The Impact of the COVID-19 Pandemic and the Russia-Ukraine War on Stock, Gold, and Bitcoin Markets: Examining Volatility Spillovers and Extreme Return Movements

Chung Baek
Troy University

Haksoon Kim
Troy University

Dylan Norris
Troy University

We examine how the COVID-19 pandemic and Russia-Ukraine war affect volatility spillovers and extreme return movements in the stock, gold, and bitcoin markets. Our study uses the post-pandemic period of up to two and a half years in order to reflect the lingering effects of the pandemic as well as its initial impact. We find that volatility spillover has weakened in the post- versus pre-pandemic period. Additionally, our results suggest that the Russia-Ukraine war has had little impact on volatility spillovers. We subsequently test for extreme return movements separately and find substantial increases in the likelihood that two assets' extreme returns move simultaneously post- versus pre-pandemic.

Keywords: COVID-19 pandemic, Russia-Ukraine war, volatility spillovers, extreme return movements

INTRODUCTION

2020 to 2023 have been characterized by two of the most influential events in recent history: the COVID-19 pandemic and the Russia-Ukraine war. During this time, we have seen measures of uncertainty and volatility at record highs. For example, the BBD Index, an economic policy uncertainty index, reached its record high in May of 2020, while on March 16, 2020 the VIX closed at its highest level since inception in 1990. These difficult economic times give rise to an opportunity to explore possible volatility spillovers and extreme return movements.

In this paper, we seek to study the volatility spillover effects between the stock, gold, and bitcoin markets caused by the COVID-19 pandemic and Russia-Ukraine war. We use a sample of daily prices for the S&P500 Index, SPDR gold ETF, and bitcoin from January 2016 to August 2022. By using an extended post-pandemic period, we hope to estimate the lingering effects of COVID-19. We create Pre- and Post-pandemic periods by splitting our sample on February 19, 2020.

We first hypothesize that there are significant volatility spillover effects across the stock, gold, and bitcoin markets stemming from both events. Employing an ARCH-GARCH model, we find strong interdependent volatility spillover in the pre-pandemic window between stock and gold, and stock and bitcoin. Gold and bitcoin show only unidirectional volatility spillover from gold to bitcoin. However, we do not find any spillover effect during the post-pandemic period, indicating risk transmission has weakened as the pandemic has continued. Despite this weakening post-pandemic, we do find a significant unidirectional spillover from bitcoin to stock attributable to the war. However, because no other assets have a significant spillover there is weak evidence that the Russia-Ukraine conflict has affected volatility spillover between these markets overall.

Given that two assets may not experience extreme losses concurrently in a market downturn despite having interdependent volatilities, we additionally investigate how extreme returns on stock, gold, and bitcoin simultaneously move. Examining extreme return co-movements enables us to identify flight-to-safety assets in a risky financial time. We use a bivariate copula to estimate the probability that two asset's returns simultaneously fall within their n^{th} percentiles, and find a substantial increase in the probability this occurs in the post-pandemic period. For stock and bitcoin returns, the probability of returns falling within the lowest 1st percentile increases over 30 times in post- versus pre-pandemic. Across all asset pairs, we find increases in probability for the lowest 1st, 5th, and 10th percentiles ranging from 1 to nearly 400 times. Our results suggest while gold was the best flight-to-safety asset for stock investors pre-pandemic, bitcoin has become the better option post-pandemic. Similarly, bitcoin takes this position for gold investors post-pandemic as well. Lastly, we find that gold is a better alternative for bitcoin investors than stocks post-pandemic.

The rest of the paper is structured as follows: Section 2 reviews the related literature. Section 3 describes the sample and variables used in empirical analysis. Section 4 describes our empirical models and results. Section 5 concludes.

LITERATURE REVIEW

Return and volatility spillover issues became popular after the globalization of international financial markets began in the 1980s. Early research looked at spillover issues in the stock market across national markets (King, Santana, and Wadhwani, 1994) as well as international markets (Yasushi, Masulis, and Ng, 1990; Lin, Engle, and Takatoshi, 1994; Koutmos and Booth, 1995). Researchers found that idiosyncratic factors are significant in spillover effects (King, Santana, and Wadhwani, 1994). Other research shows the spillover effect is observed across different international stock markets (Yasushi, Masulis, and Ng, 1990; Lin, Engle and Takatoshi, 1994), and the spillover effect is asymmetric based on good or bad news (Koutmos and Booth, 1995). Recently, Yang, Zhou, and Cheng (2020) find that there is a volatility spillover from the US. Stock market to other global markets by analyzing option-implied volatility indices.

Research has since expanded beyond the stock market to encompass many different financial markets. Dean, Faff, and Loudon (2010) find that return spills over into the bond market from the stock market and vice versa. However, volatility only spills over from the bond market to the stock market. Yip, Brooks, Do, and Nguyen (2020) find that there is a strong volatility spillover between crude oil and agricultural commodity markets. Gao, Zhao, and Zhang (2021) find that economic policy uncertainty in China creates volatility spillover the most on the gold market and the least on the oil market but find opposite results when looking at return spillover. Beyond different asset classes, other research focuses on the spillover effects in different world regions. Many studies document volatility spillover from US markets to Eurozone financial markets (Billio and Pellizon, 2003; Baele, 2005; Christiansen, 2007; Caloia, Cipollini, and Muzzioli, 2018; McDonald, Sogiakas and Tsopanakis, 2018). Additionally, spillover effects are observed from US to Pacific-Basin markets (Liu and Pan, 1997), from developed market to emerging markets (Li and Giles, 2015), across G7 financial markets (Liow, 2015), and across global financial markets (BenSaïda, Litimi, and Abdallah, 2018; Wang, Pan, and Wu, 2018).

Most recently, research has focused on the return and volatility spillover effects of the bitcoin market on the traditional financial markets. They also focus on the global financial crisis and COVID-19 pandemic periods in their analyses (Choudhry and Jayasekera, 2014; Xu, Taylor and Lu, 2018; Katsiampa, Corbet, and Lucey, 2019; Kumar, 2020; Zhang and He, 2021; Elsayed, Gozgor and Lau, 2022; Yousaf, Beljid, Chaibi and Ajlouni; 2022; Jiang, Li, Lu, Wang and Wei, 2022; Di and Xu, 2022). Some researchers find the spillover effect from the bitcoin market to other financial markets during the crisis period. However, some studies did not find spillover effects or documented weak effects due to the small sample period or the financial market of choice.

Our study focuses on the bitcoin, gold, and stock markets from 2016-2022. We believe this sample period allows for a meaningful study of the spillover effects in pre- and post-COVID-19 pandemic periods. Due to the Russia-Ukraine war's extremely negative impact on the world financial markets (Yousaf et al., 2022; Ahmed et al., 2022; Boungou and Yatie, 2022; Boubaker et al., 2022), we also explore the volatility spillover effect caused by this event across stock, gold, and bitcoin markets during this period. We additionally study how extreme returns on stock, gold, and bitcoin move together. We believe our study contributes to related literature by analyzing a meaningful sample period including both the COVID-19 pandemic risk factor and the Russia-Ukraine political risk factor. Our hypotheses are as follows:

Hypothesis 1: *There are significant changes in volatility spillover effects across stock, gold and bitcoin markets during the post-COVID-19 pandemic and Russia-Ukraine War periods.*

Hypothesis 2: *There are significant changes in extreme return co-movements across stock, gold and bitcoin markets during the post-COVID-19 pandemic period.*

DATA

We use daily prices for the S&P 500 Index, SPDR gold ETF, and bitcoin. S&P 500 Index and bitcoin data are downloadable from the Federal Reserve Bank of St. Louis, and the SPDR gold ETF data is downloadable from investing.com. Conlon and McGee (2019) show that the bitcoin market has been efficient since 2016. Thus, we collect daily data from January 2016 to August 2022. Following the period of the COVID-19 bear market proposed by Baek and Jackman (2021), we adopt February 19, 2020 as a reference point to split our complete sample into two subperiods: Pre-COVID-19 pandemic (January 1, 2016 to February 18, 2020) and Post-COVID-19 pandemic (February 19, 2020 to August 31, 2022).

TABLE 1
SUMMARY STATISTICS (DAILY RETURNS)

	SP500	GOLD	BTC
Panel A – Pre-COVID-19 pandemic (January 4, 2016 – February 19, 2020)			
Mean	0.000501	0.000375	0.002983
Standard Deviation	0.008081	0.007592	0.046350
Skewness	-0.641838	0.232805	0.088005
Kurtosis	4.610911	3.055404	4.047079
Panel B – Post-COVID-19 pandemic (February 20, 2020 – August 31, 2022)			
Mean	0.000243	0.000075	0.001154
Standard Deviation	0.016544	0.010468	0.049075
Skewness	-0.864204	-0.526027	-1.628840
Kurtosis	11.501906	3.263631	14.912635

Table 1 shows summary statistics for daily returns. The standard deviations of the S&P 500 Index, gold, and bitcoin returns significantly increase during the post-COVID-19 pandemic, which means that their volatilities rise. Kurtosis and skewness also confirm that each asset becomes more leptokurtic (fat tails) and have a long tail on the left side of the return distributions (more extreme losses) during the post-COVID-19 pandemic.

MODELS AND EMPIRICAL RESULTS

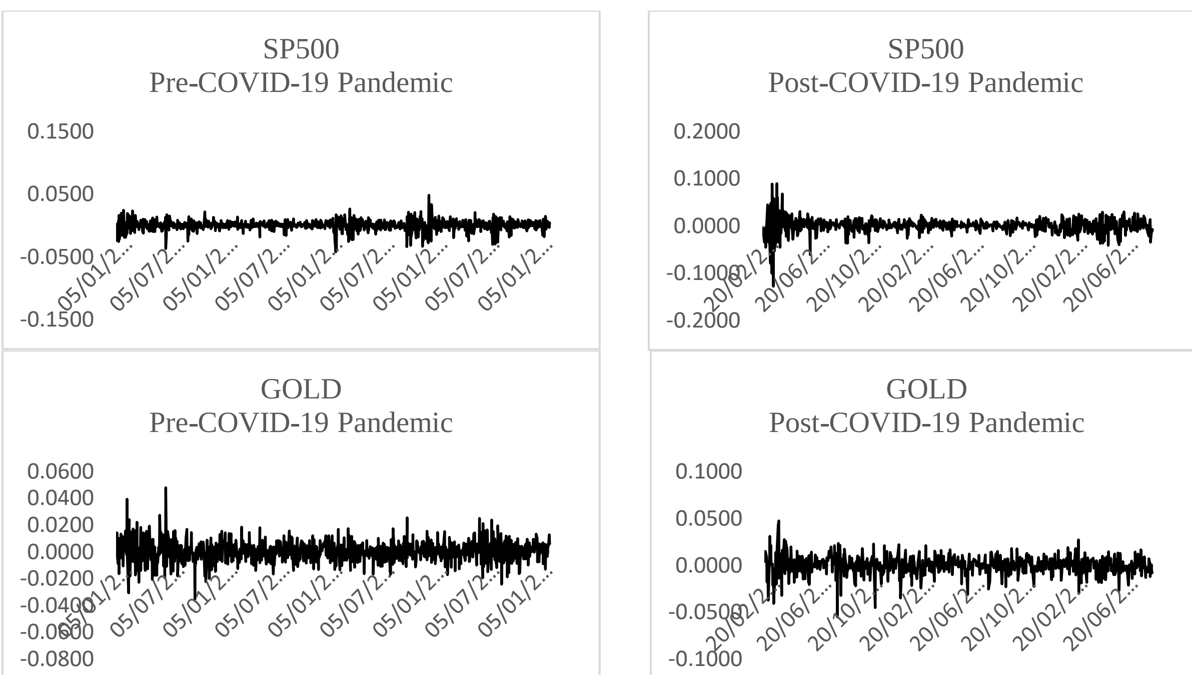
In Figure 1, it is evident that S&P 500 Index, gold, and bitcoin have time-varying volatilities for both pre- and post-pandemic periods. Thus, it is reasonable to use a GARCH-type process to model their volatilities. As shown in Ross (1989), volatilities play an important role in explaining information flows. We employ the following ARCH-GARCH model with exogeneous variables.

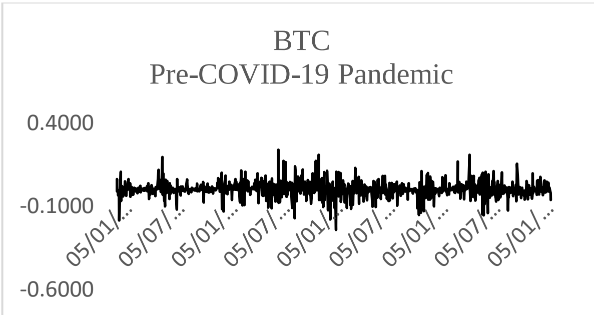
$$a_{it} = b_0 + \sum_{k=1}^{n} b_{ik}\varphi^k a_{it} + \varepsilon_{it} \tag{1}$$

$$\varepsilon_{it}|\Gamma_{it-1} \sim N\left(0, \eta_{it}^2\right)$$
$$\eta_{it}^2 = \beta_0 + \sum_{j=1}^{p} \beta_j \varphi^j \varepsilon_{it}^2 + \sum_{j=1}^{q} \gamma_j \varphi^j \eta_{it}^2 + \sum_{\ell \neq i}^{m} (\theta_\ell + \mu_{\ell,war} D_{\ell,war})\, \varepsilon_\ell^2 \tag{2}$$

Equation (1) is the autoregressive model (AR) as the mean process where a_{it} is asset i's return at time t, n is the number of lags, $\varphi^k$is a lag operator, and Γ_{it-1} is an information set at time t-1. The number of lags is determined based on the Bayesian Information Criterion. To incorporate time-varying volatilities into the variance equation, we employ the well-known GARCH (1,1) process for Equation (2) where ε_ℓ^2 are squared errors of asset ℓ. To consider the impact of the Russia-Ukraine war, we add an indicator variable, $D_{\ell,war}$, that takes a value of 1 if t is after February 24, 2022 and 0 otherwise.

FIGURE 1
PRE- AND POST-COVID-19 DAILY RETURNS





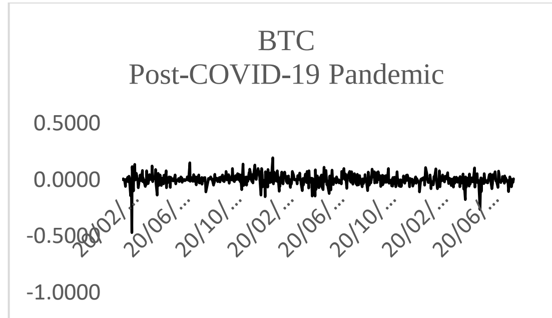


Table 2 reports the results of our AR-GARCH model, with Panel A showing pre-pandemic and Panel B showing post-pandemic results. It is evident that there is a significant difference between the periods. In the pre-pandemic period, θ_{SP500} on GOLD and θ_{GOLD} on SP500 are statistically significant at the 1% level, which means that there are strong interdependent volatility spillovers between stock and gold. Stock and bitcoin also show strong interdependent spillover effects. However, for gold and bitcoin, the volatility transmission is unidirectional from gold to bitcoin.

TABLE 2
VOLATILITY SPILLOVERS

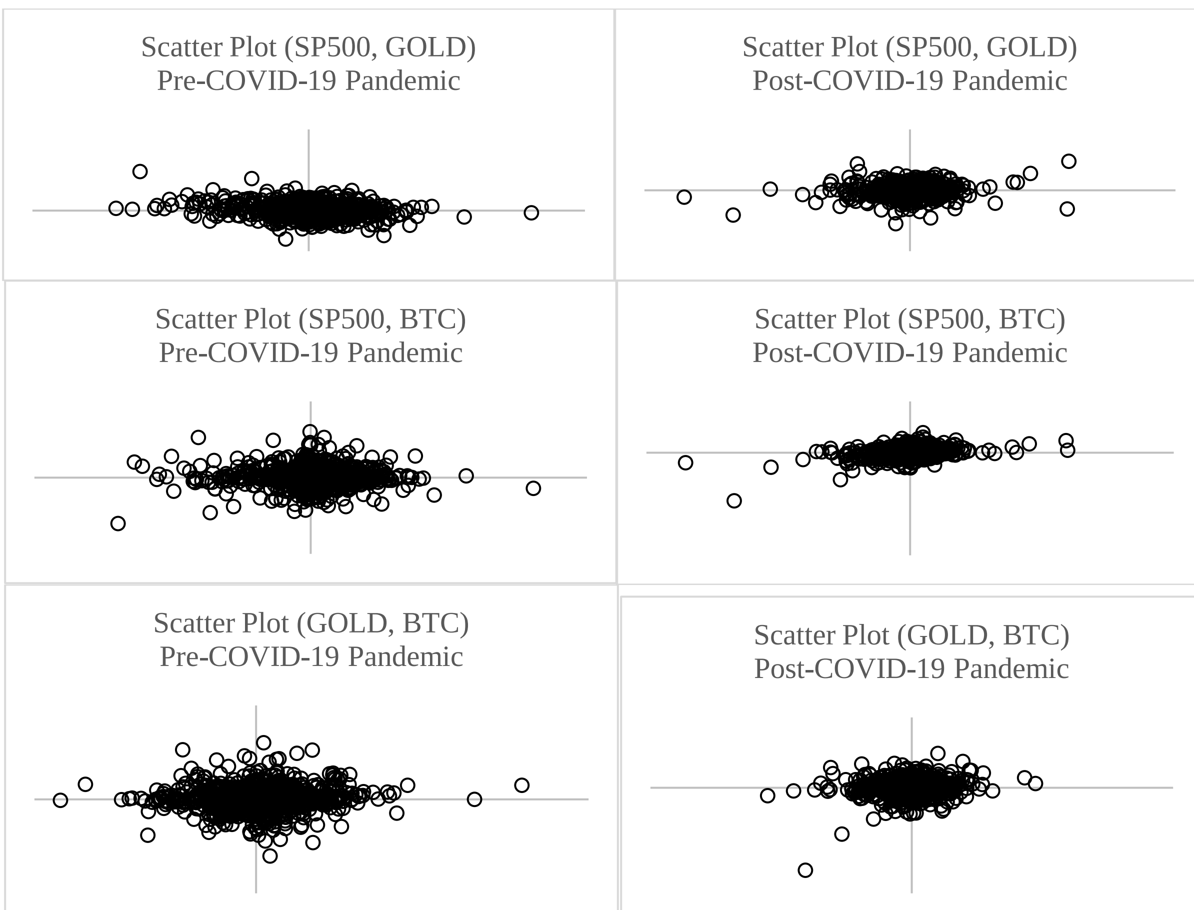
DV	SP500	GOLD	BTC
Panel A: Pre-COVID-19 Pandemic			
β_0	0.000003**	0.000053**	0.000134**
β_1	0.210300**	-0.016990	0.048597**
γ_1	0.722490**	-0.094463	0.914880**
θ_{SP500}	-	0.199890**	-0.269060**
θ_{GOLD}	0.051457**	-	-0.886470**
θ_{BTC}	-0.000369**	-0.000376	-
Panel B: Post-COVID-19 Pandemic			
β_0	0.000007*	0.000011*	0.000073
β_1	0.228850**	0.070824*	0.001056
γ_1	0.714140**	0.774590**	0.960670**
θ_{SP500}	-	0.019328	0.006441
θ_{GOLD}	0.010002	-	-0.020722
θ_{BTC}	0.000384	-0.000669	-
$\mu_{SP500,war}$	-	-0.021696	0.031644
$\mu_{GOLD,war}$	-0.163320	-	-0.037335
$\mu_{BTC,war}$	0.025357*	0.001060	-
DV – Dependent Volatility * and ** indicate statistical significance at the 5%, and 1% levels, respectively.			

In the post-pandemic period, θ_{SP500}, θ_{GOLD}, and θ_{BTC} are not statistically significant at all, which means that there are no strong volatility spillovers across stock, gold, and bitcoin. In this study, since the post-pandemic period covers the extended period from February 2020 to August 2022, our data reflect not only the initial impact of the COVID-19 pandemic but also its lingering effects. Thus, although the results in Panel B support Hypothesis 1, they imply that risk transmissions under the on-going COVID-19 pandemic become weakened rather than strengthened.

Panel B also reports the impact of the recent Russia-Ukraine war on volatility spillovers. Since $\lambda_{BTC,war}$ on SP500 is statistically significant at the 5% level, there exists a significant difference in volatility spillover unidirectionally from bitcoin to stock after the war though the volatility spillover between stock and bitcoin is not statistically significant during the post-pandemic period. However, no other dummy variables are statistically significant. As a result, the recent Russia-Ukraine conflict appears to have little impact on volatility spillovers. This does not support Hypothesis 1.

Next, we examine extreme return movements between stock, gold, and bitcoin. Extreme return movements may be considerably different regardless of volatility spillover effects. Even if two assets' volatilities are significantly interdependent, it doesn't necessarily mean that their extreme returns (e.g., lowest 1st or 5th percentile returns) also move together in bad times. We use a bivariate copula to look at extreme return movements between stock, gold, and bitcoin. We select the Clayton copula which is an asymmetric copula that gives greater dependence weight to the negative tail of the distribution. The bivariate copula provides probabilities that two assets' returns simultaneously fall within their nth percentiles. In other words, we can see how likely two assets' extreme returns are to move together.

FIGURE 2
SCATTER PLOTS



Klugman et al. (2008) provide details about many different types of copulas. According to Sklar's theorem, there exists a unique copula (C) for any joint distribution function (F), and it satisfies the following equation.

$$F(x_1, x_2) = \mathrm{C}\big(F_1(x_1), F_2(x_2)\big) \tag{3}$$

The Archimedean copula is defined as the bivariate joint distribution with marginal distributions as follows.

$$\mathrm{C}(u_1, u_2) = \mu^{-1}(\mu(u_1) + \mu(u_2)) \tag{4}$$

where $\mu(u)$ is a copula generator. Then, with $\mu(u) = \left(-\frac{1}{d}\right)\left(1 - u^{-d}\right)$, the Clayton copula is defined as follows.

$$C(u_1, u_2) = Max\left[(u_1^{-d} + u_2^{-d} - 1)^{-\frac{1}{d}}, 0\right] \tag{5}$$

$$\tau = \frac{d}{2+d} \tag{6}$$

where d is a dependence parameter. The dependence parameter of the Clayton copula is mathematically linked with Kendall's tau (τ) in Equation (6). We estimate the likelihood that extreme returns on stock, gold, and bitcoin move simultaneously.

TABLE 3
COPULA PROBABILITIES

Bivariate Returns	(SP500, GOLD)	(SP500, BTC)	(GOLD, BTC)
Panel A: Pre-COVID-19 Pandemic			
Lowest 10^{th} P	0.001391	0.009873	0.015369
Lowest 5^{th} P	0.000016	0.002446	0.004984
Lowest 1^{th} P	ND	0.000095	0.000429
Panel B: Post-COVID-19 Pandemic			
Lowest 10^{th} P	0.018119	0.038778	0.017633
Lowest 5^{th} P	0.006376	0.017841	0.006125
Lowest 1^{th} P	0.000674	0.003240	0.000627
Note: The lowest n^{th} P is the probability that both returns fall within their lowest n^{th} percentiles simultaneously. ND – Not Defined.			

Table 3 shows probabilities that two assets' returns simultaneously fall within their lowest n^{th} percentiles. Although the probabilities for lowest 1^{st}, 5^{th}, and 10^{th} percentiles are very low across pre- and post-pandemic periods, they substantially rise during the post-pandemic period. For instance, the probability that stock and bitcoin returns simultaneously fall within their lowest 1^{st} (5^{th}) percentiles increases from 0.000095 (0.002446) to 0.003240 (0.017841), which means that the probability increases almost 34 (7) times. This implies that the likelihood that stock and bitcoin's extreme returns simultaneously move significantly increases during the post-pandemic period. For stock investors, gold appears to be a better flight-to-safety asset than bitcoin across the pre- and post-pandemic periods given that the probability that stock and gold's extreme returns simultaneously move are lower than the probability that stock and bitcoin's extreme returns simultaneously move. For gold investors, while stock is a better flight-to safety asset during the pre-pandemic period, bitcoin takes this position during the post-pandemic period. Similarly, for bitcoin investors, while stock is a better flight-to-safety asset during the pre-pandemic period, gold takes this position during the post-pandemic period. Overall, the results support Hypothesis 2.

CONCLUSION

We examine volatility spillovers and extreme return movements across stock, gold, and bitcoin focusing on the impact of the COVID-19 pandemic. While there exist significant volatility spillover effects across stock, gold, and bitcoin during the pre-pandemic period, these spillover effects are substantially weakened during the post-pandemic period. Because we use a post-pandemic period of up to two and a half years in order to reflect the lingering effects of the pandemic in addition to its initial impact, our results differ with those of some recent studies that use a short post-pandemic period to focus only on its initial impact. Thus, our study shows new results with the extended data under the on-going pandemic. Our study also investigates the impact of the recent Russia-Ukraine war on volatility spillovers during the post-pandemic period. By and large, the Russia-Ukraine conflict has little impact on volatility spillover effects.

We examine extreme return movements separately. Even if two assets' volatilities are strongly interdependent, it doesn't necessarily mean that their extreme returns also move together in a bad time. Our results show that the likelihood that extreme returns simultaneously move significantly rises during the post-pandemic period. Moreover, gold appears to be a better flight-to-safety asset for stock than bitcoin in both pre- and post-pandemic periods. While stock is a better flight-to-safety asset for gold in the pre-pandemic period, bitcoin becomes a better option for gold in the post-pandemic period. Similarly, while stock is a better flight-to-safety asset for bitcoin in the pre-pandemic period, gold takes the position for bitcoin in the post-pandemic period.

In sum, it seems clear that the on-going COVID-19 pandemic has a substantial impact on volatility spillovers and extreme return movements across stock, gold, and bitcoin. Because our post-pandemic period is greatly extended to reflect the lingering effects of the COVID-19 pandemic, our results are expected to provide a new insight to policymakers as well as professional investors.

REFERENCES

Ahmed, S., Hasan, M., & Kamal, M. (2022). Russia-Ukraine crisis: The effects on the European stock market. *European Financial Management*. https://doi.org/10.1111/eufm.12386

Baek, C., & Jackman, T. (2021). Safe-Haven Assets for U.S. Equities during the 2020 COVID-19 Bear Market. *Economics and Business Letters*, *10*(3), 331–335.

Baele, L. (2005). Volatility Spillover Effects in European Equity Markets. *Journal of Financial and Quantitative Analysis*, *40*(2), 373–401.

BenSaïda, A., Litimia, H., & Abdallah, O. (2018). Volatility spillover shifts in global financial markets. *Economic Modelling*, *73*, 343–353.

Billio, M., & Pellizon, L. (2003). Volatility and shocks spillover before and after EMU in European stock markets. *Journal of Multinational Financial Management*, *13*, 323–340.

Boubaker, S., Goodell, J., Pandey, D., & Kumari, V. (2022). Heterogeneous impacts of wars on global equity markets: Evidence from the invasion of Ukraine. *Finance Research Letters*, *48*(3), 102934.

Boungou, W., & Yatie, A. (2022). The impact of the Ukraine-Russia war on world stock market returns. *Economics Letters*, *215*, 110516.

Caloia, F.G., Cipollini, A., & Muzzioli, S. (2018). Asymmetric semi-volatility spillover effects in EMU stock markets. *International Review of Financial Analysis*, *57*, 221–230.

Choudhry, T., & Jayasekera, R. (2014). Returns and volatility spillover in the European banking industry during global financial crisis: Flight to perceived quality or contagion? *International Review of Financial Analysis*, *36*, 36–45.

Christiansen, C. (2007). Volatility-Spillover Effects in European Bond Markets. *European Financial Management*, *13*(5), 923–948.

Conlon, T., & McGee, R. (2020). Safe haven or risky hazard? Bitcoin during the Covid-19 bear market. *Finance Research Letters*, *35*, 101607.

Dean, W., Faff, R., & Loudon, G.F. (2010). Asymmetry in return and volatility spillover between equity and bond markets in Australia, *Pacific-Basin Finance Journal*, *18*(3), 272–289.

Di, M., & Xu, K. (2022). COVID-19 vaccine and post-pandemic recovery: Evidence from Bitcoin cross-asset implied volatility spillover. *Finance Research Letters*, *50*, 103289.
Elsayed, A.H., Gozgor, G., & Lau, C.K. (2022). Risk transmissions between bitcoin and traditional financial assets during the COVID-19 year: The role of global uncertainties. *International Review of Financial Analysis*, *81*, 102069.
Gao, R., Zhao, Y., & Zhang, B. (2021). The spillover effects of economic policy uncertainty on the oil, gold, and stock markets: Evidence from China. *International Journal of Finance and Economics*, *26*(2), 2134–2141.
Hamao, Y., Masulis, R.W., & Ng, V.K. (1990). Correlations in Price Changes and Volatility across International Stock Markets. *Review of Financial Studies*, *3*, 281–307.
Jiang, S., Li, Y., Lu, Q., Wang, S., & Wei, Y. (2022). Volatility communicator or receiver? Investigating volatility spillover mechanisms among Bitcoin and other financial markets. *Research in International Business and Finance*, *59*, 101543.
Katsiampa, P., Corbet, S., & Lucey, B. (2019). Volatility spillover effects in leading cryptocurrencies: A BEKK-MGARCH analysis. *Finance Research Letters*, *29*, 68–74.
King, M., Sentana, E., & Wadhwani, S. (1994). Volatility and Links between National Stock Markets. *Econometrica*, *62*, 901–933.
Klugman, S., Panjer, H., & Willmot, G. (2008). *Loss models from data to decisions*. John Wiley & Sons, Hoboken, New Jersey.
Koutmos, G., & Booth, G.G. (1995). Asymmetric Volatility Transmission in International Stock Markets. *Journal of International Money and Finance*, *14*, 747–762.
Kumar, A. (2020). Testing Safe Haven Property of Bitcoin and Gold during Covid-19: Evidence from Multivariate GARCH analysis. *Economics Bulletin*, *40*(3), 2005–2015.
Li, Y., & Giles, E.G. (2015). Modelling Volatility Spillover Effects Between Developed Stock Markets and Asian Emerging Stock Markets. *International Journal of Finance & Economics*, *20*(2), 155–177.
Lin, W-L., Engle, R.F., & Ito, T. (1994). Do Bulls and Bears Move across Borders? International Transmission of Stock Returns and Volatility. *Review of Financial Studies*, *7*, 507–538.
Liow, K.H. (2015). Volatility spillover dynamics and relationship across G7 financial markets. *The North American Journal of Economics and Finance*, *33*, 328–365.
Liu, Y., & Pan, M.S. (1997). Mean and Volatility Spillover Effects in the U.S. and Pacific-Basin Stock Markets. *Multinational Finance Journal*, *1*(1), 47–62.
McDonald, R., Sogiakas, V., & Tsopanakis, A. (2018). Volatility Co-Movements and Spillover Effects within the Eurozone Economies: A Multivariate GARCH Approach Using the Financial Stress Index. *Journal of International Financial Markets, Institutions and Money*, *52*, 17–36.
Ross, S. (1989). Information and volatility: The no-arbitrage martingale approach to timing and resolution irrelevancy. *Journal of Finance*, *45*, 1–17.
Wang, Y., Pan, Z., & Wu, C. (2018). Volatility spillover from the US to international stock markets: A heterogeneous volatility spillover GARCH model. *Journal of Forecasting*, *37*(3), 385–400.
Xu, Y., Taylor, N., & Lu, W. (2018). Illiquidity and volatility spillover effects in equity markets during and after the global financial crisis: An MEM approach. *International Review of Financial Analysis*, *56*, 208–220.
Yang, Z., Zhou, Y., & Cheng, X. (2020). Systemic Risk in Global Volatility Spillover Networks: Evidence from Option-Implied Volatility Indices. *The Journal of Futures Markets*, *40*(3), 392–409.
Yip, P.S., Brooks, R., Do, H.X., & Nguyen, D.K. (2020). Dynamic volatility spillover effects between oil and agricultural products. *International Review of Financial Analysis*, *69*, 101465.
Yousaf, I., Beljid, M., Chaibi, A., & Ajlouni, A.A. (2022). Do Volatility Spillover and Hedging among GCC Stock Markets and Global Factors Vary from Normal to Turbulent Periods? Evidence from the Global Financial Crisis and COVID-19 Pandemic Crisis, *Pacific-Basin Finance Journal*, *73*, 101764.

Yousaf, I., Patel, R., & Yarovaya, L. (2022). The reaction of G20+ stock markets to the Russia–Ukraine conflict “black-swan” event: Evidence from event study approach. *Journal of Behavioral and Experimental Finance*, *35*, 100723
Zhang, J., & He, Q.-Z. (2021). Dynamic Cross-Market Volatility Spillover Based on MSV Model: Evidence from Bitcoin, Gold, Crude Oil, and Stock Markets. *Complexity*, *9912418*.