Article

Stock Market Synchronization: The Role of Geopolitical Risk

Kazi Sohag *, Rogneda Vasilyeva (ID)**, Alina Urazbaeva and Valentin Voytenkov**

Graduate School of Economics and Management, Ural Federal University, Yekaterinburg 620000, Russia;
rogneda.v@urfu.ru (R.V.); Alina.Urazbaeva@urfu.me (A.U.); Valentin.Voitenkov@urfu.me (V.V.)
* Correspondence: ksokhag@urfu.ru

Abstract: Given the importance of stock market synchronization for international portfolio diversification, we estimate the degrees of co-movements among US, Chinese and Russian markets. By applying the TVP-VAR approach, we measure total and bivariate synchronization indices utilizing daily data from 1998 to 2021. Our analysis demonstrates that the total connectedness index (TCI) is 26.15% among the three markets. We find that the US market is the highest volatility contributor, whereas the Russian market is the highest receiver. Since stock market synchronization is exposed to geopolitical risk, at the second stage, we apply the Quantile-on-Quantile framework to measure the response of total and bilateral connectedness indices to geopolitical risk (GPR). The findings affirm our proposition that GPR impedes TCI when it has a bullish state and a higher quantile of GPR. The response of bilateral connectedness is negative towards GPR concerning US–China and US–Russian pairs. However, the degree of connectedness between Russian and Chinese stock markets is less responsive to GPR.

Keywords: stock market synchronization; geopolitical risk; TVP-VAR; Quantile-on-Quantile

1. Introduction

Stock market synchronization indicates considerable degrees of co-movements of different national stock markets, which is of mounting importance for international portfolio diversification (Wälti 2011). Due to increasing trade and financial integration, liberalization and overall globalization significantly spur the magnitude of stock market synchronization (Beine and Candelon 2011). Nevertheless, the degree of co-movements is also anchored with different economic shocks and geopolitical turmoil. The relevance of geopolitical risk is more profound in the case of the US, Chinese and Russian stock markets, because of their economic and political dominance in the international market. Given this background, we are motivated to measure the response of stock market synchronization indices to mounting geopolitical risks in the context of US, Chinese and Russian stock markets.

Geopolitical turmoil can influence stock market synchronization through the sentimental response of investors. Eldor and Melnick (2004) and Kollias et al. (2011) argue that terrorist attacks trigger a decline in stock markets. Similarly, Döpke and Pierdzioch (2006) observe a weak response of the stock market to different political events (e.g., elections, international incidents, political scandals). Anecdotal evidence shows that, due to the terrorist attack on 11 September 2001, the global stock markets sharply dropped. Similarly, the US stock market, particularly S&P 500, experienced a sharp decline during the high tension of the Iraq war and the Iraq Invasion in 2002–2003. In addition, Russian stock indices dropped significantly during the Ukrainian crisis, the annexation of Crimea and Russia's sanctions in 2014. Consequently, the Russian stock market experienced a lower degree of connectedness with the rest of the global stock market (Nivorozhkin and Castagneto-Gissey 2016). The relevance of geopolitical risk was manifested during the China and US trade war in 2018, which contributed to a decline in the two largest Chinese stock markets (De Nicola et al. 2019). Such anecdotal evidence further incites the urgency to measure the response of stock market synchronization to geopolitical risk.

We classify the prior studies into two main strands. The first strand mainly highlights the degrees of stock market synchronization stratifying different markets based on income groups, integration and union. For instance, Liu and Tse (2012) document that degrees of stock market synchronization are profound in developed markets, whereas emerging markets are less connected. In contrast, Morck et al. (2000) confirm that the degree of synchronization in emerging economies is higher than it is in developed countries (Morck et al. 2000). Several studies highlight that the magnitude of stock co-movements is significantly higher for a country that belongs to economic or political integrations. For instance, the connectivity among German, French and UK stock markets was higher as European Union members (Égert and Kočenda 2011). Similarly, several studies argue that, after forming the BRICS association, stock market connectivity was significantly promoted (Bouri et al. 2020; Ji et al. 2020; Samargandi et al. 2020). Bouri et al. (2018) document that the US Volatility Index predicts the dynamics of the BRICS Volatility Index, confirming the synchronization of these markets. Furthermore, connectivity is enhanced when joining monetary unions, such as the Czech Republic, Hungary, Poland and Slovakia joining the European Union (Hanus and Vácha 2020). Camacho et al. (2020) argue that the degree of synchronization within alliances is weakened due to economic and political crises. Similarly, Xu and Hamori (2012) document that connectivity is weaker during periods of economic instability, such as the financial crisis of 2008–2009. Although many studies measure the degrees of stock market synchronization, we are concerned with its response to geopolitical risk, which remains a puzzle.

The second strand of studies scrutinizes the response of stock markets to geopolitical risk, such as Alqahtani et al. (2020), Balcilar et al. (2018), Cheng and Chiu (2018), Hoque et al. (2019) and Lehkonen (2015). For instance, Hoque et al. (2019) document that geopolitical turmoil has an asymmetric effect on the stock markets of different countries. Similarly, Balcilar et al. (2018) find that news about geopolitical tensions adversely affects stock return in BRICS countries. The study further documents that the Russian stock market is the most exposed to geopolitical risks in terms of both returns and volatility. India is the most resilient to its influence. In addition, Cheng and Chiu (2018) document that the stock market response to geopolitical shock varies across the country, which may be attributed to the level of public reaction and the intensity of the risk. Alqahtani et al. (2020) provide empirical evidence that global geopolitical risk has significant predictive power in Gulf Cooperation Council markets. Thus, the summary of the prior literature enables us to argue that stock markets are sensitive to geopolitical risk. However, our concern remains unsolved about whether the stock market's connectedness is also associated with geopolitical risk, which further motivates us to conduct this study.

The rationale for focusing on the US, Chinese and Russian stock markets lies in a few ideas. *Firstly*, the US and China are dominant players in the global economy. Statistics show that US and China account for 24% and 16% of global GDP, respectively. The total number of US stocks holds the largest share, which was about 38% of the global stock in 2019. In contrast, China holds second place, where the value of securities is more than 32% in the world. In addition, the US and China have considerable bilateral trade flows despite many political–economic disputes. Over the century, the US has been increasing its military bases in many territories around the world. In recent years, Chinese geopolitical dominance has been significantly expanded. Gradually, the conflict of interest between the two nations has been profoundly reflected by the trade war and dispute in the South China sea. *Secondly*, on the other hand, Russia is a natural-resource-abundant country with a significant role in international politics (Keppler 2007; Munoz et al. 2015). In the last two decades, Russia has significantly magnified its military profile. The Russian annexation of Crimea and its presence in the Syria conflict elevated world geopolitical tension. In addition, Russia maintains significant trade relations with China and the US simultaneously. Every single geopolitical event reorients economic and trade relations and thus stock market synchronization as well. An augmenting economic, trade and geopolitical dominance

of these three nations makes our study more exciting to scrutinize the response of stock market connectedness to mounting geopolitical turmoil.

We contribute to the existing literature in several ways. *Firstly*, to the best of our knowledge, this is the first attempt to measure stock market synchronization and its response to geopolitical risks considering US, Chinese and Russian stock markets. *Secondly*, we generate dynamic connectedness among these three stock markets by applying the Time-Varying Parameter-Vector Autoregressive (TVP-VAR) approach, which has several critical features, including nonlinearity, abnormality and robust parameters (Antonakakis et al. 2018; Bouri et al. 2021). Given high volatility in dynamic connectedness and the geopolitical risk index, we apply the Quantile-on-Quantile framework to estimate the response of connectedness to geopolitical risk under different conditional quantile. *Finally*, our empirical investigation provides some new insights. For instance, our empirical investigation reveals that the degree of synchronization among the three markets is about 26.15%, and the US stock market is the highest volatility contributor. In contrast, the Russian stock market is the highest volatility receiver. Our empirical findings contrast our proposition that stock market synchronization responds negatively towards geopolitical risk. However, there is bilateral TCI between US and Chinese markets.

The rest of the paper is organized as follows: Section 2 describes data and methodology, Section 3 discusses the main results of empirical investigations and Section 4 contains conclusions and policy implications.

2. Data and Methodology

2.1. Data Description

To assess the connectedness between the US, Chinese and Russian stock markets, we use daily data (five-day working week) on three stock indices and daily data of geopolitical risk. The indicator of geopolitical risk (GPR) is initially presented as monthly data and then converted to daily data. The sample covers 23 years, with a start date of 2 January 1998 and an end date of 29 January 2021, with a total of 6022 observations. For the US stock market, we implement Standard and Poor's index (S&P 500). The S&P 500 index is calculated using the free float weighted market capitalization methodology. This approach excludes nominal shares allocated with exercise rights to executives and other interested parties. As an indicator of the Russian stock market, we implement the Russian Trading System (RTS) indices. The RTSI is calculated as the ratio of the total value of all shares at the moment of index calculation to the value of capitalization of all shares at the date of the first index calculation, multiplied by the correction factor (Aganbegyan 2011). The Chinese stock market is represented by Shanghai Composite (SSEC) indices calculated using the Paasche weighted composite price index formula. We implement the stated indices as the main indicators of the stock markets, which contain the largest asset capitalization among the companies. Therefore, we consider S&P 500, RTS and SSEC as the relevant and sufficient indicators for our analysis.

Table 1 represents a detailed description of the variables used.

Table 1. Variables description.

Variable	Description	Source
RTSI	Russian Federation stock index	(Bloomberg 2021a)
S&P 500	United States stock index	(Bloomberg 2021b)
SSE	China stock index	(Bloomberg 2021c)
GPR	It is a monthly indicator calculated based on a tally of newspaper articles covering geopolitical tensions.	Caldara and Iacoviello (2018)

Measures of Geopolitical RISKS

Geopolitical Risk (GPR) is a monthly indicator calculated based on a tally of newspaper articles covering geopolitical tensions. To estimate the response of stock market

synchronization to geopolitical risk, we apply the geopolitical risk index (GPR) developed by Caldara and Iacoviello (2018), which precisely records the timing and intensity of increased geopolitical risk. The GPR rises indicate well-known historical events, such as military interventions, terrorist attacks and periods of tension between countries. The indexing measurement is based on the methodology presented by Saiz and Simonsohn (2013) and Baker et al. (2016). It is constructed using an algorithm that calculates the frequency of articles related to geopolitical risks in leading international newspapers published in the United States, the United Kingdom and Canada (Caldara and Iacoviello 2018). Additionally, GPR provides the most accurate assessment of the impact of geopolitical risks on equity markets.

2.2. Methodology and Empirical Model

To assess the impact of geopolitical risk on synchronization between US, Chinese and Russian markets, we apply the following steps: Firstly, we generate bi-directional connectedness between country pairs and total connectedness among three countries using dynamic connectedness under the Time-Varying Parameter-Vector Autoregression (TVP-VAR) approach (Antonakakis et al. 2018). The model is described as follows:

$$Y_t = \beta_t Y_{t-1} + \epsilon_t \; \epsilon_t | F_{t-1} \sim N(0, S_t) \tag{1}$$

$$\beta_t = \beta_{t-1} + \nu_t \; \nu_t | F_{t-1} \sim N(0, R_t) \tag{2}$$

The TVP-VAR approach employs a dynamic nature due to varying parameters. Y_t represents a conditional volatility vector, and β_t indicates a coefficient matrix variant in time. The index $t - 1$ indicates lagged values. ϵ_t and ν_t are the error disturbance vectors. The TVP-VAR approach provides robust and accurate estimations of dynamic connectedness and accounts for various sizes of the sample. Additionally, the approach is not sensitive to outliers.

As the next step following the assessment of the connectedness indices, we estimate the impact of geopolitical risk on stock market synchronization between country pairs and total connectedness. For accomplishing our analysis, we implement Quantile-on-Quantile regression to measure the stock markets' connectedness response to geopolitical risk. The Quantile-on-Quantile approach overcomes the asymmetric or abnormal distribution of variables, and it allows time-varying variance along with non-linear and asymmetric functions (Sohag et al. 2021). Coincidently, it includes a detailed investigation of the various quantiles of independent variables (IVs) on the dependent variable (DVs) along with an estimation of the effects of the IVs on the quantiles of the DVs in the presence of extreme observations (Sim and Zhou 2015). The equation specification implemented in our analysis is represented in Equation (3).

$$CON_t = \beta_0(\text{Ʊ}, \; \tau) + \alpha^\text{Ʊ} CON_{t-1} + \beta_1(\text{Ʊ}, \; \tau)(CON_t - GPR^\tau) + \mu_t^\text{Ʊ} \tag{3}$$

where CON_t indicates connectedness between country pairs, the equation represents the conditional quantile of connectedness, and $\mu_t^\text{Ʊ}$ indicates an error represented by zero Ʊ quantile.

3. Results and Discussion

3.1. Descriptive Analysis

Table 2 reports the descriptive analysis. The standard deviations are considerably high, indicating an uneven distribution of observations over time. Table 2 also highlights positive skewness and kurtosis of all respective variables. Furthermore, the significant Jarque–Bera statistics reject the normal distribution properties of the variables. We further apply the BDS test developed by Brock et al. (2001). The results from the BDS test confirm strong evidence of nonlinearity for all variables. Our descriptive analysis endorses the application of TVP-VAR and the Quantile-on-Quantile estimation approach.

Table 2. Descriptive statistics.

	CH_RUS	GPR	RTSI	SP500	SSEC	US_CH	US_CH_RUS	US_RUS
Mean	10.90237	4.674304	1006.146	1622.027	2388.949	10.27873	26.15838	19.07512
Median	8.844000	3.696022	1084.475	1353.165	2276.370	6.190000	23.66650	18.27350
Maximum	43.84100	28.18862	2487.920	3855.360	6092.060	41.81300	58.13100	47.38900
Minimum	0.229000	3.694868	38.53000	676.5300	1011.500	0.240000	4.859000	0.656000
Std. Dev.	8.409256	3.279826	577.7113	668.9518	902.7215	9.907989	12.06162	9.945539
Skewness	1.429054	2.882043	0.049084	1.185738	0.776080	1.307407	0.797993	0.807721
Kurtosis	5.153327	16.05406	2.144023	3.486554	3.822718	3.798447	2.961621	3.635217
Jarque–Bera	3213.137	51,094.97	186.2639	1470.532	774.3458	1875.543	639.4971	756.0499
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	65,654.08	28,148.66	6,059,009	9,767,848	14,386,249	61,898.51	157,525.8	114,870.4
Sum Sq. Dev.	425,778.5	64,769.47	2.01×10^9	2.69×10^9	4.91×10^9	591,071.0	875,950.9	595,559.6
Observations	6022	6022	6022	6022	6022	6022	6022	6022
BDS test								
Dimension	2	2	2	2	2	2	2	2
BDS statistics	0.197 ***	0.201 ***	0.203 ***	0.205 ***	0.202 ***	0.203 ***	0.199 ***	0.199 ***
z-statistics	158.771	153.351	327.747	187.839	244.887	165.559	207.269	200.536

*** indicates 1% significance level.

3.2. Stock Market Synchronization: Application of TVP-VAR

Table 3 highlights our first step of the analysis on connectedness among the three markets. The value of TCI is 26.15, which implies that the degrees of stock market synchronization are approximately 26.15% among our sample markets. The rows and columns of Table 3 indicate volatility receivers and contributors, respectively. The second row of Table 3 reports that the US stock market receives volatility spillover of 10.170% from SSEC and 12.677% from RTSI. Additionally, the findings imply that SSEC and RTSI contribute to S&P 500's volatility spillover by 10.170% and 12.677%, respectively. The last column of Table 3 reports the degrees of volatility that each market receives, whereas the values in the fourth row indicate the magnitudes of volatility that each market contributes. Table 3 further highlights that the US stock market is the most diminutive volatility receiver and the highest contributor. Precisely, S&P 500 receives volatility spillover of about 22.84% from Chinese and Russian stock markets, and it contributes 37.30% to both markets. Our empirical findings align with those of Xu and Hamori (2012), who observe that the US stock market is the net volatility contributor to BRIC stock markets. Figure 1 represents volatility spillover from and to the three stock markets. Figure 2 provides more insight; for instance, in 1998 and 2002–2004 the US stock market was a net volatility contributor. However, Figure 2 further shows that S&P 500 was a volatility receiver from 2004 to 2007, which can be attributed to geopolitical turmoil, particularly the terrorist attack on 11 September 2001. Afterward, during the global financial crises (GFC), S&P 500 appeared isolated, as Figure 2 shows that the market received and contributed the least volatility. Consequently, the degrees of synchronization notabley declined during the terrorist attack and GFC, which is reflected in Figure 3. However, post-global financial crisis, S&P 500 again became a net contributor but at a lower magnitude comparing 1998. The US stock market was a net volatility receiver in 2015 when oil prices historically plunged due to shale booming. Our findings are partially in line with Schmidbauer et al. (2016), who argue that Chinese and Russian stock markets contributed to the US stock market significantly.

Table 3. Total connectedness among US, Russian and Chinese stock markets.

	SP500	SSEC	RTSI	FROM
SP500	77.153	10.170	12.677	22.847
SSEC	13.117	76.578	10.305	23.422
RTSI	24.188	8.018	67.794	32.206
Contribution to others	37.305	18.188	22.982	78.475
Contribution including own	114.458	94.766	90.776	TCI
Net Spillovers	14.458	−5.234	−9.224	26.158

Source: Authors' estimations.
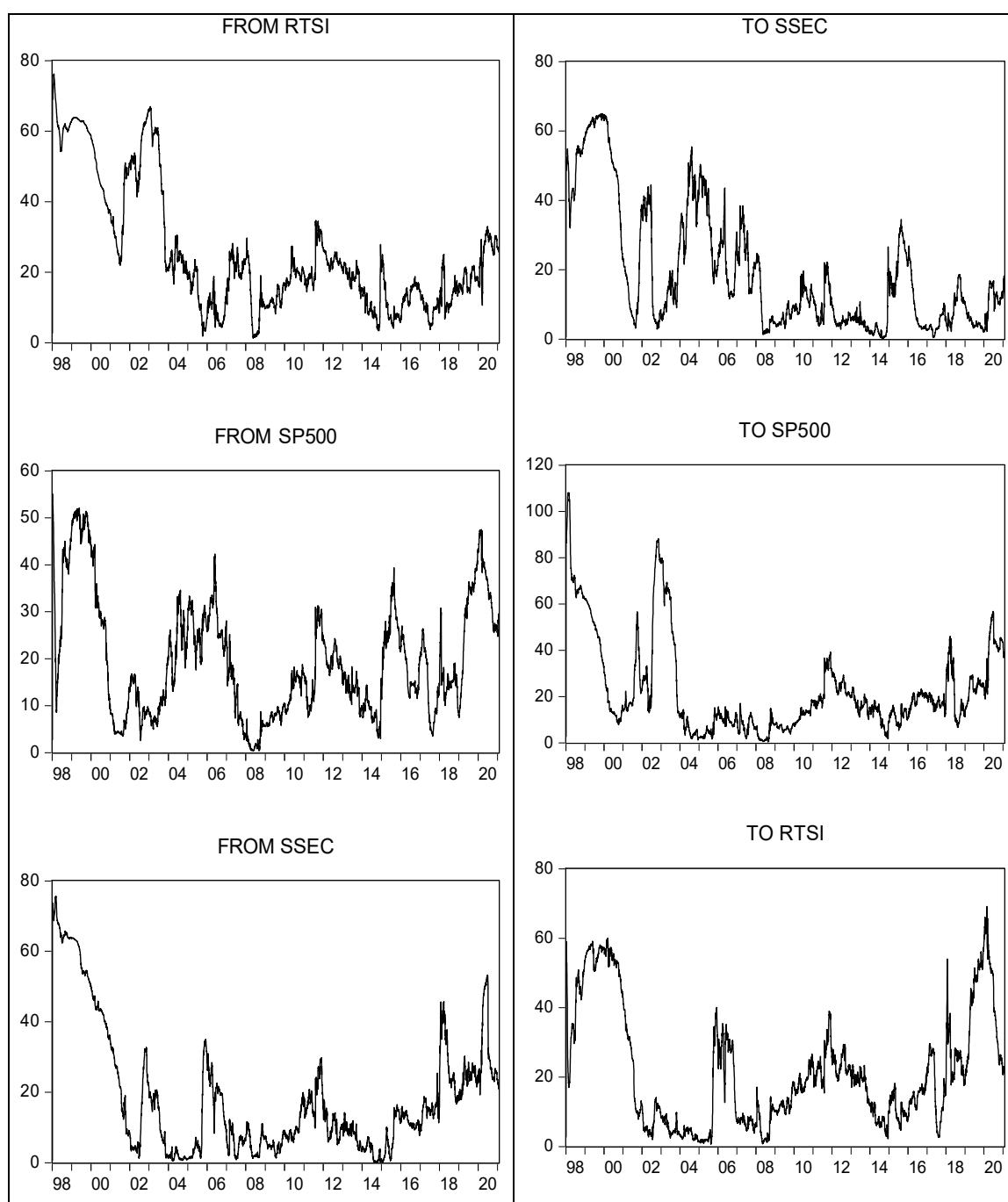
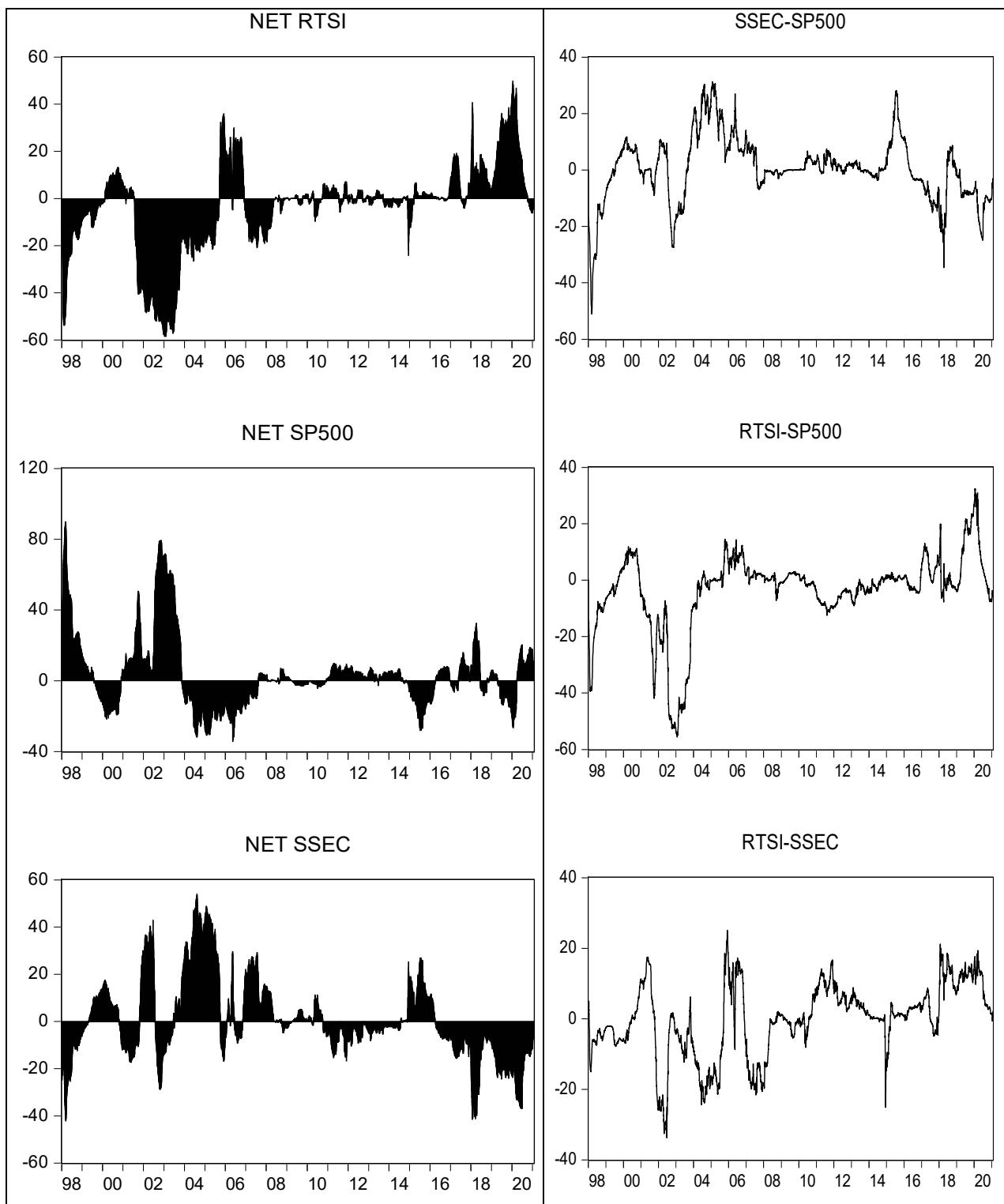**Figure 1.** Volatility spillover from and to the three stock markets.

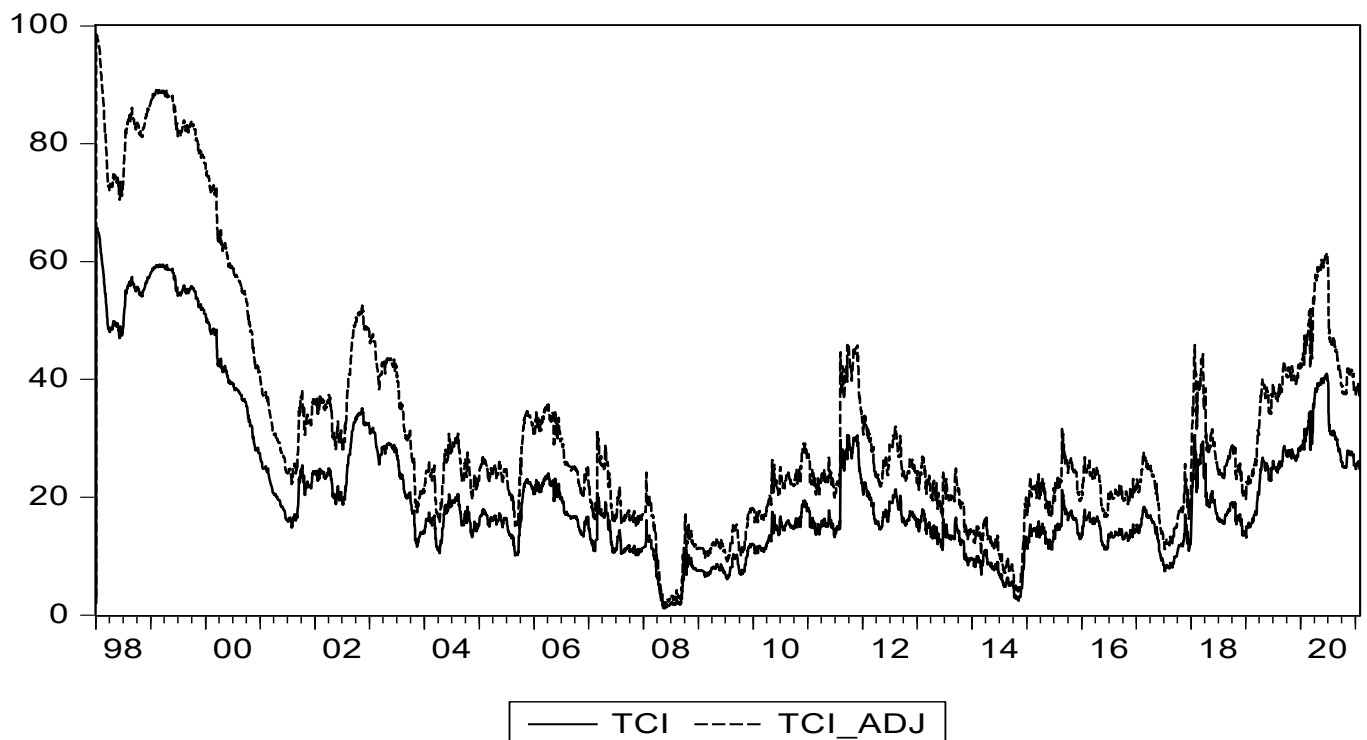**Figure 2.** Net and pairwise volatility spillover.

Figure 3. Total and Adjusted Connectivity Index.

Regarding the Chinese stock market, it contributes 10.170% and 8.018% to S&P 500 and RTSI, respectively, whereas the Chinese market receives 13.117% and 10.30% from S&P 500 and RTSI, accordingly. Eventually, SSEC became a net volatility receiver at 5.23% {(10.17 + 8.018) − (13.11 + 10.30)}. More specifically, SSEC appears to have been a net contributor in 2003 and 2004. Interestingly, SSEC became a net volatility contributor during the GFC. Although we find the Chinese stock market to be a net contributor in 2005, it received the highest volatility after the trade war (Figure 2). Our findings corroborate He et al. (2020), who document that China was a volatility receiver in 2016–2018 due to the US and China trade war. In addition, the study argues that the Chinese stock market adversely responded to news-based sentiments to US politicians. The Chinese stock market was further aggravated by the COVID-19 pandemic, which is reflected in Figure 2.

Our empirical investigation shows that RTSI is the highest volatility receiver among the three markets. Russian RTSI receives 32.206% volatility spillover combined from the US and Chinese stock markets, which echoes the findings of Hassan et al. (2020) and Tiwari et al. (2021). Specifically, Russian RTSI receives volatility spillover of 24.188% and 8.018% from S&P 500 and SSEC, respectively. Nevertheless, the Russian stock market contributes 12.677% to S&P 500 and 10.305% to SSEC, implying that RTSI is the net receiver from S&P 500 and the net contributor to SSEC. Thus, RTSI is surprisingly the second highest contributor after the US stock market. Figures 1–3 consistently highlight that RTSI received the highest volatility spillover in 1998–2000 due to Russia's economic crisis and political unrest (Anatolyev 2005). We find that RTSI was a net contributor in 2005–2006, which is consistent with the findings of Fedorova and Saleem (2009) and Goriaev and Zabotkin (2006). However, for most of the period until 2016, the Russian stock market was a volatility receiver. The influence of RTSI significantly augmented from 2017 as the size of the market increased compared to previous years.

Figure 3 represents the dynamics of the total connectedness index. The degree of synchronization is the highest from 1998 to 2000. The magnitude of synchronization sharply declined in 2001 since a terrorist attack took place in that concurrent time, which motivates us to incorporate the role of geopolitical risk in our framework in the second stage of the analysis. The degree of synchronization is close to zero lines during the

global financial crises. The rate of synchronization improved among the three markets in 2010–2012. TCI dropped in 2014, during which several global economic shocks occurred, including oil price shocks, Ukrainian crises, and Russian economic sanctions.

3.3. *The Response of Stock Market Synchronization to Geopolitical Risk: Application of Q-Q*

At this stage, we measure the degrees of stock market synchronization among the three markets. The total stock market synchronization considering the three markets is shown in Figure 3. The pairwise synchronization is shown in Figure 4. Figure 4 shows that the degrees of synchronization are apparently highest in the US and Russian stock markets. Although in terms of the size the US and Chinese stock markets are significantly more prominent than the Russian stock market, their degree of connectivity is the least, as shown in Figure 4. Since the oscillation of synchronization can be related to geopolitical events, we are motivated to measure synchronization responses to geopolitical risk. In doing so, we apply the Quantile-on-Quantile approach. We present the parameter matrix by using a heatmap diagram.
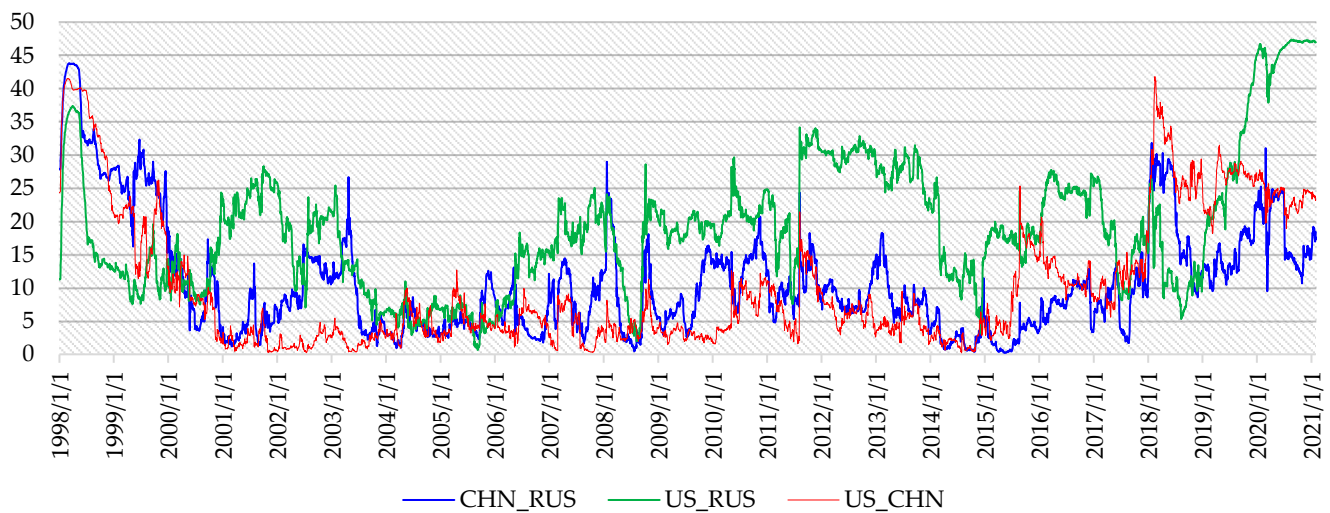

Figure 4. Pairwise dynamic connectedness. Source: Authors' estimations.

Figure 5 represents the response of total stock market synchronization to geopolitical risk. The horizontal axis indicates the quantile of GPR, whereas the vertical axis is the quantile of stock market synchronization in ascending order. The right-side color bar indicates the intensity of the response of synchronization to GPR. The dark green and yellow colors indicate the negative and positives response and synchronization to GPR, respectively. The light green color implies no or slight response of stock market connectedness to GPR. Figure 5 shows that stock market synchronization negatively responds to GPR at a higher quantile of GPR (0.7–0.9) and a higher quantile of TCI (0.8). We assume that the quantile of TCI in 2000–2001 is 80%, as the strong negative response of synchronization to GPR can be explained by the terrorist attack (Ahlgren and Antell 2010). The empirical findings affirm our proposition that GPR impedes stock market connectedness. A negative response of TCI to GPR is also observed at the upper-middle quantile of TCI (0.7) and GPR (0.8–0.85), which can be attributed to the trade war between China and the USA. In contrast, the response of TCI is positive to GPR at the lower quantile of GPR (0.3–0.6) and at the middle quantile of TCI (0.55–0.8). Apparently, at lower quantiles of synchronization, it is less exposed by geopolitical risk.
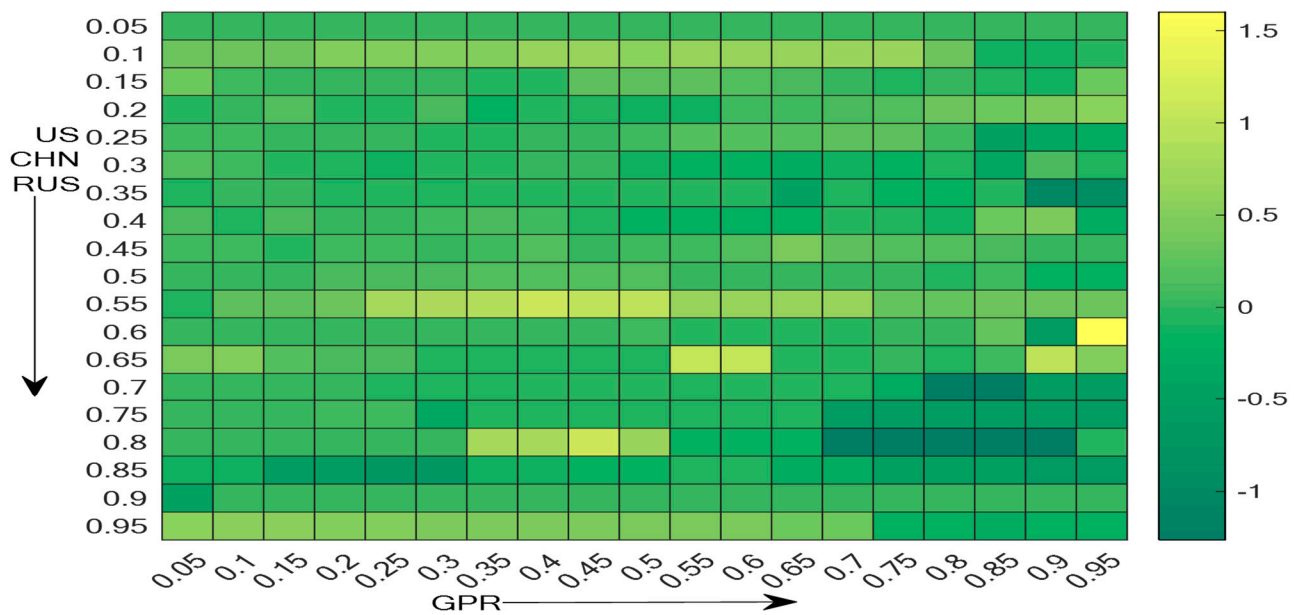
Figure 5. The response of total stock market synchronization to geopolitical risk. Note: The horizontal axis indicates the quantile of GPR, whereas the vertical axis is the quantile of stock market synchronization in ascending order. The right-side color bar indicates the intensity of the response of synchronization to GPR. The dark green and yellow colors indicate negative and positive responses and synchronization to GPR, respectively.

Figure 6 shows the response of US and Russian stock market synchronization to GPR. The response of synchronization is strongly negative to GPR at higher quantiles of connectivity (0.9) and at almost all quantiles of GPR. The synchronization between these two markets also responds negatively to GPR at a 50% and 70% quantile of synchronization and a 80% to 95% quantile of GPR. We can relate our findings with Figure 4, in which the highest synchronization appears between post-GFC and Crimean and Syrian geopolitical risk. Our findings coincide with those of Ankudinov et al. (2017), who document that economic sanctions led to increased volatility in the Russian stock market, and there appeared heavy tails. However, we observe a positive response of synchronization to GPR in general at lower quantiles of synchronization and at higher quantiles of GPR, which can be explained by the fact that geopolitical risk may reorient political and trade relations between two countries.

Figure 7 indicates the response of synchronization between the US and Chinese stock markets. We observe a negative response of connectedness to geopolitical risk at 75% synchronization and at almost all quantiles of GPR. Moreover, the responses of these two markets' synchronization to GPR are negative at the upper-middle quantile (0.85) of synchronization and at the upper quantile of GPR (0.7–0.95). A similar response is observed for a medium degree of synchronization (0.55) and a medium level of GPR (0.3–0.75). Referring to Figure 4, we observe that the synchronization between the US and Chinese stock markets weakened during the trade war in 2016–2018. Our findings are in line with those of He et al. (2020), who state that geopolitical risk negatively influenced the indices of US and Chinese stock markets during the trade war. Figure 4 shows that the degree of synchronization declined during the global pandemic of COVID-19. However, our empirical findings also report a somewhat positive response of connectivity to geopolitical risk at 40% and 70% of synchronization and at 20–30% and 55–65% of GPR.
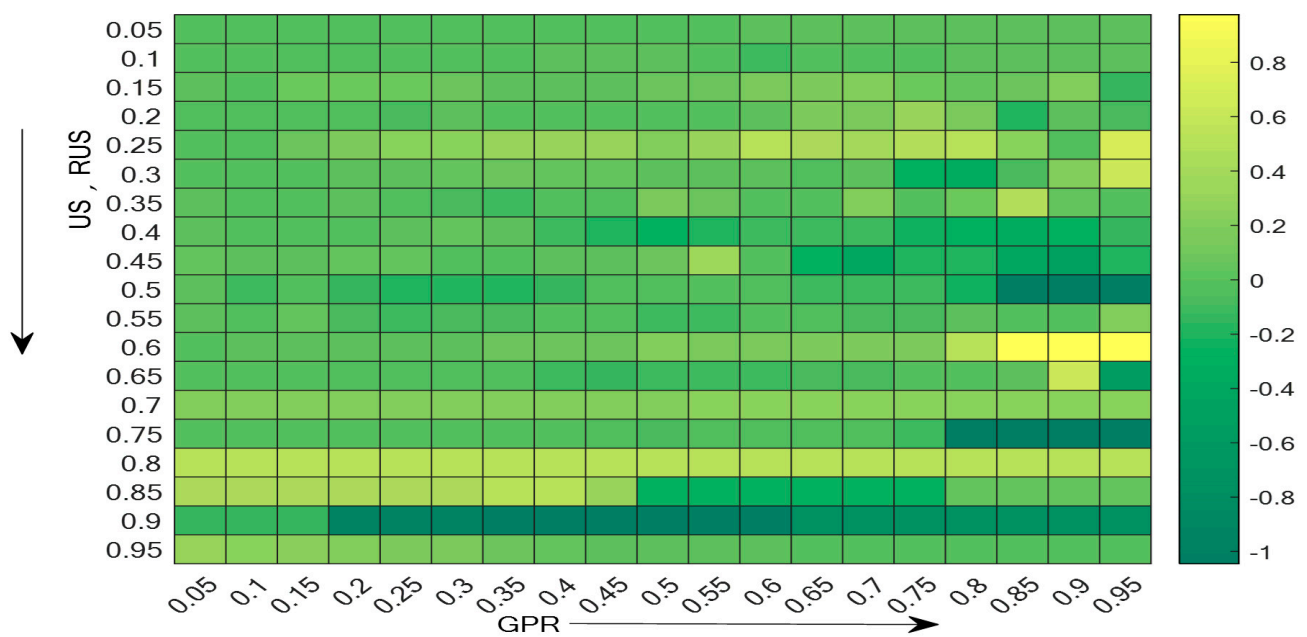
Figure 6. The response of US–RUS stock market synchronization to geopolitical risk. Note: The horizontal axis indicates the quantile of GPR, whereas the vertical axis is the quantile of stock market synchronization in ascending order. The right-side color bar indicates the intensity of the response of synchronization to GPR. The dark green and yellow colors indicate negative and positive responses and synchronization to GPR, respectively.

Figure 7. The response of US–CHN stock market synchronization to geopolitical risk. Note: The horizontal axis indicates the quantile of GPR, whereas the vertical axis is the quantile of stock market synchronization in ascending order. The right-side color bar indicates the intensity of the response of synchronization to GPR. The dark green and yellow colors indicate negative and positive responses and synchronization to GPR, respectively.
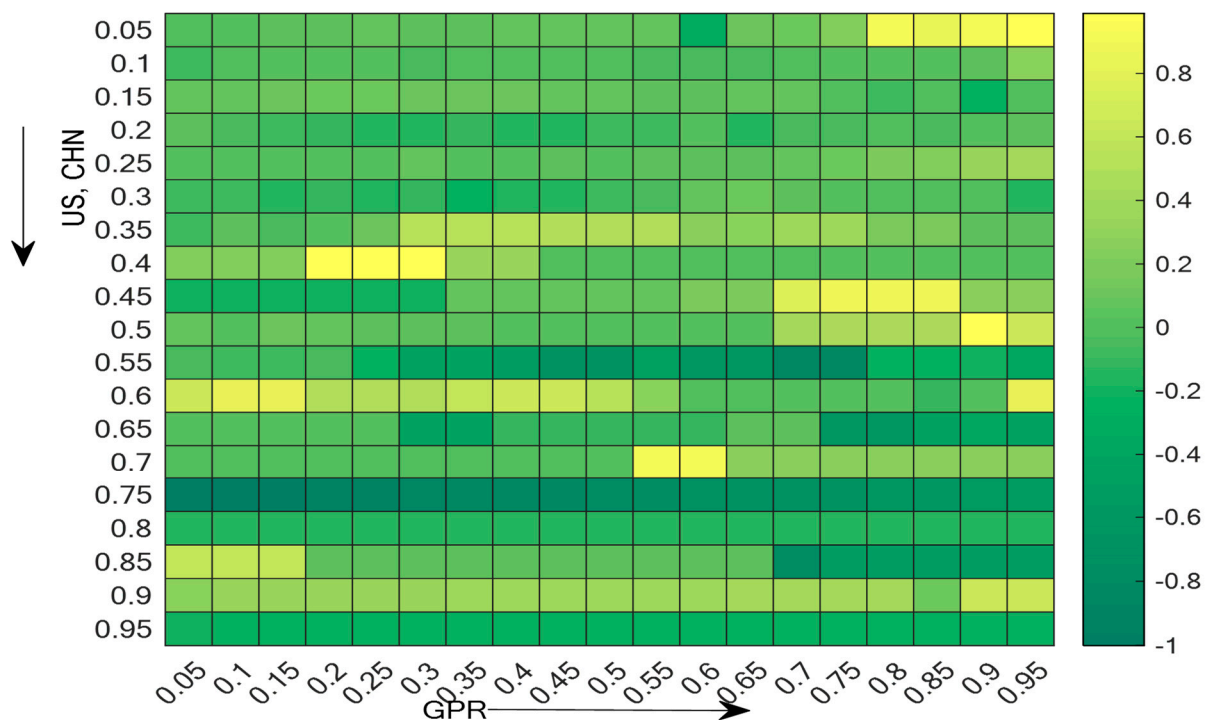
Lastly, Figure 8 represents the response of synchronization between Russian and Chinese stock markets to geopolitical risk. The co-movement between these stock markets is less responsive to geopolitical risk. Our empirical findings corroborate the reality that China and Russia maintain a solid diplomatic relationship. We instead observe that the degree of synchronization between these markets responds positively to geopolitical risk at a higher quantile of GPR [0.65–0.9] and at a middle quantile of synchronization [0.4]. Our findings are consistent with those of Kirkulak Uludag and Khurshid (2019), who document that volatility spillovers between China and the US are more profound than those between China and Russia. Although Balcilar et al. (2018) argue that Russia and China are more reactive to geopolitical risks than other BRICS, their stock markets' co-movement remain less responsive to external geopolitical risk due to their strategic relationship.
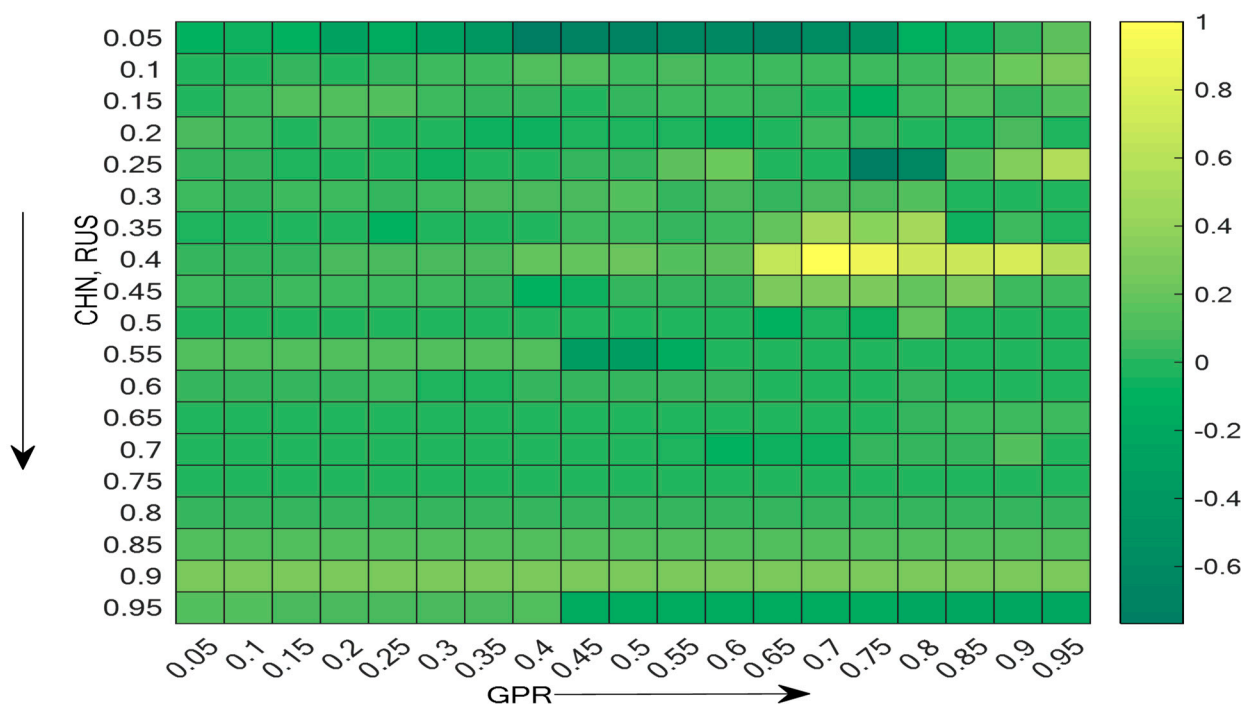

Figure 8. The response of RUS–CHN stock market synchronization to geopolitical risk. Note: The horizontal axis indicates the quantile of GPR, whereas the vertical axis is the quantile of stock market synchronization in ascending order. The right-side color bar indicates the intensity of the response of synchronization to GPR. The dark green and yellow colors indicate negative and positive responses and synchronization to GPR, respectively.

4. Conclusions

Given the importance for international portfolio diversification, we examine the degree of stock market synchronization among the US, Chinese and Russian stock markets. We apply time-varying parameters based on the vector autoregressive approach (TVP-VAR) to analyze daily data ranging from 1998 to 2021. Since stock market synchronization is significantly exposed to geopolitical risk, we further incorporate its role in our framework. We find several interesting findings. Firstly, estimation shows that the degree of stock market synchronization is 26.15% among the three markets over the sample period. S&P 500 is the net volatility transmitter, whereas Chinese and Russian stock markets are net volatility receivers. Our empirical findings report that the US is the lowest volatility receiver and the highest contributor, whereas Russia is the highest volatility receiver.

The degree of synchronization is highly anchored with geopolitical risk. Hence, at the second stage of our analysis, we highlight synchronization responses to GPR by applying the Quantile-on-Quantile approach. Firstly, we measure the response of total synchronization (for the three markets) to geopolitical risk. In general, the connectedness

among the US, Chinese and Russian stock markets respond negatively to geopolitical risk. However, positive responses are observed at lower quantiles of synchronization and middle quantiles of GPR. Secondly, we estimate the response of bilateral connectedness to geopolitical risk for each pair. Similar to total connectivity, stock market synchronization between the US and Russia responds negatively to GPR except for lower quantiles of synchronization and upper quantiles of GPR.

Regarding connectivity between the US and Chinese stock markets, it also responds negatively to geopolitical risk at upper-middle quantiles of synchronization and at upper quantiles of GPR. Our analysis reveals that the degree of synchronization between the US and Chinese stock markets significantly dropped during the trade war and global pandemic of COVID-19. Lastly, the response of synchronization between Russian and Chinese stock markets to geopolitical risk is less responsive to geopolitical risk, since China and Russia maintain a strong diplomatic relationship. We instead observe that the degree of synchronization between these markets responds positively to geopolitical risk at higher quantiles of GPR and at middle quantiles of synchronization.

The findings of this study provide several policy implications for investor risk hedging and operations in equity markets in Russia, the US and China. Strong interconnectedness among the three markets and its significant response to GPR can reduce risk. The investors should account for spillover effects received by the stock markets along with the predicted volatility induced by geopolitical risk. Our findings supplement investor knowledge, which increases the effectiveness of hedging strategies along with portfolio diversification. Moreover, the results of the study can be helpful to policy makers in the US, China and Russia regarding GPR-induced equity market risk.

Author Contributions: Conceptualization, K.S. and V.V.; methodology, K.S.; software, K.S.; validation, K.S., R.V. and V.V.; formal analysis, V.V. and A.U.; investigation, R.V., A.U. and V.V.; resources, R.V., A.U. and V.V.; data curation, V.V. and A.U.; writing—original draft preparation, R.V., A.U. and V.V.; writing—review and editing, K.S. and R.V.; visualization, K.S.; supervision, K.S.; project administration, K.S.; funding acquisition, K.S. All authors have read and agreed to the published version of the manuscript.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

Aganbegyan, Ruben Abelovich. 2011. *Methodology for Calculating the RTS Index*. Available online: https://fs.moex.com (accessed on 27 April 2022).

Ahlgren, Niklas, and Jan Antell. 2010. Stock market linkages and financial contagion: A cobreaking analysis. *Quarterly Review of Economics and Finance* 50: 157–66. [CrossRef]

Alqahtani, Abdullah, Elie Bouri, and Xuan Vinh Vo. 2020. Predictability of GCC stock returns: The role of geopolitical risk and crude oil returns. *Economic Analysis and Policy* 68: 239–49. [CrossRef] [PubMed]

Anatolyev, Stanislav. 2005. *A Ten-Year Retrospection of the Behavior of Russian Stock Returns*. BOFIT Discussion Papers. No. 9/2005. Helsinki: Bank of Finland, Institute for Economies in Transition (BOFIT), ISBN 952-462-784-1. Available online: https://nbn-resolving.de/urn:NBN:fi:bof-201408072206 (accessed on 27 April 2022).

Ankudinov, Andrei, Rustam Ibragimov, and Oleg Lebedev. 2017. Sanctions and the Russian stock market. *Research in International Business and Finance* 40: 150–62. [CrossRef]

Antonakakis, Nikolaos, David Gabauer, Rangan Gupta, and Bill Plakandaras. 2018. Dynamic Connectedness of Uncertainty across Developed Economies: A Time-Varying Approach. *Economics Letters* 166: 63–75. [CrossRef]

Baker, Scott R, Nicholas Bloom, and Steven J Davis. 2016. Measuring economic policy uncertainty. *Quarterly Journal of Economics* 131: 1593–636. [CrossRef]

Balcilar, Mehmet, Matteo Bonato, Riza Demirer, and Rangan Gupta. 2018. Geopolitical risks and stock market dynamics of the BRICS. *Economic Systems* 42: 295–306. [CrossRef]

Beine, Michel, and Bertrand Candelon. 2011. Liberalisation and stock market co-movement between emerging economies. *Quantitative Finance* 11: 299–312. [CrossRef]

Bloomberg. 2021a. Quotes of the RTS Index. Available online: https://www.bloomberg.com/quote/RTSI$:IND (accessed on 27 April 2022).

Bloomberg. 2021b. Quotes of the S&P 500 Index. Available online: https://www.bloomberg.com/quote/SPX:IND (accessed on 27 April 2022).

Bloomberg. 2021c. Quotes of the SSE Index. Available online: https://www.bloomberg.com/quote/SHCOMP:IND (accessed on 27 April 2022).

Bouri, Elie, Brian Lucey, Tareq Saeed, and Xuan Vinh Vo. 2021. The realized volatility of commodity futures: Interconnectedness and determinants. *International Review of Economics & Finance* 73: 139–51.

Bouri, Elie, Rangan Gupta, Seyedmehdi Hosseini, and Chi Keung Marco Lau. 2018. Does global fear predict fear in BRICS stock markets? Evidence from a Bayesian Graphical Structural VAR model. *Emerging Markets Review* 34: 124–42. [CrossRef]

Bouri, Elie, Riza Demirer, Rangan Gupta, and Xiaojin Sun. 2020. The predictability of stock market volatility in emerging economies: Relative roles of local, regional, and global business cycles. *Journal of Forecasting* 39: 957–65. [CrossRef]

Brock, William, W. Davis Dechert, Jose Scheinkman, and Blake LeBaron. 2001. A test for independence based on the correlation dimension. *Growth Theory, Non-Linear Dynamics, and Economic Modelling: Scientific Essays of William Allen Brock* 15: 324. [CrossRef]

Caldara, Dario, and Matteo Iacoviello. 2018. Measuring Geopolitical Risk. In *International Finance Discussion Paper*; Washington, DC: Board of Governors of the Federal Reserve System, vol. 2018. [CrossRef]

Camacho, Maximo, Angela Caro, and German Lopez-Buenache. 2020. The two-speed Europe in business cycle synchronization. *Empirical Economics* 59: 1069–84. [CrossRef]

Cheng, Chak Hung Jack, and Ching Wai (Jeremy) Chiu. 2018. How important are global geopolitical risks to emerging countries? *International Economics* 156: 305–25. [CrossRef]

De Nicola, Francesca, Martin Kessler, and Ha Nguyen. 2019. The Financial Costs of the U.S.-China Trade Tensions: Evidence from East Asian Stock Markets. In *The Financial Costs of the U.S.-China Trade Tensions: Evidence from East Asian Stock Markets*. Washington, DC: World Bank. [CrossRef]

Döpke, Jörg, and Christian Pierdzioch. 2006. Politics and the stock market: Evidence from Germany. *European Journal of Political Economy* 22: 925–43. [CrossRef]

Égert, Balázs, and Evžen Kočenda. 2011. Time-varying synchronization of European stock markets. *Empirical Economics* 40: 393–407. [CrossRef]

Eldor, Rafi, and Rafi Melnick. 2004. Financial markets and terrorism. *European Journal of Political Economy* 20: 367–86. [CrossRef]

Fedorova, Elena, and Kashif Saleem. 2009. Volatility Spillovers between Stock and Currency Markets: Evidence from Emerging Eastern Europe. Paper presented at the 22nd Australasian Finance and Banking Conference, Sydney, Australia, December 14–16.

Goriaev, Alexei, and Alexei Zabotkin. 2006. Risks of investing in the Russian stock market: Lessons of the first decade. *Emerging Markets Review* 7: 380–97. [CrossRef]

Hanus, Luboš, and Lukáš Vácha. 2020. Growth cycle synchronization of the Visegrad Four and the European Union. *Empirical Economics* 58: 1779–95. [CrossRef]

Hassan, Kamrul, Ariful Hoque, Muammer Wali, and Dominic Gasbarro. 2020. Islamic stocks, conventional stocks, and crude oil: Directional volatility spillover analysis in BRICS. *Energy Economics* 92: 104985. [CrossRef]

He, Xie, Tetsuya Takiguchi, Tadahiro Nakajima, and Shigeyuki Hamori. 2020. Spillover effects between energies, gold, and stock: The United States versus China. *Energy and Environment* 31: 1416–47. [CrossRef]

Hoque, Mohammad Enamul, Low Soo Wah, and Mohd Azlan Shah Zaidi. 2019. Oil price shocks, global economic policy uncertainty, geopolitical risk, and stock price in Malaysia: Factor augmented VAR approach. *Economic Research-Ekonomska Istrazivanja* 32: 3701–33. [CrossRef]

Ji, Qiang, Bing Yue Liu, Wan Li Zhao, and Ying Fan. 2020. Modelling dynamic dependence and risk spillover between all oil price shocks and stock market returns in the BRICS. *International Review of Financial Analysis* 68: 101238. [CrossRef]

Keppler, Jan Horst. 2007. *International Relations and Security of Energy Supply: Risks to Continuity and Geopolitical Risks Foreign Affairs*. Brussels: Directorate-General for External Policies of the Union.

Kirkulak Uludag, Berna, and Muzammil Khurshid. 2019. Volatility spillover from the Chinese stock market to E7 and G7 stock markets. *Journal of Economic Studies* 46: 90–105. [CrossRef]

Kollias, Christos, Efthalia Manou, Stephanos Papadamou, and Apostolos Stagiannis. 2011. Stock markets and terrorist attacks: Comparative evidence from a large and a small capitalization market. *European Journal of Political Economy* 27: S64–S77. [CrossRef]

Lehkonen, Heikki. 2015. Stock Market Integration and the Global Financial Crisis*. *Review of Finance* 19: 2039–94. [CrossRef]

Liu, Xiao Fan, and Chi K. Tse. 2012. A complex network perspective of world stock markets: Synchronization and volatility. *International Journal of Bifurcation and Chaos* 22: 1250142. [CrossRef]

Morck, Randall, Bernard Yeung, and Wayne Yu. 2000. The information content of stock markets: Why do emerging markets have synchronous stock price movements? *Journal of Financial Economics* 58: 215–60. [CrossRef]

Munoz, Beatriz, Javier García-Verdugo, and Enrique San-Martín. 2015. Quantifying the geopolitical dimension of energy risks: A tool for energy modelling and planning. *Energy* 11: 28040. [CrossRef]

Nivorozhkin, Eugene, and Giorgio Castagneto-Gissey. 2016. Russian stock market in the aftermath of the Ukrainian crisis. *Russian Journal of Economics* 2: 23–40. [CrossRef]

Saiz, Albert, and Uri Simonsohn. 2013. Proxying for unobservable variables with internet document-frequency. *Journal of the European Economic Association* 11: 137–65. [CrossRef]

Samargandi, Nahla, Ali M. Kutan, Kazi Sohag, and Faisal Alqahtani. 2020. Equity market and money supply spillovers and economic growth in BRICS economies: A global vector autoregressive approach. *North American Journal of Economics and Finance* 51: 101060. [CrossRef]

Schmidbauer, Harald, Angi Rösch, Erhan Uluceviz, and Narod Erkol. 2016. The Russian stock market during the Ukrainian crisis: A network perspective. *Finance a Uver Czech Journal of Economics and Finance* 66: 478–509.

Sim, Nicholas, and Hongtao Zhou. 2015. Oil prices, US stock return, and the dependence between their quantiles. *Journal of Banking & Finance* 55: 1–8. [CrossRef]

Sohag, Kazi, Anna Gainetdinova, and Oleg Mariev. 2021. The response of exchange rates to economic policy uncertainty: Evidence from Russia. *Borsa Istanbul Review*. [CrossRef]

Tiwari, Aviral Kumar, Samia Nasreen, Subhan Ullah, and Muhammad Shahbaz. 2021. Analysing spillover between returns and volatility series of oil across major stock markets. *International Journal of Finance and Economics* 26: 2458–90. [CrossRef]

Wälti, Sébastien. 2011. Stock market synchronization and monetary integration. *Journal of International Money and Finance* 30: 96–110. [CrossRef]

Xu, Haifeng, and Shigeyuki Hamori. 2012. Dynamic linkages of stock prices between the BRICs and the United States: Effects of the 2008–09 financial crisis. *Journal of Asian Economics* 23: 344–52. [CrossRef]