipients. The fact that five out of seven markets are net recipients indicates that emerging markets bear potential hedging advantages against geopolitical risk-driven shocks. This confirms the results revealed from the QQR analysis, although the QQR results hold in stressed conditions of the market. Among the G7 markets, only Japan (−30.37%) and the US (−0.99%) were net recipients of system spillovers. While the case of the US is confirmed by the QQR results, as previously analyzed, the case of Japan can be justified from the point of view that the QQR results hold for extreme (lower-tailed) conditions, as opposed to the spillover connectedness, which is a mean-based measure. It is fascinating to note that GPR is a net transmitter of spillovers to the E7 and G7 markets. Thus, shock transmission between the E7 and G7 markets is championed by the GPR.

The above-discussed results, for the full sample, are consistent with those portrayed by the sub-sample analysis. For instance, among the E7 markets, China, Indonesia, Turkey, Brazil, and Russia are net recipients while Japan and the US remain net recipients for the G7 markets. A notable observation is the fact that GPR becomes the greatest net transmitter of system spillovers—to the E7 and G7 stock markets—in the era of the geopolitical conflict between Russia and Ukraine. To analyze these results further, we delve into the overall, directional, and net time-varying spillovers in the next sub-section.

5.2. Time-varying connectedness

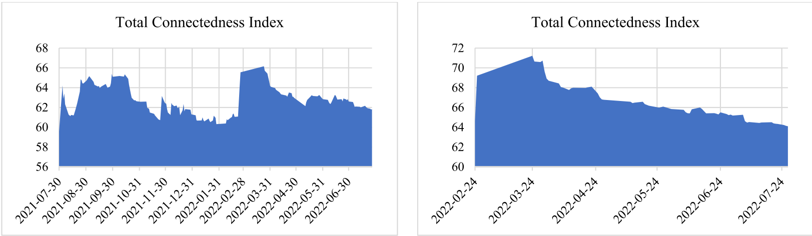
In this sub-section, we explore the connectedness between the analyzed variables in a dynamic (time-varying) setting, where the average TCI is expressed as a function of time. Fig. 3 displays the dynamic connectedness between the E7 and G7 markets amid GPR. The overall connectedness between the E7 and G7 markets was found to be reverting to an average level of around 60% between December 2021 and January 2022. However, the TCI rocketed in late February 2022—through the end of March 2022—following Russia's invasion of Ukraine. The results emphasize the impact of GPR on the E7 and G7 markets, as previously highlighted. These dynamics, particularly the influence of GPR on the connectedness between the analyzed markets, are revealed regardless of the choice of TCI being analyzed, i.e., whether the full sample (Fig. 3A) or the sub-sample (Fig. 3B). A further view of the impact of GPR on cross-market connectedness is presented by the directional (TO and FROM) spillovers, as shown in Fig. 4. The FROM spillovers are shown in Fig. 4A while the TO spillovers are shown in Fig. 4B. The results in Fig. 4B show that GPR transmits the greatest spillovers (TO all others), measuring over 150% in the era of the Russia-Ukraine military actions. This emphasizes the observation of Umar et al. [63] that risk transmission is intense in crisis periods due to amplified risk aversion.

To substantiate our conclusions on the role of various E7 and G7 stock markets in risk management, we now turn to the net spillovers in Fig. 5.

Table 3
Average spillover connectedness.

Panel A: Full sample (July 30, 2021 to July 27, 2022)	Brazil	China	India	Indonesia	Mexico	Russia	Turkey	Canada	France	Germany	Italy	Japan	UK	US	GPR	FROM
Brazil	35.02	0.78	4.54	4.13	14.66	0.38	2.51	7.21	5.3	5.72	4.44	0.64	6.68	4.86	3.12	64.98
China	1.12	65.81	0.96	0.53	0.53	2.7	0.76	3.68	2.25	2.75	2.92	2.95	5.46	1.86	5.72	34.19
India	3.4	0.43	25.71	7.52	10.37	2.42	6.38	4.87	7.84	7.6	6.36	4.16	7.92	4.88	0.14	74.29
Indonesia	6.08	0.65	14.26	49.04	9.82	0.38	2.78	2.97	1.47	2.46	1.49	1.62	2.74	3.18	1.05	50.96
Mexico	10.04	0.46	9.72	4.55	24.3	1.06	2.69	6.67	7.62	7.9	6.37	3.27	7.56	6.82	0.94	75.7
Russia	0.5	2.08	4.98	0.21	1.87	58.25	2.65	1.71	5.07	4.86	6.97	0.93	6.42	0.17	3.35	41.75
Turkey	2.23	0.18	9.22	2.02	4.06	1.62	37.06	5.4	7.36	8.02	7.11	2.44	8.18	4.76	0.34	62.94
Canada	4.25	1.27	3.86	1.28	5.5	1.57	3.4	22.96	9.2	9.11	8.22	3.28	9.9	16.07	0.13	77.04
France	2.03	0.89	5.82	0.46	5.25	2	3.69	7.66	18.52	16.11	15.32	2.63	13.99	5.33	0.3	81.48
Germany	2.25	0.85	5.54	0.68	5.51	1.98	3.99	7.53	16.07	18.5	15.25	2.75	13.75	5.16	0.2	81.5
Italy	1.73	0.94	5.09	0.56	4.48	3.03	3.76	7.05	16.22	16.16	19.66	2.42	14.16	4.67	0.1	80.34
Japan	2.19	1.79	5.94	1.82	5.34	1.13	3.15	8.37	6.84	7.05	5.38	36.79	4.71	8.37	1.14	63.21
UK	2.74	1.37	6.17	0.81	5.38	2.71	4.2	8.28	14.26	14.09	13.86	1.88	19.07	5.15	0.04	80.93
US	3.71	0.86	4.9	1.75	6.46	0.44	3.5	18.83	7.16	7.37	6.34	3.41	7.36	27.43	0.48	72.57
GPR	0.07	0.61	0.28	0.51	0.06	0.06	0.3	0.38	0.51	0.57	0.2	0.47	0.05	0.3	95.64	4.36
TO	42.32	13.16	81.26	26.82	79.3	21.48	43.78	90.6	107.15	109.78	100.23	32.84	108.88	71.58	17.05	**TCI**
NET	−22.66	−21.03	6.97	−24.14	3.6	−20.27	−19.16	13.56	25.67	28.27	19.89	−30.37	27.96	−0.99	12.69	63.08
Panel B: Sub-sample (24 February to July 27, 2022)	Brazil	China	India	Indonesia	Mexico	Russia	Turkey	Canada	France	Germany	Italy	Japan	UK	US	GPR	FROM
Brazil	26.13	1.4	5.33	5.81	19.05	2.02	3.98	6.39	3.58	4.12	3.62	1.51	3.85	5.6	7.62	73.87
China	1.69	40.32	2.13	2.45	1.08	4.82	3.09	4.48	6.89	6.13	4.71	2.1	9.93	2.48	7.71	59.68
India	5.93	0.87	30.85	9.94	9.7	0.68	7.41	3.7	5.13	4.38	3.32	4.51	6.85	3.24	3.5	69.15
Indonesia	10.47	2.25	14.91	45.47	9.83	1.34	2.89	1.16	0.82	0.77	0.83	0.77	1.02	1.43	6.03	54.53
Mexico	15.48	0.61	6.96	4.53	21.95	0.9	4.54	6.89	5.4	5.76	4.84	2.18	5.81	6.65	7.51	78.05
Russia	4.26	7.26	1.32	1.52	1.06	65.26	1.23	0.35	2.14	1.22	2.72	1.12	3.77	0.92	5.84	34.74
Turkey	3.36	0.5	7.85	1.87	6.52	1.52	33.92	4.25	5.77	6.19	5.2	0.63	9.7	3.64	9.08	66.08
Canada	3.79	1.77	2.56	0.32	5.53	0.93	2.44	19.49	10.77	11.36	10.19	3.67	12.11	14.24	0.81	80.51
France	1.06	2.54	3.12	0.09	3.77	1.34	3.21	9.57	17.71	16.52	14.94	4.08	14.23	7.06	0.76	82.29
Germany	1.37	2.23	2.69	0.06	4.05	0.98	3.44	10.08	16.64	17.7	14.99	3.5	13.64	7.61	1.02	82.3
Italy	1.16	1.7	2.11	0.13	3.34	1.27	3.04	9.69	16.37	16.4	19.36	2.61	14.75	6.74	1.33	80.64
Japan	2.86	1.82	5.92	1.03	4.29	3.85	1.02	7.37	8.38	6.98	5.18	38.72	7.82	3.44	1.32	61.28
UK	0.96	3.54	4	0.15	3.76	2.07	5.17	10.66	14.06	13.4	13.43	3.42	17.62	6.97	0.78	82.38
US	4.13	1.09	3.2	0.45	6.61	1.11	2.48	16.83	9.53	10.36	8.55	2.33	9.48	22.6	1.23	77.4
GPR	0.14	1.72	0.02	1.98	0.94	2.66	1.07	1.34	0.19	0.29	0.99	1.32	0.37	1.15	85.82	14.18
TO	56.67	29.3	62.11	30.32	79.54	25.49	45.01	92.77	105.68	103.89	93.49	33.75	113.35	71.18	54.53	**TCI**
NET	−17.2	−30.38	−7.04	−24.2	1.49	−9.25	−21.07	12.26	23.39	21.59	12.85	−27.52	30.97	−6.22	40.34	66.47

Notes: This Table presents the spillover connectedness matrix between the stocks markets of the top-emerging seven economies (namely, Brazil, China, India, Indonesia, Mexico, Russia, and Turkey), the group of top-developed seven economies (Canada, France, Germany, Italy, Japan, the UK, and the US), and the geopolitical risk index (GPR).



Panel A: Full sample Panel B: Sub-sample

Fig. 3. Time-varying total connectedness between E7, G7, and GPR. *Notes:* This figure presents the dynamic (time-varying) total connectedness index (TCI) between the stocks markets of the top-emerging seven economies (namely, Brazil, China, India, Indonesia, Mexico, Russia, and Turkey), the group of top-developed seven economies (Canada, France, Germany, Italy, Japan, the UK, and the US), and the geopolitical risk index (GPR). Panel A shows the TCI for the full sample, which covers one year from July 30, 2021 to July 27, 2022 while panel B shows the TCI for the sub-sample, which covers the peak of the Russian-Ukrainian conflict spanning from February 24, 2022 to July 27, 2022. Panel A: Full sample. Panel B: Sub-sample.

The results from Fig. 5 (i.e., the full sample—Fig. 5A and the sub-sample—Fig. 5B) demonstrate that since the commencement of the geopolitical conflict between Russia and Ukraine, several E7 stock markets (Brazil, China, Russia, Indonesia, and Turkey) vis-à-vis a few G7 stock markets (Japan and the US) are net recipients, emphasizing their hedging potential against market shocks propagated by geopolitical risk (i.e., GPR) and other members belonging to either the E7 or G7 markets, as already highlighted. This finding is consistent with existing works that find emerging market assets as suitable diversifiers for those from developed markets [1,16–20]. Moreover, the results show that GPR remains a consistent transmitter of spillovers over the analyzed period, emphasizing that risk transmission, contagion, and spillovers are intense in crisis periods due to heightened risk aversion levels [63].

Overall, the robustness of the findings from the QQR analysis is ascertained, suggesting that the conclusions drawn from the study's findings are robust to different techniques, in general, and the TVP-VAR connectedness metric, in particular.

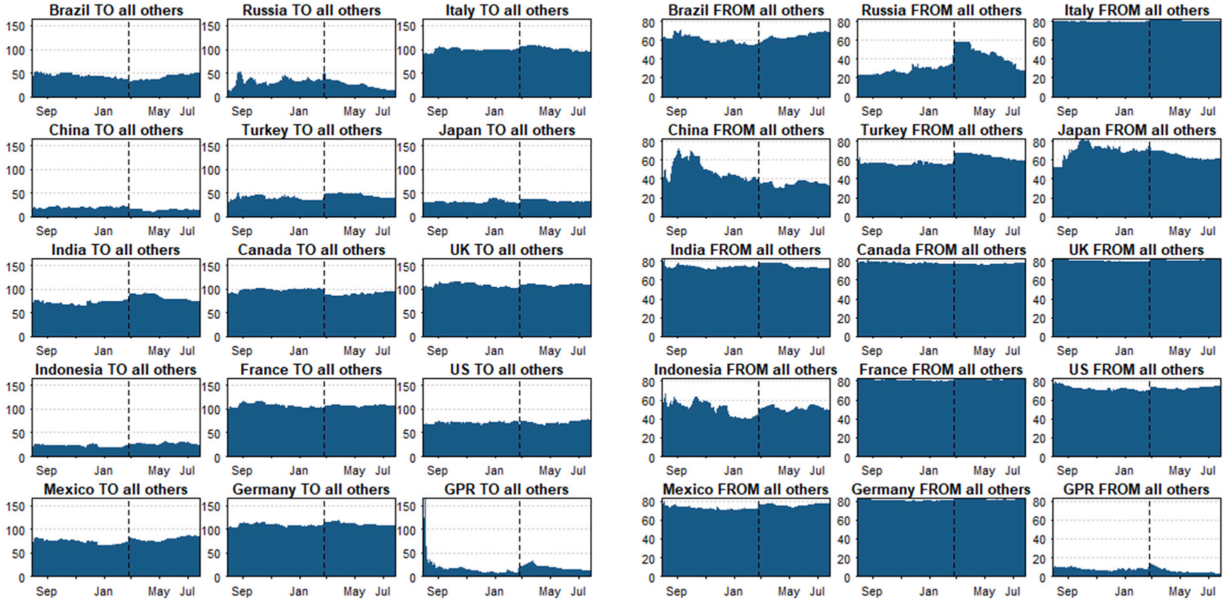
6. Conclusions

This study investigates the asymmetric financial impact of the geopolitical risk induced by the Russian-Ukrainian military conflict on the top-seven emerging (E7) and the top-seven developed (G7) stock markets. The QQR approach of Sim and Zhou [22] is employed after confirming the stationarity and nonlinear character of the data series using unit root and BDS tests, respectively. The study employs a nonparametric approach to ascertain the effect of GPR on stock prices at different normal, bullish, and bearish market conditions. To confirm the results' robustness, the TVP-VAR spillover metric is used.

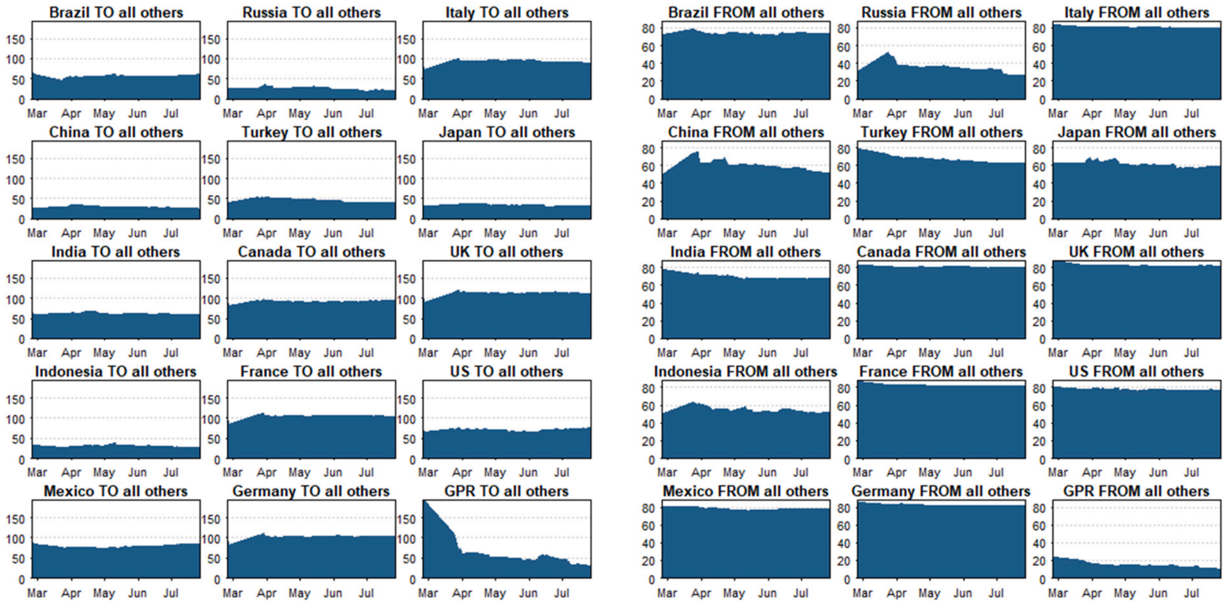
Our findings communicate the asymmetric impact of GPR on emerging and developed market equities. Among both the E7 and G7 stock markets, we document that the effect of GPR on stock prices is market-specific, particularly across the extreme—either bullish or bearish—quantiles. These findings lend support to the conclusion of Umar et al. [13] that GPR shows a mix of favorable and adverse impacts on most assets. Thus, our findings divulge that the direction and quantum of the GPR effect on stock prices are dependent upon the type of market and the conditions of both the market or GPR. Due to amplified risk aversion among market participants, we document a peaked total connectedness index, which is attributable to increased geopolitical risk, following Russia's invasion of Ukraine in late February 2022. Furthermore, we note that during the bearish stages of stock markets and GPR, the stock markets of Brazil, China, Russia, and Turkey are the resilient E7 stocks against GPR while from the G7 stock markets, stocks from Canada, France, Germany, Italy, and the US provide higher resilience. Hence, these stocks may be pivotal in hedging geopolitical shocks during the ongoing geopolitical conflicts of military origin. When these market dynamics are analyzed from a mean-based spillover framework, we confirm the results and also add that in a mean-based setting, representing the normal market, several E7 markets serve as potential diversification and hedge surrogates for G7 markets from which only a few hedge or safe-havens may be found.

Notable implications are worth mentioning. First, based on the findings, equity investors could monitor both the market conditions and the GPR level to undertake a timely and effective rebalancing of their portfolios. Second, given that almost all E7 and G7 stock markets—except Russia and China—directly (positively) respond to GPR in normal market conditions, it would be prudent that GPR is carefully managed around its normal levels to allow opposing (inverse) dynamics that facilitate diversification and risk management. Following these implications, proactive formulation and timely amendments of regulations could also be adopted by regulators and policymakers to respond to internal and/or external shocks associated with geopolitical risk, thereby limiting the cross-market transmission of shocks.

Despite the several contributions it offers, this study may have a few limitations, such as not covering a large sample size and the fact that the GPR index may be limited to historical events. We overcome this by adopting the QQR approach, which works well even with small samples and is not affected by outliers. For future studies, the hedging effectiveness of portfolios containing the E7 and G7 stocks may be ascertained. The role of forward-looking sentiment measures in a system containing the E7 and G7 stocks may also be explored. Similarly, the impact of geopolitical risk on assets from other market blocs could also be considered in future studies.

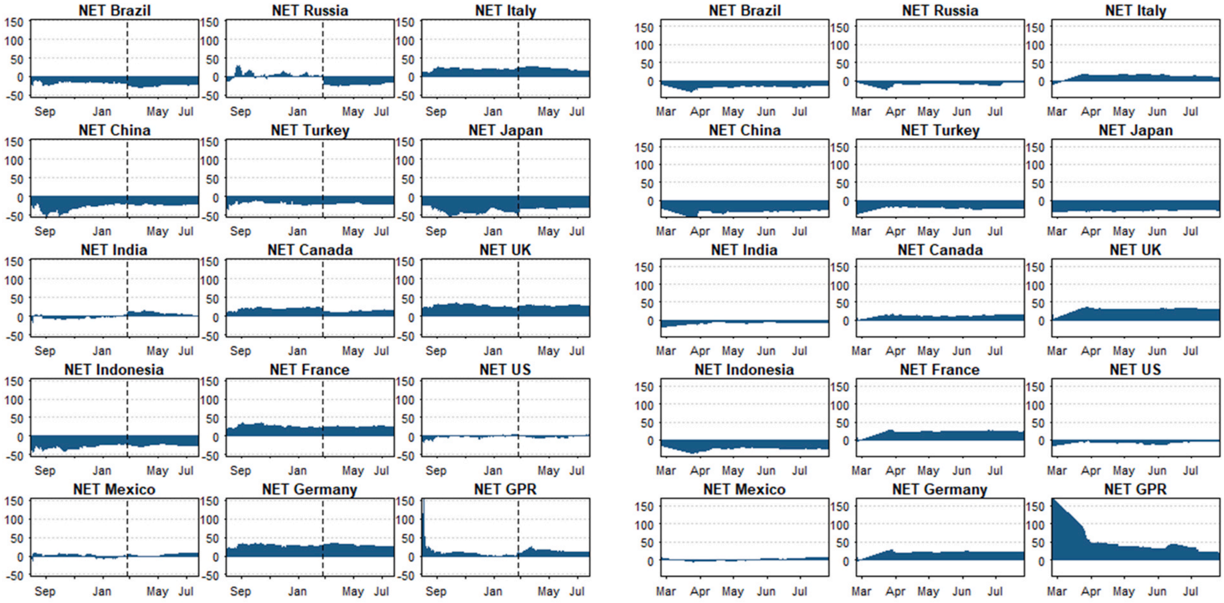


Panel A: Full sample.



Panel B: Sub-sample.

Fig. 4. Time-varying directional connectedness between E7 and G7 stocks and GPR. *Notes:* This figure presents the dynamic (time-varying) directional (TO (left sub-panel) and FROM (right sub-panel)) connectedness between the stocks markets of the top-emerging seven economies (namely, Brazil, China, India, Indonesia, Mexico, Russia, and Turkey), the group of top-developed seven economies (Canada, France, Germany, Italy, Japan, the UK, and the US), and the geopolitical risk index (GPR). Panel A shows the directional connectedness for the full sample, which covers one year from July 30, 2021 to July 27, 2022 while panel B shows the directional connectedness for the sub-sample, which covers the peak of the Russian-Ukrainian conflict spanning from February 24, 2022 to July 27, 2022. Panel A: Full sample. Panel B: Sub-sample.



Panel A: Full sample. Panel B: Sub-sample.

Fig. 5. Time-varying net connectedness between E7 and G7 stocks and GPR. *Notes:* This figure presents the dynamic (time-varying) net connectedness between the stocks markets of the top-emerging seven economies (namely, Brazil, China, India, Indonesia, Mexico, Russia, and Turkey), the group of top-developed seven economies (Canada, France, Germany, Italy, Japan, the UK, and the US), and the geopolitical risk index (GPR). Panel A shows the net connectedness for the full sample, which covers one year from July 30, 2021 to July 27, 2022 while panel B shows the net connectedness for the sub-sample, which covers the peak of the Russian-Ukrainian conflict spanning from February 24, 2022 to July 27, 2022.

Author contribution statement

1) conceived and designed the experiments: AB, MG
2) performed the experiments: AB, MG
3) analyzed and interpreted the data: AB, MG
4) contributed analysis tools and data:AB, MG
5) wrote the paper: AB, MG

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Data availability statement

Data will be made available on request.

Declaration of interest's statement

The authors declare no competing interests.

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