Journal of Economics and Financial Analysis
Type: Double Blind Peer Reviewed Scientific Journal
Printed ISSN: 2521-6627 | Online ISSN: 2521-6619
Publisher: Tripal Publishing House | DOI:10.1991/jefa.v8i2.a73
Received: 07.02.2024 | Accepted: 15.05.2024 | Published: 14.07.2024
Journal homepage: ojs.tripaledu.com/jefa

Spillover Volatility Effect Return Of Stock, Gold, and Cryptocurrency: Evidence of Peak Pandemic and Transition towards Endemic COVID-19 in Indonesia

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Abstract

This study examines the volatility spillover effects among stock, gold, and cryptocurrency returns during the peak of the COVID-19 pandemic and the transition to the endemic phase. The objective is to identify and model the volatility of these three investment instruments using GARCH/EGARCH for univariate modeling and BEKK-GARCH/BEKK-Asymmetric GARCH for multivariate modeling.

The study utilizes daily highest price data from November 1, 2020, to April 30, 2022, and from May 1, 2022, to December 31, 2022. The findings reveal that cryptocurrency is the most volatile asset during both the peak of the pandemic and the transitional period towards endemic COVID-19. Gold serves as a safe haven for cryptocurrency in both periods. Additionally, gold acts as a diversifier for stocks, and vice versa, while stocks also diversify cryptocurrency risk during the pandemic peak. These insights hold significant implications for portfolio risk management, enabling investors to diversify portfolios across instruments with varying risk profiles.

Keywords: *Volatility; BEKK-AGARCH; Stocks; Gold; Cryptocurrency; COVID-19.*

JEL Classification: *G11, C22, C32.*

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1. Introduction & Literature

The Coronavirus Disease in 2019 (COVID-19), defined by the World Health Organization (WHO), is an infectious disease caused by a newly discovered virus that led to a global pandemic. To curb the spread of COVID-19, governments worldwide implemented various policies that limited outdoor activities. These restrictions hindered economic activity, as highlighted by Solow's theory of economic growth, which posits that investment can spur economic growth by increasing capital stock (Mankiw, 2019). This study examines the impact of the pandemic on different financial instruments to understand the resultant market dynamics.

In Indonesia, financial investments, according to a report by Badan Pusat Statistik (2022)[1], are made through various instruments such as stocks, gold, and cryptocurrencies. The proportion of financial investments increased from 38.91% in 2020 to 43.86% in 2021, indicating improved public sentiment in the financial market post-pandemic. This trend reflects how the COVID-19 pandemic influenced investor behavior, prompting a closer look at specific investment choices during this period.

Stocks, representing ownership in a company (Oei, 2009), had significant activity during the pandemic. Data from KSEI reveals a consistent annual increase in listed companies, with a notable rise of 15.71 percentage points by December 2022 compared to early 2020[2]. The number of stock investors also surged, with a drastic 155.04 percentage point increase in November 2022 compared to the beginning of the pandemic. These changes suggest a growing confidence in the stock market despite economic uncertainties.

Simultaneously, cryptocurrencies emerged as a new financial investment field. These digital currencies, based on cryptographic protocols, ensure anonymity, low costs, and fast peer-to-peer transactions (Ghorbel et al., 2022). Cryptocurrency was introduced to Indonesia in 2014 through the Indodax exchange. The increasing interest in cryptocurrencies during the pandemic period warrants an examination of their volatility and risk compared to traditional assets.

Alternatively, the gold, traditionally viewed as a hedge against inflation, a safe haven investment, and a tool for portfolio diversification (Henriques & Sadorsky, 2018), also saw increased interest. Data from the Jakarta Futures

[1] Badan Pusat Statistik. (2022). Annual Indonesian flow of funds accounts 2017-2021. Badan Pusat Statistik. https://www.bps.go.id/en/publication/2022/09/30/ec0149e9ba9597328f991662/annual-indonesian-flow-of-funds-accounts-2017-2021.html

[2] The data from PT Kustodian Sentral Efek Indonesia (KSEI), https://www.ksei.co.id

Exchange (JFX) indicates that gold was a preferred asset during the pandemic, with increasing trading volumes of gold futures[3]. This behavior highlights gold's role as a stabilizing force in volatile times.

The spread of the mutated COVID-19 virus caused panic and uncertainty in financial markets, leading to heightened volatility (Haroon & Rizvi, 2020). The impact of COVID-19 on market volatility surpassed that of the 2008 Global Financial Crisis (Zhang & Hamori, 2021). The Jakarta Composite Index (JCI) experienced significant fluctuations, mirroring past financial crises and showing the sensitivity of the stock market to global disruptions.

Similar fluctuations were experienced in cryptomarkets as well. Bitcoin, the first cryptocurrency with the largest market capitalization, has undergone several market downturns during COVID-19 period. These declines highlight the inherent risks of cryptocurrency as an investment. Therefore, understanding the volatility of cryptocurrencies relative to traditional assets like gold and stocks can provide valuable insights for investors (Rahmi and Nasrudin, 2023; Putra, 2022; Puryandani and Robiyanto, 2019; Dyhrberg, 2016; Ibrahim, 2012).

With this motivation, this study aims to examine the volatility spillover effects among stock, gold, and cryptocurrency during COVID-19 period. This volatility, a risk proxy, can be measured using variance or standard deviation using GARCH/EGARCH univariate techniques. However, the volatility spillover, where the volatility of one market affects another, can be examined using multivariate volatility modeling (Xiong & Han, 2015). These methods provide a comprehensive understanding of market dynamics during the pandemic.

Even though there are sizeable liturature on related topic such as Ghorbel et al. (2022), and Yousaf and Ali (2021), Shen (2023), Ustaoglu (2022), Hsu et al. (2021), Huynh et al. (2020), Liu and Serletis (2019), Malhotra and Gupta (2019), Warsito and Robiyanto (2020), and Syahri and Robiyanto (2020), but these studies do not cover transition periods of the COVID-19 pandemic specifically. Therefore, this study provides significant contribution by examining volatility of stock market, gold, and cryptocurrencies during three COVID-19 waves and the transition to endemic status and offers a novel perspective on investment behavior during distinct phases of the pandemic. These insights help investors avoid concentrating on high-risk assets.

The remainder of this paper is structured as follows: Section 2 reviews the literature, Section 3 outlines the data and methodology, Section 4 presents the empirical findings, and Section 5 concludes the study.

[3] The data from Jakarta Futures Exchange (JFX). https://www.jfx.co.id/media?hal=home

2. Literature Review

The impact of the COVID-19 pandemic on financial markets has been a significant area of study, with various researchers examining how different asset classes responded to the crisis. Ghorbel et al. (2022) analyzed the volatility spillovers among stocks, gold, and cryptocurrencies during the pandemic. Their study found that cryptocurrencies exhibited the highest volatility, followed by stocks and gold. They concluded that gold acted as a safe haven during the peak of the pandemic, providing stability in highly volatile market conditions.

Yousaf and Ali (2021) explored the dynamic correlations between financial assets during the COVID-19 pandemic. Their research focused on the interdependencies among stocks, gold, and cryptocurrencies. They discovered that the correlations between these assets increased significantly during the pandemic, highlighting the interconnected nature of financial markets in times of crisis. The study emphasized the importance of diversification strategies for investors to mitigate risks associated with highly correlated assets.

Shen (2023) investigated the hedging and safe-haven properties of gold and cryptocurrencies during the COVID-19 pandemic. Using a multivariate GARCH model, Shen found that gold consistently served as a hedge against stock market volatility, while cryptocurrencies exhibited mixed results. The study suggested that while cryptocurrencies could offer diversification benefits, their role as a safe haven was not as robust as that of gold.

Ustaoglu (2022) examined the impact of the COVID-19 pandemic on cryptocurrency markets, focusing on Bitcoin. The study employed an EGARCH model to analyze the volatility dynamics and found that Bitcoin's volatility was significantly affected by pandemic-related news and events. The research highlighted the sensitivity of cryptocurrency markets to global uncertainties and the importance of considering such factors in investment decisions.

Hsu et al. (2021) conducted a comparative analysis of traditional and digital assets during the pandemic. Their study found that while both asset classes experienced increased volatility, cryptocurrencies were more sensitive to market shocks. The findings suggested that traditional assets like gold provided more stable returns during the crisis, reinforcing their role as safe-haven assets.

Huynh et al. (2020) explored the flight-to-quality phenomenon during the COVID-19 pandemic, where investors shift from riskier assets to safer ones. Their study indicated that gold experienced increased demand as a safe-haven asset, while cryptocurrencies saw mixed reactions from investors. The research underscored the complexity of investor behavior during periods of extreme market stress and the varying roles of different assets.

Liu and Serletis (2019) investigated the volatility and spillover effects in cryptocurrency markets prior to and during the pandemic. Their findings revealed that the volatility in cryptocurrency markets was exacerbated during the pandemic, with significant spillover effects to other financial markets. The study highlighted the interconnectedness of global financial markets and the systemic risks posed by cryptocurrencies.

Malhotra and Gupta (2019) focused on the diversification benefits of including cryptocurrencies in investment portfolios. They found that cryptocurrencies offered potential diversification benefits due to their low correlation with traditional assets like stocks and gold. However, their research also cautioned about the high volatility and risk associated with cryptocurrencies, emphasizing the need for careful risk management.

Warsito and Robiyanto (2020) examined the formation of dynamic portfolios between cryptocurrencies and stocks in Indonesia. Their study did not cover the pandemic period but provided insights into the potential benefits of including cryptocurrencies in investment portfolios. They found that while cryptocurrencies could enhance portfolio performance, the associated risks required careful consideration.

This study builds on the existing literature by analyzing the volatility of stock, gold, and cryptocurrency returns during the peak of the pandemic and the transition towards endemic COVID-19 in Indonesia. It employs advanced volatility modeling techniques such as GARCH/EGARCH and BEKK-GARCH to provide a comprehensive understanding of the risk dynamics.

3. Data and Methodology

3.1. Data

The data used in this study is secondary data time series of the highest prices with daily observation units. Stock data uses the Jakarta Composite Index (JCI) approach obtained through Yahoo Finance[4], gold data use gold futures prices obtained through investing.com[5] and cryptocurrency data uses the CCi30 index approach obtained through the website cci30.com[6]. For the analysis, price data is changed in the form of returns. The following is the return calculation formula according to (Brooks, 2008).

$$Return = Ln\left(\frac{P_t}{P_{t-1}}\right) \times 100\% \tag{1}$$

Where a return is expressed in percentage form, P_t is the t-time price.

[4] Website to retrieve the data https://finance.yahoo.com
[5] Website to retrieve the data https://www.investing.com
[6] Website to retrieve the data https://cci30.com

We classify transition periods of COVID-19 as table 1.

Table 1. Transition Periods of Covid-19 Pandemic

Period	Start	End
Peak of The Pandemic COVID-19	1st November 2020	30th April 2022
Transition Towards Endemic COVID-19	1st May 2022	31st December 2022

3.2. GARCH/EGARCH Model

This study first identifies whether stock, gold, and cryptocurrency returns have volatility by univariate volatility modeling using GARCH/EGARCH. If volatility is detected, then multivariate modeling is continued using BEKK-GARCH/BEKK-AGARCH. The software used in univariate volatility modeling is EViews 10. For asymmetric univariate volatility modeling or using EGARCH, multivariate modeling uses BEKK-AGARCH. Conversely, if the univariate volatility modeling is symmetrical then the multivariate modeling uses BEKK-GARCH.

The GARCH/EGARCH analysis stage begins with stationarity testing using the Augmented Dickey-Fuller (ADF) test with a random walk without drift model. Gujarati, D.N (2004), The following is the Augmented Dickey-Fuller (ADF) test equation.

$$\Delta Return_t = \delta * Return_{t-1} + \sum_{i=1}^{m} \omega_i * \Delta Return_{t-\mathrm{i}} + \varepsilon_t \tag{2}$$

The test statistic used is $\tau = \frac{\hat{\delta}}{se(\hat{\delta})}$. The test statistic is then compared with the critical value of the MacKinnon ($\tau_{\alpha(n-k)}$). If the value $\tau > \tau_{\alpha(n-k)}$with k is the number of parameters and n is the number of observations, it means that the decision is rejected H_0or the time series is stationary.

Forming a model with ARMA, first tentatively identified to find out the appropriate values of p and q by trial and error. Then determine the best model using a number of criteria, with the largest value of log-likelihood, the smallest value of Akaike info criteria, and the smallest value of Schwarz criteria. After determining the best model using some of these criteria, estimate the ARIMA model. The following is the ARMA(p,q) model equation (Makridakis et al., 1997).

$$Return_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Return_{t-i} + \sum_{j=1}^{q} \beta_j u_{t-j} + u_t \tag{3}$$

Where α_0 is the intercept coefficient, the α_i is autoregressive coefficient i-th, where i=1,2,…,p and is the error at time t. The ARMA model diagnostic testing includes simultaneous tests, partial tests, and evaluation after estimation. Evaluation after estimation includes residual ADF test and ARCH-LM test (Gujarati, D.N, 2004). The following is the ARCH-LM testing equation.

$$\hat{u}_t^2 = \alpha_0 + \alpha_1 \hat{u}_{t-1}^2 + \cdots + \alpha_q \hat{u}_{t-n}^2 + v_t \tag{4}$$

Where $\hat{u}_t$ obtained by estimating the model for the conditional mean of the observed time series $y_t$under the null hypothesis. With test statistics $LM = TR^2$. Where T is the number of observations and $R^2$is the coefficient of determination of the model. The decision is rejected $H_0$when the test statistic $LM > X_n^2$with n is the number of observations. Rejected H_0 means that there is a residual ARCH effect. The analysis is continued using the GARCH/EGARCH model.

After establishing the ARCH/GARCH model, perform a diagnostic test that has the same stages as the ARMA model. The following is the general model GARCH(r,s) according to (Enders, 2014).

$$\sigma_t^2 = \lambda_0 + \sum_{t=i}^{s} \lambda_i u_{t-i}^2 + \sum_{t=j}^{r} \gamma_j \sigma_{t-j}^2 \tag{5}$$

Where σ_t^2 is the conditional variance of error the t-time variance equation and u_{t-i} is white noise, lag error of the ARIMA equation at the i-th time, with i=1,…,s.

Formation of an asymmetric EGARCH model using EGARCH. The following is the general model EGARCH(r,s) according to (Enders, 2014).

$$\ln(\sigma_t^2) = \lambda_0 + \sum_{i=1}^{s} \lambda_i \left|\frac{u_{t-i}}{\sigma_{t-i}}\right| + \sum_{k=1}^{n} \varphi_k \left(\frac{u_{t-k}}{\sigma_{t-k}}\right) + \sum_{j=1}^{r} \gamma_j \ln(\sigma_{t-j}^2) \tag{6}$$

Where $\varphi_k$is the leverage effect coefficient. If $\frac{u_{t-k}}{\sigma_{t-k}}$positive, the effect of the shock on the log of the conditional variance is $\lambda_i + \varphi_k$. If $\frac{u_{t-k}}{\sigma_{t-k}}$it is negative, the effect of shocks on the conditional log variance is $\lambda_i - \varphi_k$. Next, diagnostic tests such as ARIMA modeling namely simultaneous tests, partial tests and evaluation after estimation include residual ADF tests and ARCH-LM tests (Gujarati, D.N, 2004). After modeling using GARCH/EGARCH, estimate the conditional variance as a proxy for risk.

3.3. BEKK-GARCH Model

When the univariate volatility modeling is asymmetric or uses EGARCH, then the multivariate modeling uses BEKK-AGARCH. Conversely, if the univariate volatility modeling is symmetrical then the multivariate modeling uses BEKK-GARCH. The BEKK-GARCH methodology is the multivariate volatility analysis methodology that has advantages over other methods, in terms of the positive definite matrix of variance-covariance proposed by (Kroner and Ng, 1998). Thus, using the BEKK-AGARCH methodology, 4 effects can be analyzed, namely the auto effect, news spillover effect, volatility spillover effect, and an asymmetric spillover effect in the past. Meanwhile, if you use BEKK-GARCH, you can only analyze 3 effects, that cannot do an asymmetric spillover effect analysis in the past. In conducting multivariate volatility modeling using BEKK-GARCH it can be done with RATS software. The following is the estimation of the BEKK-AGARCH Model Parameters (Tsay, 2014).

$$\boldsymbol{\Sigma_t} = \boldsymbol{C}'\boldsymbol{C} + \boldsymbol{A}'u_{t-1}u_{t-1}'\boldsymbol{A} + \boldsymbol{B}'\boldsymbol{\Sigma_{t-1}}\boldsymbol{B} + \boldsymbol{D}'v_{t-1}v_{t-1}'\boldsymbol{D} \tag{7}$$

$$\boldsymbol{\Sigma_t} = \begin{bmatrix} \sigma_{11,t} & \sigma_{12,t} & \cdots & \sigma_{1k,t} \\ \sigma_{21,t} & \sigma_{22,t} & \cdots & \sigma_{2k,t} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{k1,t} & \sigma_{k2,t} & \cdots & \sigma_{kk,t} \end{bmatrix} \quad \boldsymbol{A} = \begin{bmatrix} \alpha_{11} & \alpha_{12} & \cdots & \alpha_{1k} \\ \alpha_{21} & \alpha_{22} & \cdots & \alpha_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{k1} & \alpha_{k2} & \cdots & \alpha_{kk} \end{bmatrix}$$

$$\boldsymbol{B} = \begin{bmatrix} \beta_{11} & \beta_{12} & \cdots & \beta_{1k} \\ \beta_{21} & \beta_{22} & \cdots & \beta_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{k1} & \beta_{k2} & \cdots & \beta_{kk} \end{bmatrix} \boldsymbol{C} = \begin{bmatrix} c_{11} & 0 & \cdots & 0 \\ c_{21} & c_{22} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ c_{k1} & c_{k2} & \cdots & c_{kk} \end{bmatrix} \boldsymbol{D} = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \cdots & \gamma_{1k} \\ \gamma_{21} & \gamma_{22} & \cdots & \gamma_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{k1} & \gamma_{k2} & \cdots & \gamma_{kk} \end{bmatrix}$$

Test the significance of the parameters of the BEKK-GARCH model. Parameter significance testing was carried out on each matrix element A, B and D to see the effect of the previous period's residual and conditional variance from other variables as well as the variable itself on the conditional variance value of the variables studied in the current period. Testing the significance using the t-test.

The BEKK-GARCH model diagnostic test includes testing on residuals that give residual white noise results. Testing on multivariate cases is the portmanteau test using standardized residuals. With the test statistics,

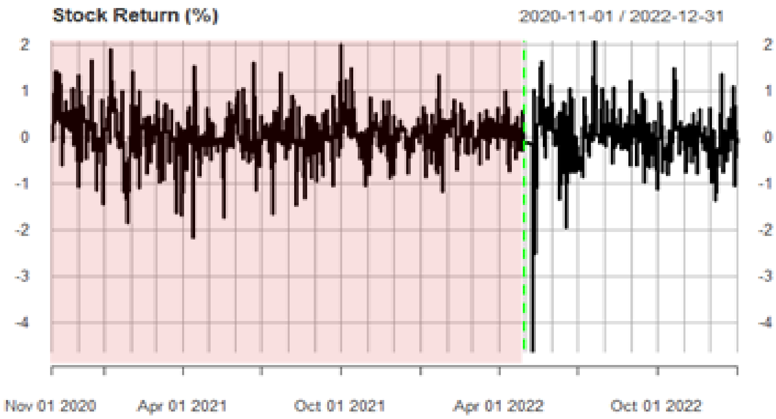
$$Q_k^*(m) = T^2 \sum_{i=1}^{m} \frac{1}{T-i} b_i' \left(\widehat{\boldsymbol{\rho_0}}^{\boldsymbol{-1}} \otimes \widehat{\boldsymbol{\rho_0}}^{\boldsymbol{-1}} \right) b_i \tag{8}$$

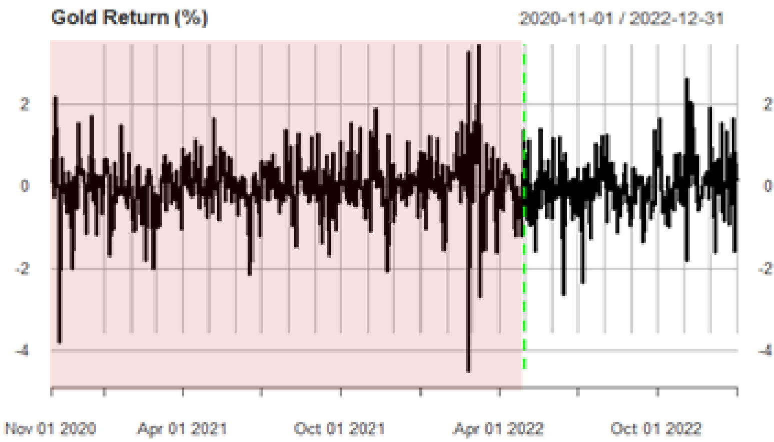
Rejected H_0 when $Q_k^*(m)$> $\chi^2_{k^2m}$. Where T is the number of observations, k is the number of dimensions, and m is the number of lags equal to ln T. If failed to rejected H_0, means that residuals is white noise.

Finally, calculate the time-varying correlation with the formula $\rho_{ij,t} = \frac{\sigma_{ij,t}}{\sqrt{\sigma_{ii,t}}\sqrt{\sigma_{jj,t}}}$ where $\rho_{ij,t}$ is the correlation of variables i and j in the t-period, $\sigma_{ij,t}$ is the covariance of variables i and j in the t-period, $\sigma_{ii,t}$ is the variance of variable i in the t-period and $\sigma_{jj,t}$ is the variance of variable j in the t-period.

4. Empirical Findings

The following figures show the returns of stocs, gold, and cryptocurrency at the peak of the COVID-19 pandemic and the transition period towards the endemic of COVID-19.





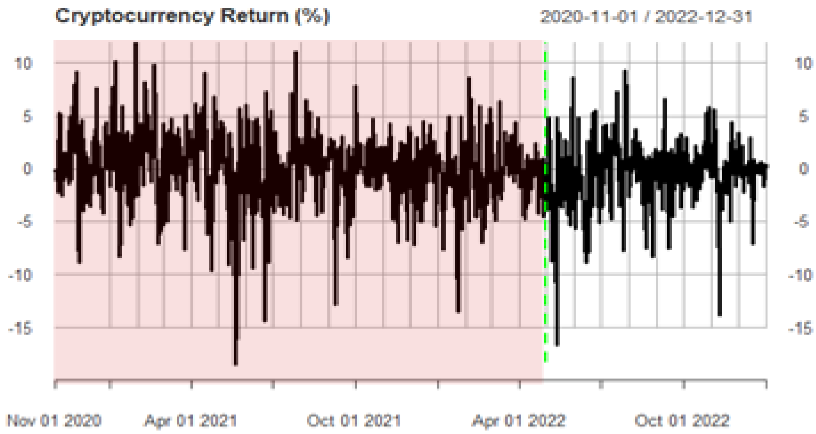


Figure 1. Returns of Stocks, Gold, and Cryptocurrency during the peak Covid-19

Notes: Red Background is Peak of the Pandemic COVID-19 and White Background Transition Towards Endemic COVID-19

Source: Yahoo Finance,investing.com and cci30.com.

At table 2, we present descriptive analysis of the returns of stocks, gold, and cryptocurrency markt during the peak COVID-19 and transition towards endemic COVID-19.

Table 2. Descriptive Statistics of Returns of Stocks, Gold, and Cryptocurrency

	Stock		**Gold**		**Cryptocurrency**	
	Peak	**Transition**	**Peak**	**Transition**	**Peak**	**Transition**
Average	0.063	-0.021	0.002	-0.017	0.21	-0.38
Median	0.072	0.013	0.019	-0.007	0.317	-0.155
Minimum	-2.179	-4.639	-4.517	-2.648	-18.475	-16.59
Maksimum	1.998	2.066	3.43	2.595	11.906	9.235
St. Deviation	0.511	0.631	0.677	0.664	3.658	3.242
Skewness	-0.295	-1.648	-0.631	1.034	-0.658	-0.857
Kurtosis	2.728	12.59	7.988	12.622	-0.658	3.71
Obs.	546	245	546	245	546	245

During the peak of the COVID-19 pandemic, stock returns were notably stable. This stability may be attributed to the improved performance of the Jakarta Composite Index (JCI) in response to the availability of COVID-19 vaccines in 2021 (Sitohang, 2021). The average return for stocks during this period was positive, standing at 0.063. Therefore, investors in the stock market, on average, benefitted from their investments during this time.

In contrast, during the transition period towards the COVID-19 endemic, the average return of stocks turned negative, recording at -0.021. This indicates that investors in the stock market, on average, experienced losses during this transitional phase. Despite the negative average return, a positive median suggests that while there were instances of negative shocks affecting returns, the overall distribution of returns was not skewed towards extreme losses.

In the case of gold, returns appear to be more stable during the transition towards the COVID-19 endemic. Overall, the average return of gold decreased by -0.017 during this transition period. This average is lower compared to the peak of the COVID-19 pandemic, implying that investors in the gold market during this period experienced losses on average. The median value of -0.007 and the standard deviation of 0.664 indicate that gold returns did not fluctuate as much as they did during the peak period of the COVID-19 pandemic.

In cryptocurrency market, returns were more volatile during the peak of the COVID-19 pandemic. During the transition period towards the COVID-19 endemic, the average return of the cryptocurrency market decreased to -0.38 percent. This average is lower compared to the peak period of the COVID-19 pandemic. Investors in cryptocurrencies typically exhibit a risk-taking behavior, as evidenced by the high volatility, frequent shocks, and susceptibility to news throughout this period. Such investors take substantial risks in anticipation of potentially high returns. On average and median, investors tend to benefit more from investing in cryptocurrencies. However, cryptocurrencies are riskier than stocks and gold, as indicated by their larger standard deviation..

4.1 GARCH/EGARCH Modeling

After conducting the stationarity test, the ARMA model formation proceeded according to Gujarati, D.N. (2004), utilizing the Box-Jenkins (BJ) methodology, which involves three sequential steps: identification of a tentative model, estimation of the ARMA model parameters, and diagnostic testing of the ARMA model. The following section presents the diagnostic tests conducted for the ARMA model.

Table 3. Best ARMA Model Results

Markets	Assumption	Period	
		Peak	***Transition***
Stock	*Model*	AR(1)	MA(3)
	ARCH-LM	0.005***	0.341
	ADF	0.000***	0.000***
	Conclusion	There is an ARCH Effect	Assumptions fulfilled
Gold	*Model*	ARMA(2.3)	ARMA(2.2)
	ARCH-LM	0.000***	0.077*
	ADF	0.000***	0.000***
	Conclusion	There is an ARCH Effect	There is an ARCH Effect
Crypto Currency	*Model*	AR(1)	AR(1)
	ARCH-LM	0.0020*** lag(2)	0.070*
	ADF	0.000***	0.000***
	Conclusion	There is an ARCH Effect	There is an ARCH Effect

Note: The ***, **, and * implies statistical significance at 1%, 5%, and 10% levels

The ARCH-LM test results reveal that ARIMA models derive significant ARCH effects for the three investment instruments at the peak of the COVID-19 pandemic at 1% level. However, in transitional period towards the COVID-19 endemic, only gold and cryotocurrency returns derive ARCH effect despite their statistical significance decreases to 10% level. On the other hand, the statistical significance of stocks returns dissapears during this period.

Consequently, GARCH/EGARCH technique is applied during the peak and the transition periods for all three investment instruments. The results of this analysis are given at table 4, where all chosen models seem to be appropriate and robust. The results show that EGARCH(1,1) is most appropriate model for stock returns during the peak COVID-19 pandemic period. Its diagnostics confirm that the variance of the residuals is constant over time. With another words, the residuals of these models do not comprise time-varying volatility, having white noise characteristics.

In table 5, we summarize estimated best models for each instrument during the peak and transitions periods.

Table 4. Results of GARCH/EGARCH Models

Markets	Assumption	Period	
		Peak	***Transition***
Stock	*Model*	EGARCH(1,1)	
	ARCH-LM	0.213	
	ADF	0.000***	
	Conclusion	Assumptions fulfilled	No ARCH Effect
Gold	*Model*	EGARCH(0,1)	GARCH(1,1)
	ARCH-LM	0.505	0.489
	ADF	0.000***	0.000***
	Conclusion	Assumptions fulfilled	Assumptions fulfilled
Crypto Currency	*Model*	EGARCH(1,1)	ARCH(1)
	ARCH-LM	0.967	0.421
	ADF	0.000***	0.000***
	Conclusion	There is an ARCH Effect	There is an ARCH Effect

Note: The ***, **, and * implies statistical significance at 1%, 5%, and 10% levels

Table 5. Choosen Models

Period	Investment Instrument	Model
Peak	*Stock*	AR(1) + EGARCH(1,1)
	Gold	ARMA(2,3) + EGARCH(0,1)
	Cryptocurrency	AR(1) + EGARCH(1,1)
Transition	*Gold*	ARMA(2,2)
		GARCH(1,1)
	Cryptocurrency	AR(1)
		ARCH(1)

Table 6. Results of BEKK-GARCH Model

Peak			Transition		
BEKK-AGARCH(1.1)			**BEKK-GARCH(1.1)**		
Parameter	***Coefficient***	***St. Error***	***Parameter***	***Coefficient***	***St. Error***
C(1.1)	0.417***	0.036	C(1.1)	0.591***	0.038
C(2.1)	-0.072	0.089	C(2.1)	0.203	0.447
C(2.2)	0.506***	0.075	C(2.2)	0.000	0.194
C(3.1)	0.314	0.371	α_{11}	0.361***	0.098
C(3.2)	0.275	0.488	α_{12}	0.157	0.459
C(3.3)	0.000	1.469	α_{21}	-0.053***	0.019
α_{11}	0.240***	0.076	α_{22}	0.067	0.05
α_{12}	-0.093	0.081	β_{11}	-0.083	0.266
α_{13}	1.402***	0.377	β_{12}	-0.329	0.801
α_{21}	0.067	0.041	β_{21}	0.021	0.034
α_{22}	0.442***	0.069	β_{22}	1.001***	0.009
α_{23}	0.059	0.263			
α_{31}	0.021*	0.011			
α_{32}	-0.043***	0.013			
α_{33}	0.208***	0.067			
β_{11}	0.283	0.190			
β_{12}	0.495**	0.221			
β_{13}	2.515***	0.960			
β_{21}	0.108	0.097			
β_{22}	0.184	0.139			
β_{23}	-0.528	0.587			
β_{31}	-0.026	0.016			
β_{32}	-0.025	0.026			
β_{33}	0.845***	0.058			
γ_{11}	0.351***	0.107			
γ_{12}	-0.064	0.117			
γ_{13}	-0.260	0.684			
γ_{21}	0.196***	0.071			
γ_{22}	-0.013	0.164			
γ_{23}	-0.119	0.398			
γ_{31}	-0.006	0.014			
γ_{32}	0.006	0.015			
γ_{33}	-0.168	0.110			

Subsequently, we employ BEKK-AGARCH (Asymmetric BEKK-GARCH) analysis. This is a multivariate extension of the GARCH model used to capture the volatility and spillover effects between multiple time series. It helps to model the conditional covariance matrix of multiple time series and captures the dynamic interrelationships and volatility spillovers between the series. Table 6 presents results of this analysis where we analyse four main components: Auto Effect, News Spillover Effect, Volatility Spillover Effect, and Asymmetric Spillover Effect. The BEKK-GARCH(1,1) model, in contrast, does not account for asymmetric spillover effects.

Auto Effect

The auto effect is observed through the main diagonals of matrices A and B. At the peak of the COVID-19 pandemic, all main diagonal elements in matrix A were significant at 5% level. This indicates that the volatility of returns for stocks, gold, and cryptocurrency is influenced by past news related to these instruments. This finding aligns with univariate volatility modeling, which shows that past news significantly affects current volatility for these three instruments. Malhotra and Gupta (2019) found similar results in their study of five Asian market exchanges and four cryptocurrencies, where past news significantly impacted current volatility. Yousaf and Ali (2021) also observed that shocks significantly influenced the conditional volatility of Bitcoin during the pandemic.

For matrix B, only the main diagonal element β_{33} for cryptocurrency was significant at 5% level, suggesting that the volatility of cryptocurrency is influenced by its own past volatility, while stock and gold are not. This contrasts with univariate volatility modeling, which shows that current volatility in stocks and cryptocurrencies is influenced by their past volatility, whereas gold is not. Similarly, Ustaoglu (2022) also found that past volatility and news increased current volatility in the BIST100 index.

During the transition towards the COVID-19 endemic, the main diagonal element α_{11} for gold was significant at 5% level, indicating that gold's current volatility is influenced by past news. Only the main diagonal element β_{22} for cryptocurrency was significant, indicating that its current volatility is influenced by its past volatility, while gold's is not.

News Spillover Effect

Matrix elements A and B, outside the main diagonal, represent the spillover effects of news and volatility from other instruments. At the peak of the COVID-19 pandemic, there was a significant news spillover from stock returns to cryptocurrency returns (1.402) and from cryptocurrency returns to gold returns (-0.043). This implies that past news in the stock market increased current volatility in the cryptocurrency market, while past news in the cryptocurrency market decreased current volatility in the gold market. Liu and Serletis (2019) found similar one-way spillover effects from the S&P 500 to Bitcoin. Ustaoglu (2022) reported no significant spillover from cryptocurrencies to the BIST100 index, but did observe significant spillover from BIST100 to XRP.

During the transition towards the COVID-19 endemic, there was a significant news spillover from cryptocurrency returns to gold returns (-0.053), indicating that gold continued to serve as a safe haven for cryptocurrency, similar to the peak pandemic period. Ghorbel et al. (2022) and Huynh et al. (2020) also found that gold acts as a safe haven and diversifier for cryptocurrency investments.

Volatility Spillover Effect

At the peak of the COVID-19 pandemic, there was significant volatility spillover from stock returns to both gold (0.495) and cryptocurrency (2.515) returns, suggesting that past stock market volatility increased current volatility in both markets. This result aligns with Ustaoglu (2022), who found significant positive spillover from BIST100 to BTC, and Ibrahim (2012), who reported a positive relationship between gold and stock returns. Syahri and Robiyanto (2020) also found that changes in gold prices significantly affected stock price volatility.

During the transition towards the COVID-19 endemic, there were no significant two-way or one-way volatility spillovers between gold and cryptocurrency.

Asymmetric Spillover Effect

At the peak of the COVID-19 pandemic, a significant asymmetric spillover effect was observed from gold returns to stock returns (0.196), indicating that negative shocks in gold returns had a greater impact on stock volatility than positive shocks of the same magnitude. This finding is consistent with Adewuyi et al. (2019), who found positive cross-market asymmetric spillovers from gold to stock markets in South Africa and Nigeria. However, no significant asymmetric coefficients were found between stock and cryptocurrency, aligning with Yousaf and Ali (2021), who reported non-significant asymmetric coefficients between Bitcoin and the S&P 500.

Overall, the BEKK-AGARCH(1,1) model provides valuable insights into the interdependencies and volatility dynamics between stocks, gold, and cryptocurrency during the COVID-19 pandemic and the transition towards the endemic phase. These findings highlight the importance of understanding volatility spillovers and asymmetric effects for effective risk management and investment strategies.

Assumption Check

We also pursue diagnostics test on residuals of the model. The results given at table 7 confirms White Noise characteristics of our models.

Table 7. Diagnostic Test for BEKK-GARCH Model

Period	Multivariate Q Test	
	Q Statistic	68.574
Peak period	Prob.	0.188
	Conclusion	white noise
	Q Statistic	20.812
Transition period	Prob.	0.650
	Conclusion	white noise

Risk Comparison

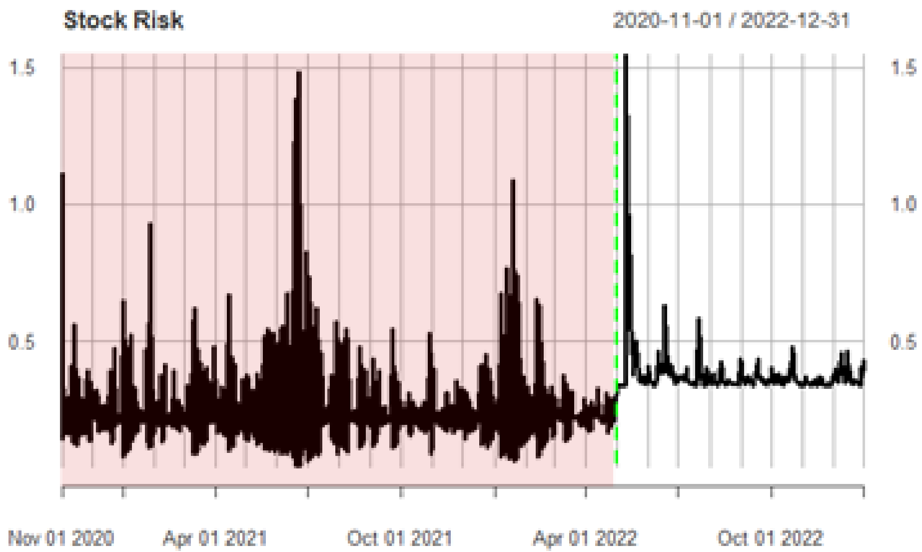
We compare risks based on volatility of average return of each investment intrument. During the transition period towards the COVID-19 endemic, the risk associated with stock investments diminished, indicating no risk. This improvement can be attributed to the increased participation of young investors under the age of 30. The number of Single Investor Identifications (SIDs) grew significantly by 33.53%, from 7,489,337 at the end of 2021 to 10,000,628 on November 3, 2022.

For gold, risks persisted in both periods. However, similar to stocks, the average volatility decreased from 0.48 at the peak of the pandemic to 0.432 during the transition towards the COVID-19 endemic. This decline in volatility suggests an improvement in the stability of gold investments.

Cryptocurrency exhibited persistent risk during both the peak of the COVID-19 pandemic and the transition period towards the endemic phase. This aligns with Dyhrberg's (2016) research, which found that Bitcoin's returns share similarities with gold, particularly in response to exchange rates and significant risk persistence. Among the investment instruments, cryptocurrency experienced the highest volatility, with an average of 13.784, compared to 0.284 for stocks and 0.480 for gold. During the transition period, stock volatility was absent, whereas gold and cryptocurrency continued to exhibit risk. Cryptocurrency maintained the highest risk with an average volatility of 8.657, while gold's average risk was 0.432.

Table 8. Risk Comparison of Investment Intruments

Instrument	Peak Period	Transition Period
Stock	0.284	-
Gold	0.480	0.432
Cryptocurrency	13.784	8.657



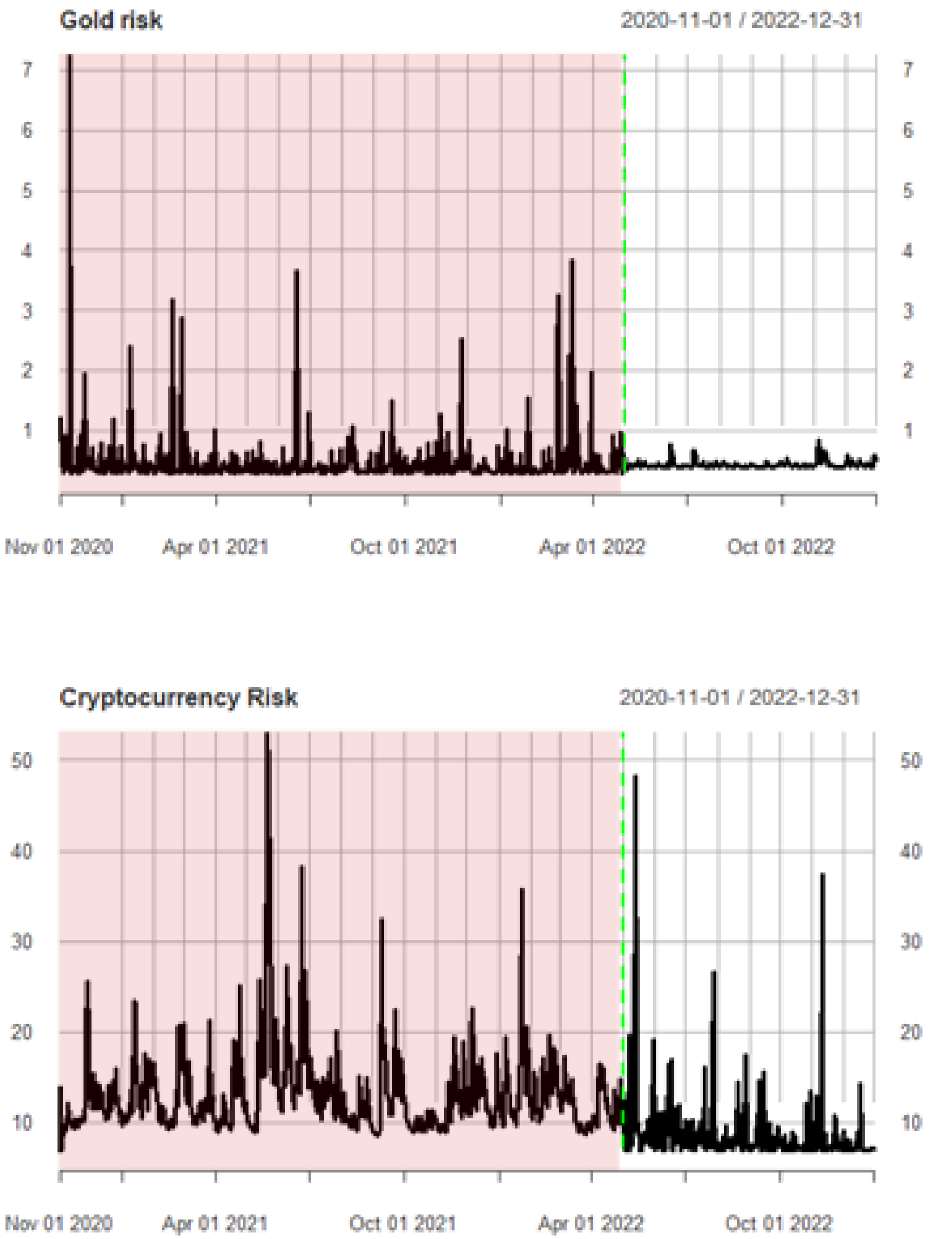


Figure 2. Graphical Risk Comparison

Notes: Red Background is Peak of the Pandemic COVID-19 and White Background Transition Towards Endemic COVID-19

Cryptocurrency's elevated risk during the peak of the pandemic and the transition period can be attributed to the collapse of the cryptocurrency market following the FTX bankruptcy on October 28, 2021 (Maheshwari, 2023). According to Putra (2022), cryptocurrency was the riskiest investment before and during the COVID-19 pandemic, evidenced by a higher standard deviation of Bitcoin returns compared to other instruments. As the pandemic transitioned towards the endemic phase, the overall risk of investing in the three instruments decreased, as indicated by improving average risks and the absence of stock volatility. The lack of volatility suggests relatively low risk, as seen in the risk graphs showing less fluctuation.

For risk-seeking investors, investing in cryptocurrency during the peak of the COVID-19 pandemic could be advantageous. High-risk periods often lead most investors to sell stocks and cryptocurrencies, causing prices to fall. Risk-seeking investors can capitalize on these low prices, potentially yielding maximum profits when prices rise. Putra (2022) supports this view, indicating that cryptocurrency is suitable for risk-seeking investors.

Conversely, risk-averse investors might consider investing in stocks as conditions normalize, given that the risk associated with investing tends to decrease with improvements in the COVID-19 situation.

Diversifier and Safe Haven

At the peak of the COVID-19 pandemic, gold served as a safe haven for cryptocurrency during market turbulence. This is evidenced by the negative spillover effect from cryptocurrency returns to gold returns, although the effect was minimal. There was no volatility spillover or asymmetric spillover effect observed. During the transition period towards the COVID-19 endemic, gold continued to act as a safe haven for cryptocurrency due to the negative spillover effect from cryptocurrency returns, while volatility spillover effects remained absent.

During the transition period, gold also functioned as a diversifier for stocks, and vice versa. Domestic research by Syahri and Robiyanto (2020) found a weak positive correlation between the Jakarta Composite Index (JCI) and gold. However, this finding contradicts earlier research by Puryandani and Robiyanto (2019), which indicated a significant correlation between gold and the JCI from 1999 to 2013, suggesting that gold was neither a safe haven nor a diversifier in the Indonesian capital market during that period.

Stocks acted as diversifiers for cryptocurrency during the pandemic peak. This is indicated by the time-varying correlation, which shows an average positive correlation between stocks and cryptocurrency that is not perfect, suggesting diversification benefits. According to Shen (2023), this phenomenon may be due to Bitcoin's highly volatile and erratic returns. The crash in the Indonesian stock market in 2020, when the JCI index fell, also contributed to this positive correlation, indicating that cryptocurrency was not an effective safe haven during market downturns.

Ghorbel et al. (2022) suggest that cryptocurrencies can diversify stock portfolios and potentially reduce volatility, especially during crises. Liu and Serletis (2019) found that the impact of cryptocurrencies varies across countries, likely due to different levels of cryptocurrency integration.

In Indonesia, Wisnu and Dharmawan (2021) classify cryptocurrencies as intangible goods that can be legally traded through technological intermediaries. Although crypto assets are legally recognized commodities on the futures exchange, they cannot be used as a payment method. This is supported by Regulation No. 99 of 2018 by the Indonesian Ministry of Trade, which categorizes crypto assets as commodities subject to contracts regulated by the Commodity Futures Trading Regulatory Agency (BAPPEBTI). Additionally, Law No. 7 of 2011 and Bank Indonesia Regulations (PBI) 18/40/PBI/2016 and 19/12/PBI/2017 stipulate that crypto assets are not recognized as payment instruments, prohibiting their use for transactions in Indonesia.

5. Conclusion

This study aimed to analyze the spillover volatility effect on returns from stocks, gold, and cryptocurrency during the peak of the COVID-19 pandemic and the transitional period towards the COVID-19 endemic. The univariate modeling (GARCH/EGARCH) reveals neccesity of EGARCH model for stocks, gold, and cryptocurrency instruments during the peak of the COVID-19 pandemic. However, in transition towards the COVID-19 endemic period, only gold and cryptocurrency required GARCH models. These findings highlight that cryptocurrency remained the riskiest asset during both periods. For risk-seeking investors, the peak of the pandemic and the transitional period offered opportunities in cryptocurrencies due to their high volatility and potential for significant returns. Conversely, risk-averse investors were better positioned to invest in stocks as market conditions normalized, given the decreased risk associated with stock investments.

On the other hand, the study examines spillover volatility effect using multivariate modeling (BEKK-GARCH/BEKK-AGARCH). The model reveals that gold acted as a safe haven for cryptocurrency during both periods, providing stability amidst market turmoil. However, gold did not serve as a safe haven for stocks but acted as a diversifier. Similarly, stocks provided diversification benefits for cryptocurrency investments during the peak of the pandemic. Based on these findings, investors are advised to include gold in their portfolios when investing in cryptocurrencies during periods of market crisis. Investing in both gold and stocks, or in stocks and cryptocurrencies, during peak pandemic periods is less advisable due to the lack of safe haven benefits and potential for increased risk.

In conclusion, the study underlines the importance of considering asset-specific risk and volatility dynamics when making investment decisions during periods of crisis. The role of gold as a safe haven for cryptocurrency and its diversifying benefits for stocks are particularly noteworthy. These insights offer valuable guidance for portfolio management in uncertain times. Future research can build on these findings by examining more recent data from the transition period towards the COVID-19 endemic or other similar conditions to deepen the understanding of the evolving relationships between these asset classes.

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