Volatility Spillover Effects on the Gold and Stock Markets of the BRIC Countries

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Abstract

This study investigates gold and stock market correlations and volatility spillovers in BRIC countries during January 2015-November 2022, encompassing both the pre- and post-pandemic periods. Univariate and BEKK DCC-GARCH (1, 1) specifications and CoVaR analysis were employed. The findings indicate stationary volatility transmission not only within individual markets, but also across stock and gold markets in BRICs, advocating for diversified cross-market portfolios to mitigate risks. Notably, China shows no volatility spillovers from gold to stock market, whereas Russia exhibits singular volatility from gold to stock. This study highlights potential directional speculation, especially the COVID-19's impact on uneven economic growth in Brazil and India. This stresses the importance of adapting investment portfolios to varying market impacts and rational capital allocation for desired returns and risk management. Governments are urged to develop diversified economies and flexible market structures to navigate global economic homogeneity and to enhance market responsiveness and resilience.

Keywords: Volatility spillovers, DCC-BEKK-GARCH (1, 1) model, DCC- GARCH (1, 1) CoVaR model, BRIC.

Introduction

Global financial markets have witnessed increased uncertainty and volatility amid ongoing globalization. A notable example occurred in 2018, when American futures markets experienced a significant reversal. The Dow Jones Industrial Average dropped by 1,179 points, accompanied by declines of 4.10% and 2.64% in the S&P 500 and FTSE 100 indices, respectively. The emergence of the COVID-19 pandemic further exacerbated global economic turmoil, with major indices, such as the S&P 500, FTSE 100, and Nikkei 225, experiencing drastic

falls by March 6, 2020. This simultaneous decline across markets signaled an unprecedented liquidity crisis triggered by the COVID-19 pandemic.

This study focuses on the COVID-19 pandemic as a structural breakpoint to investigate the nature of its turmoil and nonlinear dynamics of risk transfer between gold and stock markets. Specifically, it examines gold-stock-market contagion, identifies the main contagion channels, and dynamically assesses upside and downside risk spillovers during the pre- and post-COVID-19 periods.

Commodity indices, influenced by long-term cycles and macroeconomic swings, have been extensively studied for their correlation with stock markets in developed nations. However, little attention has been paid to the interactions between commodity prices and stock changes in developing economies, particularly among the BRIC countries. This study fills this gap by examining the dynamic spillovers between gold and stock markets in BRIC countries.

Existing research on COVID-19's impact on stock and gold markets lacks a comprehensive analysis using optimized methods to explain fluctuations in risk correlation. While various models such as GARCH, VAR-GARCH, and CoVaR have been employed, they often overlook the dynamic nature of shocks, such as COVID-19. This study innovates by integrating the DCC-BEKK-GARCH (1, 1) model with the CoVaR procedure and the COVID-19 structural component to accurately measure the dynamic volatility effects between the stock and gold markets in BRIC regions.

The study’s innovation lies in its examination of risk contagion movements before and after the COVID-19 outbreak and its detection of dynamic spillovers between gold and BRIC countries' stock markets. By understanding the varying impacts of different financial markets, investors can rationally allocate capital to effectively manage the desired returns and risk ratios.

The structure of the paper is as follows: Section 2 reviews the relevant literature; Section 3 presents the econometric methodology; Section 4 describes the data and empirical findings; and Section 5 concludes with policy implications.

Literature Review

In financial markets, commodities interact with stocks, bonds, and foreign exchanges (Aayale, et al., 2022; Farooq & Shawkat, 2007; Fayyad & Daly, 2011; Papadamou, et al., 2017; Ramzi, et al., 2018; Sadorsky, 1999; Spagnolo, et al., 2009; Walid, et al., 2014; Zhao, et al., 2022). Engle introduced the ARCH model in 1982 and revolutionized volatility forecasting.

Bollerslev (1986) extended this model to the GARCH model, allowing conditional and lagged variances. Engle's (2002) DCC-GARCH model assesses the correlation and volatility spillovers used in this study.

Sadorsky (1999) illustrated the links between S&P 500 returns, oil prices, and interest rates using the GARCH model. However, inconsistent findings have emerged regarding the extent of transmission and its significance across different markets (Farooq & Shawkat, 2007; Spagnolo, et al., 2009). While Farooq and Shawkat (2007) confirm significant volatility transmission among the US, Gulf, and global crude oil markets using multivariate GARCH models, Spagnolo, et al. (2009) highlight varying degrees of volatility transmission from mature to emerging economies, suggesting a nuanced understanding of market dynamics during volatile periods.

Beckmann, et al. (2014) determine the links between global liquidity and agricultural futures markets, which are relevant to this study's GARCH test. However, the findings may vary depending on the specific context and time period studied. Similarly, Walid, et al. (2014) find that OPEC decisions influence the oil and cereal markets via VAR-BEKK-GARCH models, highlighting the role of external factors in commodity market dynamics. Nonetheless, inconsistent findings regarding the magnitude of fluctuations and the impact of structural breaks pose challenges to understanding these relationships comprehensively.

COVID-19 contracted the global economy in early 2020, impacting various sectors. Mahmudul, et al. (2021) explore sector sensitivity to volatility, yet inconsistencies in findings may arise due to differences in methodologies and sample periods. Similarly, Nwakoby and Manasseh (2021) study Nigeria's export, welfare, and economic growth, but variations in results may reflect the diverse impacts of the pandemic across regions and industries. Ran, et al. (2022) examine volatility spillovers between global oil stock markets, emphasizing the importance of considering different market conditions and geopolitical factors. Inconsistencies in the findings underscore the complexity of market dynamics and the need for robust methodologies to effectively analyze them. This study focuses on BRIC countries, which represent emerging economies amidst COVID-19's influence on commodity prices, aiming to provide insights into the diverse impacts of the pandemic on global financial markets.

Methodology

This paper uses the DCC-GARCH (1, 1) CoVaR and DCC- BEKK-GARCH (1, 1) model to estimate the spillovers between the gold markets and stock indexes in BRIC. It will evaluate stock indexes and commodity representatives in four member countries.

The GARCH (1, 1) model is a well-known approach for estimating the performance and volatility of return series. Francq and Zakoian (2010) discover that the GARCH (1, 1) model outperforms the GARCH (1, 2), GARCH (1, 3), GARCH (1, 4), and GARCH (2, 1) models and may be considered the benchmark model. In the GARCH (1, 1) model, the Gaussian quasi-maximum likelihood (QMLE) estimator is consistent with the asymptotically normal distribution with the asymptotic covariance matrix (Berkes, et al., 2004; Yakoub & Jean-Marc, 2022). It is created by maximizing a function using the logarithm throughout the modeling process. Based on the mechanism of QMLE, GARCH (1, 1) model is used in this research and is expressed as:

$$R_t = \mu + \rho R_{t-1} + \varepsilon_t \quad (1)$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (2)$$

where the ω indicates the average level of volatility; σ_t^2 is defined independently as the conditional variance at the time t; The sum of α and β measures the volatility persistence for a particular shock.

The DCC progress of Engle (2002) is consistent with the previous idea of volatility modeling. The correlation coefficient construction through the DCC model changes from the stable one to the time-varying returns. The DCC (1, 1) model is then given at:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}\varepsilon'_{t-1} + \beta\sigma_{t-1}^2 \quad (3)$$

where ω = (1-α-β)$\overline{\sigma_t^2}$. $\overline{\sigma_t^2}$ is defined as the standardization of the conditional variance at the time t. The absolute value of the correlation coefficient is guaranteed to be less than or equal to one.

The bivariate DCC-GARCH (1, 1) model is designed with the conditional variance and covariance of time series, but the conditional correlation remains constant. The function for the bivariate DCC-GARCH (1,1) model with structural breakdowns is as follows:

$$Q_t = C'C + B'H_{t-1}B + A'\varepsilon_{t-1}\varepsilon'_{t-1}A \quad (4)$$

$$C = \begin{pmatrix} C_{11} & C_{12} \\ 0 & C_{21} \end{pmatrix} \quad B = \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix} \quad A = \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix}$$

In equation four, C represents the matrix with three parameters ($\mathbf{C_{11}}$, $\mathbf{C_{12}}$, $\mathbf{C_{21}}$); B is the squared sigma between two variables; A means the extent of the correlation between the conditional variances and the squared errors in the last period; $\mathbf{X_i}$ is the matrix of volatility regime control variables.

All GARCH estimations are consistent with the quasi-maximum likelihood to minimize information loss (Young Shin, et al., 2015; Zhu, 2022). The conditional at-risk value (CoVaR) then measures the value of gold to the stock market on this DCC- GARCH (1, 1) basis. According to (Adrian & Brunnermeier, 2016; Zhu, 2022), the CoVaR of gold market return g represents the degree of risk of the stock return s when the institution experiences a negative shock, with the following general expression:

$$P\left(X^s \leq CoVaR_m^{s|g} \middle| X^g\right) = VaR_m^g = m \qquad (5)$$

$$CoVaR_{m,t}^{s|g} = \theta^{-1}(m)\,\sigma_{s,t}\sqrt{1-\rho_{gs,t}^2} + \theta^{-1}(m)\rho_{gs,t}\sigma_{s,t}$$

where m represents the confidence interval, equal to 0.05; when the confidence level is 5%, $\theta^{-1}(m) = 1.645$; $\rho_{gs,t}$ is the correlation coefficient between gold returns and stock returns from the DCC-GARCH (1,1) model; $\sigma_{s,t}$ means the conditional variance of stock market returns from the DCC-GARCH (1,1) model.

The above DCC- GARCH (1, 1) CoVaR model can examine the existence and direction of dynamic spillover effect between stock market and gold market returns. The empirical section aims to verify the transmission trend of risk spillover between stock market and gold market returns in this paper. BEKK is a potent instrument for investigating the direction of risk spillovers, as it investigates not only the correlation coefficient change of the conditional second moment between two markets but also the Granger causality relationship of market fluctuations (Caporin & McAleer, 2012; zhanglu, 2019; Zhu, 2022). Once the conditional

variance of the index return obeys the DCC-GARCH (1, 1) process, the DCC-BEKK-GARCH (1, 1) equation has the following general set form:

$$q_{11,t} = C_{11}^2 + B_{11}^2 H_{11,t-1}^2 + A_{11}^2 \varepsilon_{1,t-1}^2 + 2B_{11}\, B_{21} H_{12,t-1} + B_{21}^2 H_{21,t-1} + 2A_{11}\, A_{21} \varepsilon_{1,t-1} \varepsilon_{2,t-1} + A_{21}^2 \varepsilon_{2,t-1}^2 \quad (6)$$

$$q_{12,t} = C_{11} C_{21} + B_{11} B_{21} H_{11,t-1} + A_{11} A_{12} \varepsilon_{1,t-1}^2 + (A_{21} A_{12} + A_{11} A_{22}) \varepsilon_{1,t-1} \varepsilon_{2,t-1} + (B_{21}\, B_{12} + B_{11}\, B_{22}) H_{12,t-1} + B_{21} B_{22} H_{22,t-1}$$

$$q_{22,t} = C_{11}^2 + C_{22}^2 + B_{12}^2 H_{11,t-1}^2 + A_{12}^2 \varepsilon_{1,t-1}^2 + 2B_{12}\, B_{22} H_{12,t-1} + B_{22}^2 H_{22,t-1} + 2A_{12}\, A_{22} \varepsilon_{1,t-1} \varepsilon_{2,t-1} + A_{22}^2 \varepsilon_{2,t-1}^2$$

where $\mathbf{q_{11,t}}$ and $\mathbf{q_{22,t}}$ mean the conditional variance of stock and gold market returns. $\mathbf{q_{12,t}}$ represents the conditional covariance of stock and gold market returns.

Empirical Findings and Discussion

In this paper, the closing price of gold futures is chosen as a proxy for the price of the gold market, labeled as Gold. The IBOVESPA index in Brazil, the MOEX Russia Index, the India Mumbai 30 index in India, and the Shanghai Composite Index in China are chosen as the price indices of the stock markets of four countries: Brazil, Russia, India, and China. These indexes form a time-series sample to analyze the dependence between BRIC country's stock markets and the gold market. The economic variables in this research comprise daily indices from the gold market and stock markets in four BRIC countries from 1st January 2015 to 31st December 2022. All data sources from the INV (2023). After excluding non-trading days and mismatched data, there are 1,713 valid observations. Figure 1 depicts the trend of each stock price index and gold futures price during the sample interval.

The ongoing trends of Brazil, Russia, and India stock indexes are incredibly similar. In contrast, China's stock index trend is substantially distinct from those of the other three countries- the trend of the stock index of each country and the gold price exhibits a degree of synergy. Massive work stoppages in China to combat the epidemic significantly affected the economy, as evidenced by significant stock market volatility. As a result of globalization, China's economy has a more significant international impact than in the past. All these factors motivate the market to increase its gold holdings. However, this synergy is not static

throughout the sample interval, and its relationship with time varies, i.e., it exhibits a time-varying correlation.

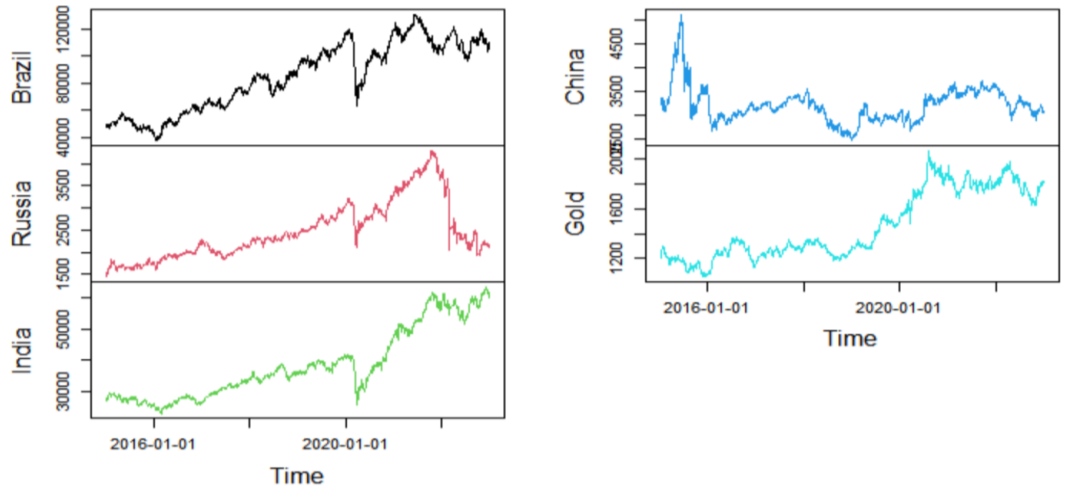

Figure 1: The trend of stock price indices and gold futures prices in BRIC countries

In addition, all stock price indices have a localized minimum around 2020, primarily influenced by the pandemic. The stock market dropped significantly, especially for Brazil, Russia, and India, which were hardest affected by the epidemic. However, China experienced the lightest fluctuations during the epidemic. It is mainly because of China's stringent policies regarding preventing and controlling epidemics. This paper treats all the price series by logarithmic differencing to obtain their logarithmic yield series, still denoted as Brazil, Russia, India, China, and Gold. The formula for the continuously compounded daily return series is $R_t = \ln P_t / P_{t-1}$. R_t is the yield series, and P_t and P_{t-1} are the closing prices at moments t and t-1, respectively. The descriptive analysis demonstrates BRIC's stock and gold market indexes (Table 1).

Table 1 outlines the statistical parameters for the logged returns in stock and gold markets in BRIC. The mean values of the stock market and gold market returns in four countries are near zero. Notably, the negative result indicates that the stock return in China generally presents a downward trend. There are two main reasons for the reverse shift. First, the Chinese government's strict control of the coronavirus has reduced people's panic. The implied volatility of the Shanghai 50 option tripled from 0.15 in the early days of the coronavirus outbreak before falling back to around 0.20. Coupled with the RMB exchange rate appreciation

after the US dollar started the unlimited Quantitative Easing policy[1], the gold price in RMB has room to depreciate. The standard deviations of the returns are large relative to the mean values, indicating significant fluctuation in each country's stock market and gold market returns.

Table 1: Daily Logged-returns Summary Statistics (whole sample)

	Brazil	Russia	India	China	Gold
Minimum	-0.1599	-0.4047	-0.1410	-0.1083	-0.0511
Maximum	0.1302	0.1826	0.0859	0.1005	0.0578
Mean	0.0005	0.0002	0.0005	-0.0001	0.0002
St dev	0.0174	0.0178	0.0120	0.0147	0.0100
Skewness	-0.8911	-6.8126	-1.2813	-1.0142	-0.1254
Kurtosis	14.1727	166.0823	18.3901	8.8172	4.0898
Jarque-Bera	14596***	1985565***	24659***	5857***	1203***

*Note: Stdev denotes standard deviation. The '***' in means p-values in Jarque-Bera tests are less than 0.01, indicating that the original hypothesis that the sequences do not adhere to normal distribution can be rejected with 99% confidence.*

The standard deviation of the stock index in Brazil is the largest, indicating that the profitability of the eight markets fluctuates the most and their performance is unstable. The skewness of the stock market and gold market returns is less than zero, indicating that the frequency of losses is greater than the frequency of gains. In addition, the kurtosis of each series is more significant than three, indicating that the distribution exhibits pronounced acute peaks and fat tails compared to the normal distribution. Both kurtosis and skewness tests imply that the series is not normally distributed. The original hypothesis that the sequences do not follow the normal distribution can be rejected with 99% assurance, i.e., all the sequences do not follow the normal distribution. The Jarque-Bera test reveals that none of the sequences adhere to normal distribution.

[1] From August to October 2019, the Federal Reserve lowered the federal interest rate for three consecutive times to 1.5%. In March 2020, it started Quantitative Easing and lowered the federal interest rate to 0.

ADF Unit root test for each indicator

The purpose of the Augmented Dickey-Fuller (ADF) test and Phillips and Perron (Appiah, et al., 2021) test is to detect the property of stationarity, hence validating the correct application of the ARMA model. Both tests assume that the null hypothesis is the existence of a unit root (non-stationary). According to the results of Table 2, the critical values at the significance level of 99% in all stock and gold markets are all bigger than the t-test statistic value. The null hypothesis (p=1) can be rejected, and the original series is a stationary time series. Then, it is necessary to employ the ARMA procedure to minimize this association. In addition, this test is compatible with the DCC GARCH (1, 1) model.

Table 2: The ADF and PP test results for each market return series

	ADF Test	PP Test	Result
Brazil	-10.892***	-1842.1***	Stationary
Russia	-13.364***	-1870.1***	Stationary
India	-11.385***	-1797.2***	Stationary
China	-12.183***	-1600.0***	Stationary
Gold	-11.260***	-1684.9***	Stationary

*Note: the '***' represents the 99% confidential levels of critical value, and all results are highly significant.*

ARCH Effect test

Due to autocorrelation and conditional heteroskedasticity, financial time series typically exhibit an evident fluctuation clustering effect, in which large fluctuations are closely followed by large fluctuations and small fluctuations are closely followed by small fluctuations. The GARCH family model is a widely employed model for depicting such fluctuations. In the GARCH family modeling analysis, it is essential to determine if the series satisfies the application postulate of the GARCH family model, i.e., if there is an evident volatility aggregation effect. The yield series plot shows the volatility aggregation characteristics. Figure 2 depicts the time series diagram of each produce series.

Heteroskedasticity is another critical assumption of GARCH models. Straumann and Mikosch (2006) point out that the error terms may change in proximity to earlier terms. It emphasizes the presence of the uneven variance of error terms across the period. The null

hypothesis of the ARCH LM test is that all regression coefficients in the ARCH model are zero simultaneously. When using the residual ARCH LM test before the GARCH model, it is necessary to expect that the probability of minor residual performance from the first order is reasonable. In Table 3, the absolute value of the ARCH-LM test statistic for each series is immense, and the p-value is much less than 0.01. Consequently, the original hypothesis that no ARCH effect exists in the series can be rejected at the 99% confidence level. The residual has an ARCH effect, satisfying the premise of the GARCH model.

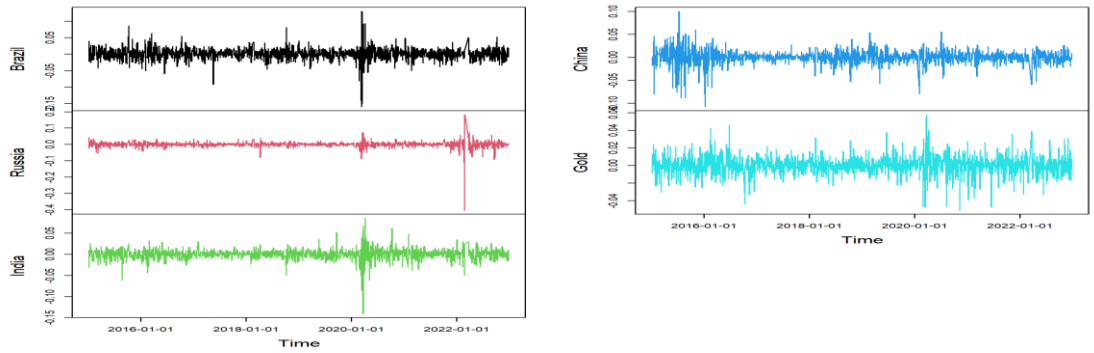

Figure 2: Time series plot of each market return series in BRIC countries

Table 3: The ADF test results for each market return series

	BRAZIL	CHINA	INDIA	RUSSIA*	GOLD
Statistics	758.600	71.713	453.610	206.220	107.130
P Value	0	0	0	0	0

Univariate GARCH (1.1) Model

Table 4 displays the statistical characteristics of the univariate GARCH (1, 1) model. This paper uses standard Box–Jenkins techniques and the identical mean equation from the univariate model. The null hypothesis assumes there is no transmission of market volatility. Alpha and beta are estimated parameters of the residual series. The total also determines how long variance shocks take to return to their long-term mean (Ling & McAleer, 2001). The sum of alpha and beta for each variable is exceptionally close to one, indicating that the fluctuations are all highly persistent (Table 4). It promises the volatility persistence of the return series.

After detecting the univariate spillover in five indexes, the ARCH test retests the existence of the ARCH effect. For China, the test p-value is 0.0536, representing that the original hypothesis of no ARCH effect in its residual series cannot be rejected at the 95% confidence level. The null hypothesis cannot be rejected with a 90% confidence level for the remaining variables. It demonstrates that the GARCH model filters the ARCH effect in the original series better, and the model fitting effect is generally better. All apparent values show this GARCH (1,1) model eliminates the arch effect well.

Table 4: Estimation Results of The Univariate GARCH (1, 1) Model

Parameters / Index	α	β	α+β	Prob. of ARCH
BRAZIL	0.0673***	0.8905***	0.9579	0.5531
RUSSIA	0.1006***	0.8629***	0.9635	0.9056
INDIA	0.0738***	0.8994***	0.9732	0.7820
CHINA	0.0687***	0.9260***	0.9947	0.0536
GOLD	0.0263***	0.9671***	0.9933	0.5871

*Note: The '***' means the highly significant coefficient estimates.*

The bivariate GARCH (1, 1) Model

The paper then constructs a DCC-GARCH model to examine the dynamic interdependence between each country's stock market and gold market. Using the R programming language, Table 5 displays the parameter estimation results of the DCC-MVGARCH (1,1) model between the stock market returns and gold returns.

Table 5: Estimation Results for bivariate DCC-GARCH (1, 1) models。

Parameters / Index	α	standard error	β	standard error	α+β
Brazil-Gold	0.0034	0.0037	0.9874	0.0054	0.9908
Russia-Gold	0.0125	0.0081	0.9353	0.0217	0.9478
India-Gold	0.0099	0.0059	0.9811	0.0121	0.9910
China-Gold	0.0042	0.0033	0.9854	0.0075	0.9896

Note: Standard errors are based on robust standard errors calculated according to the method created by Bollerslev and Wooldridge (1992). All standard resids in estimation show a significant value (P<0.1). It indicates that GARCH can extract the sequence fluctuation well, and the GARCH model is effective.

The bivariate DCC-MVGARCH model pairs each country's stock price index return with the gold futures price return in two pairs. The DCC parameters' sum between each country's stock market returns and the gold market returns are closer to one, of which the largest is 0.9910 and the smallest is 0.9478. The values close to one indicate that the correlation between the stock market and the gold market has a long memory. The dynamic dependence between the stock yields and gold series can last long. Based on DCC-MVGARCH, the dynamic dependence coefficient correlation between the stock market and the gold market of BRIC countries can be shown in Figure 3.

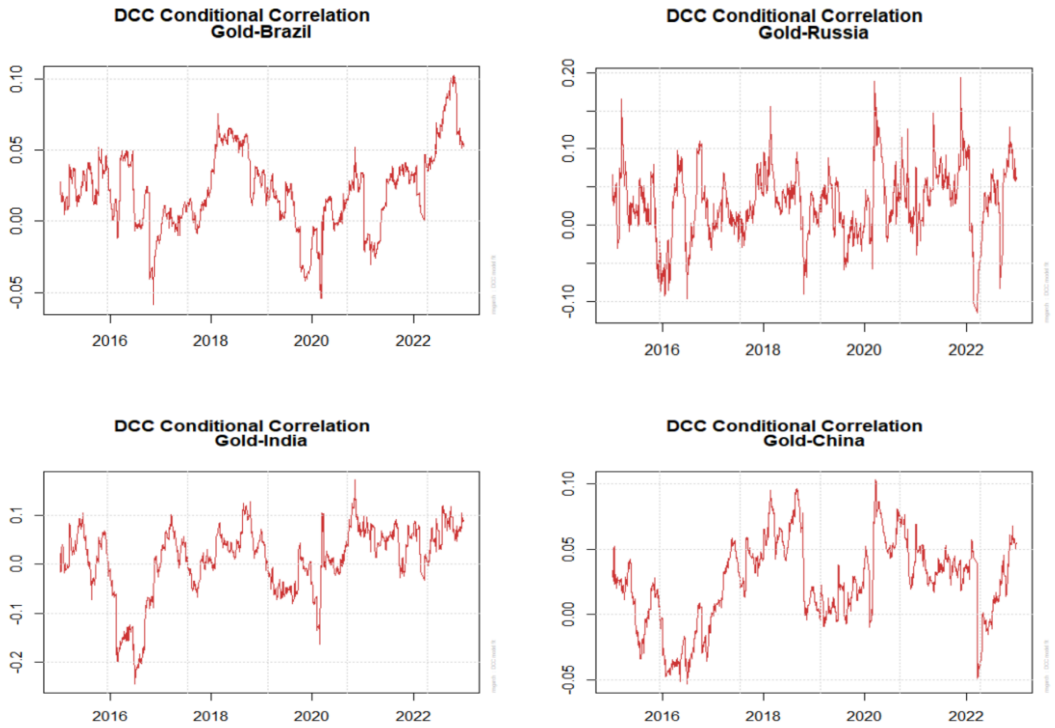

Figure 3: The DCC Conditional Correlation in BRIC countries

The dynamic coefficients of dependence between the stock markets and gold markets of BRIC nations exhibit significant time-varying characteristics. Russia exhibits a stronger correlation with the gold index than the other three stock markets, followed by India and Brazil. It displays more volatility fluctuation and higher fluctuation. The Russia-Ukraine conflict and the impact of the novel coronavirus pneumonia are closely related to the evident coefficient for Russia. Residents are reluctant to alter the holding basket or take the uncertainty-based problems considering the political factors. Specifically, stocks suffered heavy selling on the eve of Russia's month-long market break. The stock index fell nearly 1,000 points to 2470.48 on 20th February 2022. It supports the loss aversion theory (Tversky & Kahneman, 1991) that people are more discouraged by failure than success. Unsafe domestic conditions urge people to choose safer tools than they think, such as holding cash. However, the correlation between the Chinese stock market and the gold market is the weakest. The weakness is because the Chinese government's strict control of the coronavirus has reduced people's panic.

DCC-GARCH-CoVaR Model

The time varying CoVaR can be obtained from the dynamic correlation coefficients. $\rho_{is,t}$ and $\delta_{i,t}$ calculated by previous GARCH estimations. It represents the aggregate level of risk in each country's stock market concerning the risk of the gold market. The conditional at-risk value between the BRIC country and the gold market is depicted in Figure 4.

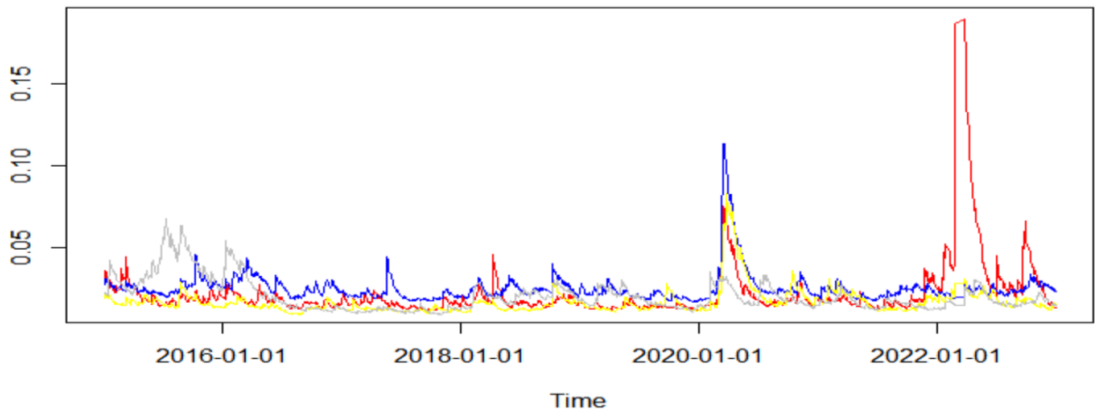

Figure 4: Time series of time-varying risk spillovers between stock markets and gold markets in BRIC countries

Note: Blue, red, yellow, and gray lines are the levels of risk spillover between the Brazilian, Russian, Indian, and Chinese stock markets and the gold market, respectively.

A similar time-varying profile exists throughout the sample interval in the level of risk spillovers between BRIC stock markets and the gold market. In the triad of Brazil, Russia, and India, there is a large climax around 2020, corresponding to the critical moment in the COVID-19 epidemic. On the other hand, China's risk premiums around 2020, while also increasing, were not as high as those of the other three countries. It is most likely due to China's more stringent epidemic prevention and open economic and fiscal policies, which mitigated the epidemic's negative impact. In addition, the Russian equity and gold market risk premiums reached a very high apex in early 2022, which could be attributed to the Russian-Ukrainian conflict.

DCC-BEKK GARCH (1, 1) Model

This paper further develops a DCC-BEKK GARCH (1,1) model to analyze the direction of risk spillover. This model can verify the direction of dynamic risk spillover between the gold markets and stock markets of BRIC countries. Table 6 displays the results of the DCC-BEKK

GARCH (1,1) model between stock market returns and gold futures returns for each BRIC country.

Table 6: The results of the DCC-BEKK GARCH (1,1) model in BRIC countries before and after COVID-19

		Brazil-Gold		Russia-Gold		India-Gold		China-Gold	
Before Covid-19	Matrix B	0.9822	-0.0619	0.9574	0.0204	0.9767	-0.1312	0.9632	-0.0974
		0.1846	0.9801	0.1438	0.5566	0.1068	0.9450	-0.0832	-0.1988
	Matrix A	-0.0970	-0.0559	0.2499	-0.0592	-0.1764	-0.1431	0.2429	0.0743
		0.2178	-0.0725	0.1090	-0.1127	0.1194	-0.0070	0.0130	0.0566
After Covid-19	Matrix B	0.7762	0.2600	0.7638	0.4042	0.9148	0.2312	0.9091	-0.0015
		-0.7399	0.8185	-0.8143	0.6061	-0.3055	0.8901	0.0036	0.9919
	Matrix A	0.3428	-0.0148	0.3250	-0.2416	0.3181	-0.0475	0.2996	0.0453
		-0.0622	-0.1931	-0.1023	-0.1969	0.0188	-0.1706	-0.0612	0.0998
Wald Test 1- Hypothesis: No spillover between stock and gold									
Before Covid-19		Wald=605.56 P =0.0000		Wald= 25.98 P =0.0000		Wald= 65.59 P =0.0000		Wald=18.6063 P =0.0009	
After Covid-19		Wald= 806.68 P =0.0000		Wald= 1360.26 P =0.0000		Wald=684.93 P =0.0000		Wald=16.0806 P =0.0029	
Wald Test 2- Hypothesis: No spillover from stock to gold									
Before Covid-19		Wald=277.29 P =0.0000		Wald=0.7019 **P=0.7040**		Wald= 39.78 P =0.0000		Wald=16.89 P =0.0002	
After Covid-19		Wald=199.10 P =0.0000		Wald=548.07 **P =0.7040**		Wald=315.45 P =0.0000		Wald= 12.71 P =0.0017	
Wald Test 3- Hypothesis: No spillover from gold to stock									
Before Covid-19		Wald=327.48 P =0.0000		Wald=13.7691 P=0.0010		Wald= 38.56 P =0.0000		Wald= 1.1905 **P=0.5514**	
After Covid-19		Wald=445.93 P =0.0000		Wald=392.21 P =0.0000		Wald= 433.70 P =0.0000		Wald= 2.8702 **P =0.2381**	

The test results depict the market volatility spillover between the stock market and gold index of BRIC countries before and after the COVID-19 pandemic (Table 6). The companion probability of the first inter-market Wald test is less than 0.01. The null hypothesis is that the two markets have no directional risk spillover. When the Wald value is relatively large, and the p-value is less than 0.01, the original hypothesis can be rejected at the 99% confidence level. This value indicates the existence of a bi-directional volatility spillover between the BRIC stock market and the gold market. The results are shown in Figure 4.

For BRIC countries' flow from the stock markets to the gold market, except for Russia, the other three countries' Wald companion probabilities of the test are also all less than 0.01. The other three BRIC countries, except Russia, have experienced unidirectional volatility spillovers from the stock market to the gold market. It is primarily because of the ceased purchasing gold on the Russian domestic precious metals market on 1st April 2020. Since 2018, the Russian central bank has been purchasing gold, creating a financial "shield" to withstand the effects of sanctions. As of March 2020, its gold accounted for approximately 21% of its foreign exchange reserves, making it the fifth-greatest gold reserve globally. However, Russia has ceased purchasing gold on its domestic precious metals market as of 1st April 2020 due to the epidemic induced by the high price of gold. Thus, the Russian gold market is impacted by the economy. Other financial markets in Russia, including the stock, do not affect the gold market.

For gold market to stock market flows in BRIC countries, except for China, the companion probabilities of the three Wald tests are also all less than 0.01. There is a one-way volatility spillover from the gold market to the stock market in the three BRIC countries. In contrast, China shows no spillover from gold to the stock market. The significant work stoppages in China to control the epidemic have had a more negative impact on the economy, with stock market volatility evident. With the development of globalization, China's economy is more influential than in the past, causing international markets to be more concerned about its economic outlook. These factors justify the market's increased gold holdings. However, despite the epidemic's impact on the gold price, the epidemic's effect on the gold market is relatively minor, and there is a specific latency. The gold price fluctuation is primarily a reflection of the epidemic's impact. On the other hand, the epidemic's impact on the gold price is modest and lagging. The primary cause is the problem of investor behavior. Most domestic investors prefer interest-bearing bonds, making the bond market more sensitive to the epidemic's effects. The impact of significant domestic risk events on the gold price is relatively minimal.

Conclusion and Implication

In this study, the authors assess the volatility transmission between the gold and stock returns of BRIC countries through the univariate GARCH (1, 1) model, CoVaR analysis, and BEKK analysis based on the DCC GARCH (1, 1) model. The sum of alpha and beta for each variable is exceptionally close to one in the univariate GARCH (1, 1) process. The result shows highly persistent volatility transmission in the stock markets of BRIC countries and the gold future

index. Russian stock returns offer a better response to uncertainty. It is probably due to the political shock and military move against Ukraine in March 2022. It supports the loss aversion theory that residents are reluctant to alter the holding basket or take the uncertainty-based problems considering the political factors. BRIC economies should strengthen international cooperation and promote global market integration in this context. The potential of the BRIC trade agreement should be unleashed to pool our strength through greater openness and to mitigate the impact of COVID-19 and conflicts on global economic development.

Bivariate DCC-GARCH (1, 1) model results show the extended memory in the dynamic coefficient correlation between the stock market and the gold market of BRIC countries. Russia exhibits a stronger correlation with the gold index than the other three stock markets, followed by India and Brazil. Its high fluctuation is because of the Russia-Ukraine conflict and the impact of the Covid-19 pneumonia. Unsafe political conditions urge residents to choose less risky tools like holding cash. India and Brazil were also significantly hit by COVID-19 but recovered quickly thanks to indispensable and stimulating recovery policies. The Brazilian economy is supported mainly by its overdeveloped commodity markets, mainly in raw materials, livestock meat products, agricultural commodities, and small amounts of crude oil exports. Its GDP quickly recovered from -10.9 % in the second quarter to -3.7% in the third quarter of 2020 (Statista). However, the correlation between the Chinese stock market and the gold market is the weakest. This weak correlation is mainly because the Chinese government's strict control of the coronavirus has reduced people's panic. It offers more opportunities for speculation and risk-hedging activities. Speculators might engage in directional price gambles to achieve greater profits or sustain more significant losses than the original margin. Spillover effects allow investors to hedge against uncertainty. Compared to volatility spillovers in a single market, cross-markets are more stable. This suggests that investors should buy portfolios across financial markets.

Based on the time-varying CoVaR analysis, a similar time-varying profile detects the level of risk spillovers between BRIC stock markets and the gold market. In the triad of Brazil, Russia, and India, there is a large climax around 2020, corresponding to the critical moment in the COVID-19 epidemic. On the other hand, China's risk premiums around 2020, while also increasing, were not as high as those of the other three countries. It is most likely due to China's more stringent epidemic prevention and control policies, which mitigated the epidemic's negative impact. In addition, the Russian equity and gold market risk premiums reached a very high apex in early 2022, which could be attributed to the Russian-Ukrainian conflict.

Lastly, the BEKK estimations survey significant directional fluctuation effects of COVID-19. There are bi-directional risk spillovers in the gold indices and stock markets in BRIC nations. However, China and Russia perform differently in a single-directional market volatility spillover. For the stock markets' risk flow to the gold market, Russia has proclaimed a ban on trading gold due to its ample gold reserves and the epidemic's impact on the price of gold. As a response, Russia has experienced non-directional volatility spillovers from the stock market to the gold market. On the other hand, regardless of whether or not coronavirus pneumonia is considered, there are no risk spillovers from China's gold market to the stock market. Historically, epidemics have affected the price of gold, and investors use gold as an investment vehicle during periods of stability. During the epidemic impact phase, however, people invest in stable instruments for the short term. Once the market stabilizes, however, they will abandon the gold market in favor of more lucrative markets. The risk contagion effect of the gold market on the stock market is reflected in the developed commodity markets of Brazil, Russia, and India. Nonetheless, there is insignificance in China. The fundamental cause is investor behavior. Most domestic investors favor interest-bearing bonds, making the bond market more susceptible to the effects of a pandemic. Overall, the impact of significant domestic risk events on gold prices is moderate.

From the perspective of each member state, Brazil exhibits more spillover effects than the other three nations, which is over-dependent on commodity markets. India is more vulnerable to COVID-19 in labor and manufacturing. Even though China was the origin of the epidemic, the country's open economic and fiscal policies and the shift in investor preferences to bonds meant that the impact of the gold market on stocks does not reach the predicted level. Investors could take the varying impact status of different financial markets into account and then allocate capital rationally to achieve the desired return and risk ratio. Furthermore, Russia's gold trading ban from April 2020 to early 2022 has also ended the risk spillover from the equity market to the gold market. Countries should develop diversified economies, strive to build independent, controllable, and mutually supportive industrial chains, and actively build a large circulation of the national economy. With the homogeneity of the global economy and trade, developing economies should improve the market response mechanism and enhance market resilience.

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