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Bitcoin and Gold USD: An Empirical Study of Asymmetric Volatility and the Spillover Effect

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Abstract
This research investigates the asymmetric volatility and spillover effects between Bitcoin and Gold USD using sophisticated econometric models, namely EGARCH (Exponential Generalized Autoregressive Conditional Heteroskedasticity) and DCC-GARCH (Dynamic Conditional Correlation GARCH). The EGARCH model demonstrates divergent volatility patterns for the two assets, with Bitcoin displaying a strong leverage effect, whereby negative shocks considerably enhance volatility compared to positive shocks, indicative of its speculative and high-risk characteristics. In contrast, Gold USD exhibits positive asymmetry, displaying heightened volatility in reaction to positive shocks, which aligns with its function as a safe-haven asset. The DCC-GARCH model elucidates the dynamic correlation and spillover effects between the two markets, demonstrating how volatility in one asset affects the other, especially during times of economic uncertainty. The findings highlight Bitcoin's increased vulnerability to negative news and Gold USD's resilience during market declines, providing essential insights for portfolio diversification, hedging methods, and risk management. This study enhances comprehension of the dependency and volatility dynamics between digital and conventional financial assets, offering essential insights for investors and regulators managing the intricacies of contemporary financial markets.

Keyword: Bitcoin, Gold USD, Volatility, EGARCH Model, DCC GARCH Model

JEL Classification: C22, C58, G15, Q02

Introduction

The volatility of financial assets is essential for risk assessment, portfolio management, and investment decision-making. Bitcoin and Gold USD exemplify two distinct asset classes, each exhibiting distinctive volatility traits and market dynamics. Bitcoin, a speculative and decentralized cryptocurrency, is characterized by substantial price volatility, often influenced by governmental pronouncements, technical advancements, or changes in market opinion (Bouri et al., 2017; Yermack, 2015). Conversely, Gold USD, a conventional safe-haven asset, has rather consistent price dynamics and is often pursued during times of economic instability or market upheaval (Baur & Lucey, 2010; Coudert & Raymond-Feingold, 2011).

An expanding corpus of work underscores the significance of asymmetric volatility in comprehending the risk dynamics of these assets. Asymmetric volatility denotes the occurrence in which positive and negative shocks have disparate effects on an asset's conditional volatility (Nelson, 1991). The EGARCH (Exponential Generalized Autoregressive Conditional Heteroskedasticity) model is very adept at capturing this imbalance. Research indicates that Bitcoin often has a significant leverage effect, whereby negative shocks increase volatility to a greater extent than positive shocks of equivalent size (Katsiampa, 2017). In contrast, Gold USD exhibits positive asymmetry, showing heightened volatility in reaction to favorable market movements (Baur & McDermott, 2010). The interdependence of financial markets highlights the importance of spillover effects among assets,

especially during times of increased uncertainty. The DCC-GARCH (Dynamic Conditional Correlation GARCH) model provides a solid framework for examining the time-varying correlations and volatility spillovers across financial assets (Engle, 2002). Recent research has recorded substantial spillovers between cryptocurrency markets and conventional assets such as gold, indicating a dynamic and developing link (Klein et al., 2018; Ji et al., 2019).
This study seeks to investigate the asymmetric volatility and spillover effects between Bitcoin and Gold USD using EGARCH and DCC-GARCH models. This research offers useful insights into the risk attributes and diversification potential of various assets by examining their unique volatility patterns and interrelationships. The results enhance the existing literature on financial market dynamics, providing practical insights for investors, portfolio managers, and policymakers addressing the intricacies of contemporary financial markets.

Literature Review
The literature study delves into past research on the volatility of Bitcoin and Gold, with a particular emphasis on their functions as financial assets and safe-haven vehicles. It emphasizes the evaluation of volatility patterns and dynamic correlations using EGARCH and DCC-GARCH models.

Nguyen et al. (2022) examined financial contagion from the U.S., Japanese, and Chinese markets to Asian markets during the Global Financial Crisis and COVID-19 pandemic. Stock market correlations and volatilities were estimated using DCC-EGARCH and daily stock return data from 2005 to 2021. Results showed a substantial link between U.S., Japanese, and developing Asian markets, implying interdependence. The Global Financial Crisis saw U.S. equities market contagion to advanced and developing nations. Only 30% of Asian developing markets were infected by U.S. Covid-19. Contagion effects are not strongly connected with global integration, and Japanese and Chinese contagion seems to impact Asian markets more.

Trifonov and Potanin (2022) simulated conditional volatility across various financial assets with an asymmetric relationship between volatility and return shocks (leverage impact). A dynamic correlation matrix is used in the innovative multivariate asymmetric conditional heteroskedasticity model DCC-EGARCH. The proposed method simulates the dynamics of many financial assets, including financial market leverage. DCC-EGARCH model has two major advantages over preceding multivariate asymmetric formulations. This optimization problem is simplified without conditional correlation time invariance. These properties make the model more usable. Estimator features were assessed using simulated data analysis. They found statistical evidence that the DCC-EGARCH model outperformed the symmetric DCC-GARCH process in leverage effect data. They examined Rosneft stock return volatility and Brent oil price volatility using the recommended approach. The DCC-EGARCH model showed the leverage impact and dynamic correlation structure in oil price data, making the technique realistic.

Gupta and Chaudhary (2022) analyzed the risk and return parameters of four popular cryptocurrencies. The GARCH model family was used to examine return and return volatility across currencies using daily closing prices from January 1, 2017, to June 30, 2022. Both spillover and asymmetric volatility effects were examined using the DCC-GARCH and EGARCH models. Granger causality was used to examine cryptocurrency causality. Bitcoin and Ether, the two largest cryptocurrencies, have a considerable spillover impact. These two have asymmetric volatility relative to Litecoin and XRP.

Ozdemir (2022) studied volatility spillovers in eight major cryptocurrencies (Bitcoin, Ethereum, Stellar, Ripple, Tether, Cardano, Litecoin, and Eos) from November 17, 2019, to January 25, 2021.

This study examines investors' financial behavior during the COVID-19 pandemic due to national lockdowns and production slowdowns. High volatility exposure of cryptocurrency markets was examined using EGARCH, DCC-GARCH, and wavelet approaches. Unlike GARCH family models, wavelets capture asset returns across frequencies without losing temporal inputs. Bitcoin, Ethereum, and Litecoin showed volatility and dependency throughout the investigation. Investors may react similarly to a shock in one market, causing volatility spillovers. After the second lockout in November 2020, bitcoin volatility spillover increased, according to the research. Financial risk is estimated using value-at-risk (VaR) and conditional value-at-risk (CVaR) methods using two stock indexes (Shanghai Composite Index and S&P 500). Crypto assets, save USDT, have substantially more downside risk than SSE and S&P 500, regardless of investing confidence.

Ampountolas (2023) examined bitcoin return volatility, global financial market indices, and COVID-19 pandemic spillover effects. They employed two-stage multivariate volatility exponential GARCH analysis with integrated dynamic conditional correlation (DCC) to evaluate the impact on financial portfolio returns from 2019 to 2020. They also measured value-at-risk (VaR) and CFVaR. The empirical results showed considerable long- and short-term spillover effects. The two-stage multivariate EGARCH model showed that both asset portfolios respond well to early shocks and boost conditional volatilities after favorable news. Financial assets have low unconditional volatility and risk without external interruptions. Financial assets are susceptible to shocks yet resilient to market confidence changes. VaR and asset portfolios function differently. VaR dropped most in the Dow (DJI) index during the COVID-19 pandemic, followed by the S&P500. The CFVaR shows negative risk for all cryptocurrencies except Ethereum (ETH) throughout the pandemic.

Yousaf et al. (2024) examined green bond yields and crude oil dynamic frequency spillovers, co-movements, and volatility transmission. They employed BK-18, DCC-GARCH, BEKK-GJR-GARCH, and Wavelet coherence. BK-18 showed that short-term green bond spillover is greater than intermediate and long-term. Green bonds are also somewhat connected to industrial and securitized ABS bonds. The BEKK-GJR-GARCH model showed a negative unidirectional volatility spillover from oil to global GB markets, indicating green bonds' oil hedging potential. Over the research period, negative dynamic correlations between oil and Industrial and Securitized ABS suggest they might hedge and protect against oil. Wavelet Coherence study demonstrates a poor medium- and long-term relationship between crude oil and green bonds. Short-term, oil was the biggest driver against green bonds. Finally, spillovers and hedging effectiveness show that crude oil and green-bond portfolios diversify investors and managers.

Apostolakis (2024) studied bitcoin spot and futures volatility transmission. Daily series sampling covered December 2017–September 2022. The 2020 COVID-19 epidemic, 2021 government announcements and environmental concerns, and 2022 crypto-winter heightened crypto market danger. Symmetric and asymmetric volatility impulse responses were created using a VEC-BEKK-MGARCH model and the Hafner and Herwartz (2006) framework. The VIRF study found that the COVID-19 epidemic affected the futures market more than the spot market. They also examined volatility spillovers between the two markets using Diebold and Yilmaz's (2012, 2014) connectivity approach, modified by Gabauer (2020), and a DCC-GARCH model. The bitcoin spot market seems to be the main source of futures market volatility shocks.

Javadi et al. (2024) studied how price volatility from poultry input markets such soybean meal, day-old chicks, maize, and the foreign currency market affected Iran's wholesale egg market. Experimental research uses dynamic conditional correlation (GARCH-DCC). This conditional variance-based market volatility analysis technique is usually considered one of the best. In contrast, Iranian families rely heavily on eggs, boosting food security. However, input price volatility, which accounts for approximately 70% of egg production expenses, causes pricing instability and uncertainty among producers. Volatility spillover effects on agricultural product markets, especially domestically, are little studied.

Joseph et al. (2024) studied the relationship between bitcoin and conventional financial markets in five major African nations to address concerns about spillover effects owing to excessive volatility and lack of regulation. The study examined marketplace correlations and spillover effects using diagonal BEKKGARCH and DCC-GARCH. Daily time series data from January 1, 2017, to December 31, 2021 was used to examine contagion effect. Cryptocurrencies have a minor but growing influence on the African traditional financial market. Cryptocurrencies' short-term influence on Egypt and Morocco's financial markets is unclear. In South Africa, Nigeria, and Kenya, research reveals cryptocurrencies have a small but growing influence on the banking sector. The African financial sector and bitcoin market had no spillover effects. DCC GARCH conditional correlation findings show a modest to moderate positive link between cryptocurrency volatility and the African financial market. The DCC-GARCH model revealed growing market integration over time. This research has policy implications for financial regulators and investors seeking portfolio diversification in both markets.

Smales (2024) analyzed the correlation between Bitcoin and other cryptocurrency returns and inflation expectations, comparing them to gold, a classic inflation hedge. They control for economic policy, cryptocurrency, and financial market uncertainty and find that cryptocurrency gains are positively correlated with US inflation forecasts under certain conditions. Short-term inflation expectations and inflation below 2% (the Fed's objective) are the only meaningful correlations, unlike gold. Additionally, bitcoin returns decrease on days with monthly CPI releases and react adversely to CPI shocks. Current research indicated that cryptocurrencies are not a viable replacement for gold for inflation hedging.

Research Methodology

The study analyzes Bitcoin and Gold USD's dynamic volatility and correlation using daily log-returns data employing EGARCH and DCC-GARCH models.

Data Collection

Daily price data for Bitcoin was sourced from *CoinMarketCap* (www.coinmarketcap.com), while Gold USD data was obtained from the *World Gold Council* (www.gold.org). The dataset spans the period from 1 April 2019 to 31 March 2024, comprising 1,305 trading days.
Daily logarithmic returns were calculated for both assets using the formula below:

$$r_t = In\left(\frac{P_t}{P_{t-1}}\right)$$

r_t = Daily log return of cryptocurrency at day t
P_t = Closing price of crypto at day t
P_{t-1}= Closing price of crypto at day $t-1$

Descriptive Statistics

As seen in Table 1, the descriptive data indicate notable volatility and distribution characteristics for Bitcoin and Gold USD. Bitcoin has considerable volatility, characterized by a price range from $4,1 58.18 to $73,083.50, a standard deviation of $16,688.01, and a variance over $278 million. This corr esponds with Bitcoin's standing as a speculative and high-risk asset. The positive skewness (0.55787) signifies that Bitcoin has more frequent little gains with occasional substantial positive outliers, wh ilst its negative kurtosis (-0.66880) implies a distribution that approximates normality with somewha t lighter tails. Gold USD has much reduced volatility, characterized by a narrower price range of $1, 269.50 to $2,214.35 and a standard deviation of only $193.33. The negative skewness (-0.77341) ind icates that negative price fluctuations occur with somewhat greater frequency or intensity, underscor ing its reliability as a safe-haven asset. The near-zero kurtosis (0.16580) indicates a distribution that approximates normality.

Table 1: Descriptive Statistics for Bitcoin and Gold US

Statistic	Bitcoin	Gold USD
Number of Obs.	1,305	1,305
Missing Values	0	0
Minimum	4,158.18	1,269.50
Maximum	73,083.50	2,214.35
1st Quartile	10,575.53	1,702.60
3rd Quartile	39,845.55	1,920.70
Mean	27,041.76	1,778.79
Median	24,829.15	1,808.45
Sum	35,289,493.24	2,321,320.15
Std. Error Mean	461.95	5.35
95% CI Lower Mean	26,135.50	1,768.29
95% CI Upper Mean	27,948.01	1,789.29
Variance	278,489,600.43	37,378.27
Standard Deviation	16,688.01	193.33
Skewness	0.55787	-0.77341
Kurtosis	-0.66880	0.16580

The divergent attributes highlight the synergistic relationship between Bitcoin and Gold USD in port folio management. Bitcoin's significant volatility presents speculative prospects, but Gold USD ensu res stability during economic instability. Collectively, they function as efficient instruments for diver sification and risk mitigation, particularly in volatile market environments.

Unit root test

It is essential to possess stationary data; otherwise, it will produce spurious regression outcomes. If t he series is non-stationary, its distribution will vary in each period, making it challenging to establis h a link or forecast. If the series is stationary, it means that the data structure of the time series is sta ble, indicating a consistent mean, variance, and covariance throughout time.

To assess the unit root issue, the augmented Dickey-Fuller (ADF) test was used (Dickey and Fuller 1981), whereby the null hypothesis posits that the data are non-stationary.

$$\Delta y_t = \propto_0 + \theta y_{t-1} + \sum_{i=1}^{n} \propto \Delta y_t + e_t \tag{1}$$

In the mentioned above equation (1), 'y_t' represents the data at time t, 'n' is the optimal number of de lays, '$\propto_0$ ' is the constant, and 'e_t' is the error term.

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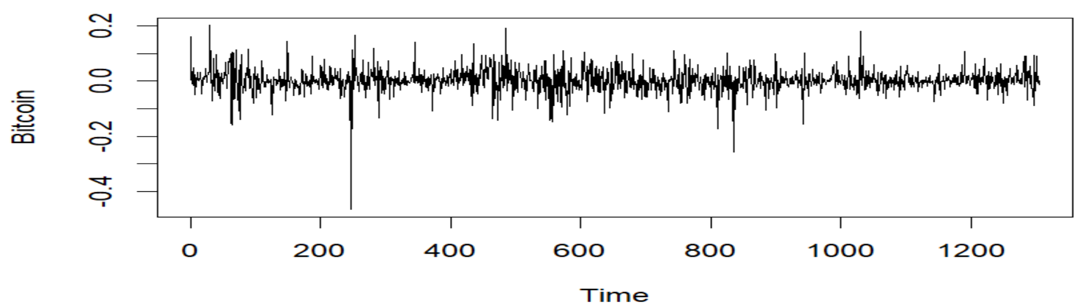
Augmented Dickey-Fuller (ADF) test

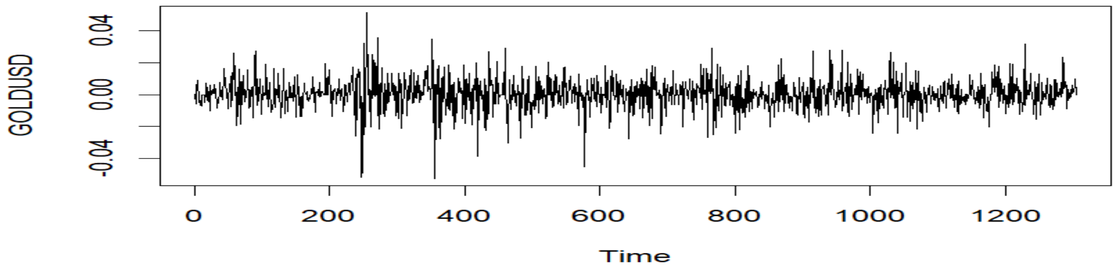
Table 2: ADF Statistics

	Bitcoin	GOLDUSD
T Statistics	-10.116	-11.806
P-Value	0.01	0.01

As per Table 2, the Augmented Dickey-Fuller (ADF) test findings for Bitcoin and GOLDUSD show that the time series are stationary. The test statistic for Bitcoin is -10.116, with a p-value of 0.01, wh ile for GOLD USD, it is -11.806, with the same p-value of 0.01. Because the p-values for both asset s are less than the standard significance level of 0.05, the null hypothesis of non-stationarity is reject ed. This verifies that both time series exhibit consistent statistical qualities throughout time, such as mean and variance, making them appropriate for future time series analysis and modeling.



Daily Returns of Bitcoin



Daily Returns of Gold USD

Figure 1: Log Returns

As shown in Figure1, Bitcoin and Gold USD log return time series charts reveal volatility characteristics and market behavior. Bitcoin's volatility is high, especially around observation 200, when huge negative returns are seen. Speculative assets exhibit volatility clustering when high volatility periods follow one other. These high-amplitude oscillations demonstrate Bitcoin's susceptibility to market shocks, underscoring its image as a high-risk, speculative asset with significant profits and losses. However, the Gold USD time series has far lower volatility, with returns ranging from -0.04 to 0.04. Some clustering is noticeable, but the oscillations are lower than Bitcoin, confirming Gold USD's safe-haven reputation. Risk-averse investors choose it amid economic or financial turmoil because to its steadiness.

Gold USD is more stable and resilient than Bitcoin, which is riskier. These discrepancies show how Gold USD can moderate Bitcoin's dramatic price volatility in a diverse portfolio. This disparity highlights the need for sophisticated volatility models like EGARCH to capture asymmetric volatility responses and DCC-GARCH to examine dynamic correlations and possible spillover effects between these assets.

ARCH TEST

The existence of heteroscedasticity in residuals is evaluated using the ARCH-LM test (autoregressive conditional heteroscedasticity–Lagrange multiplier test) (Ljung and Box 1978).

$$u_t^2 = \gamma_0 + \gamma_1 u_{t-1}^2 + \gamma_2 u_{t-2}^2 + \ldots\ldots + \gamma_p u_{t-p}^2 + v_t, \quad (2)$$

u is the squared residual of the Mean regression model, whereas p signifies the lag duration in the residual regression model.

The null hypothesis of the ARCH–LM test posits that the coefficients of the squared residuals in Equation (2) are unimportant, implying that 0 = 1 = 2 = p = 0; hence, there is no heteroscedasticity in the time series data, indicating the absence of an ARCH effect.

Table 3: ARCH LM Test Results

Asset	Chi-Squared	Degrees of Freedom (df)	p-value
Bitcoin	28.076	12	0.0054
Gold USD	101.88	12	2.38e-16

As observed in Table 3, the ARCH LM test determines if the time series exhibits time-varying volatility due to ARCH (Autoregressive Conditional Heteroscedasticity) effects. The test statistic for Bitcoin is 28.076, with a p-value of 0.0054 and 12 degrees of freedom. Likewise, for GOLDUSD, the p-value is 2.38e-16, the test statistic is 101.88, and there are 12 degrees of freedom. The null hypothesis that there are no ARCH effects is rejected in both instances since the p-values are significantly below the conventional significance threshold (e.g., 0.05). This indicates that the volatility of both time series is not constant across time and validates the existence of ARCH effects in both. These results provide credence to the usage of ARCH/GARCH models for modeling and capturing the fluctuating volatility.

EGARCH Model

Financial data time-varying volatility is modeled using Nelson (1991)'s EGARCH model. Negative shocks (e.g., bad news) might have a bigger influence on volatility than positive shocks of the same size (leverage effect), unlike the GARCH model. Without non-negativity requirements, the logarithmic model ensures positive variance. Past variance, shock size, and direction are included in the conditional variance equation (3), making financial time series volatility modeling more flexible and realistic.

$$\mathrm{In}(h_t) = \alpha_0 + \alpha_1 \left|\frac{u_{t-1}}{\sqrt{h_{t-1}}}\right| + \gamma \frac{u_{t-1}}{\sqrt{h_{t-1}}} + \beta In(h_{t-1}) \quad (3)$$

This section provides a detailed comparative analysis of the volatility dynamics of Bitcoin and GOLD USD using Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) models. Both time series were fitted with EGARCH (1,1) models, incorporating ARFIMA (1,0,1) mean structures to account for their unique volatility clustering and asymmetric behavior. The results highlight the similarities and differences in the conditional variance dynamics of these two assets, offering insights into their behavior under varying market conditions. The EGARCH (1,1) models for Bitcoin and Gold USD provide insights into their distinct volatility behaviors.

Table 4: Summarizes the key parameter estimates of EGARCH Model:

Parameter	Bitcoin Estimate	GOLDUSD Estimate
μ (mean)	0.000416	0.000158
ar1	-0.082500	0.032172
ma1	0.073922	-0.045617
ω	-0.300977	-0.193456
α_1 (alpha1)	0.041576	0.062843
β_1 (beta1)	0.967052	0.911645
γ_1 (gamma1)	0.108310	-0.025394

Bitcoin's higher β_1 indicates that its volatility persists for a longer duration compared to GOLD USD. The positive γ_1 in Bitcoin signifies the presence of a leverage effect, meaning that negative returns result in greater increases in volatility than positive returns. Conversely, GOLD USD shows no significant leverage effect.

Asymmetry and Goodness-of-Fit

The sign bias test indicates that Bitcoin's EGARCH model exhibits significant asymmetry, as seen by the positive γ_1 (gamma1). This illustrates the leverage effect, when negative returns amplify volatility to a greater extent than positive returns. Conversely, GOLD USD has no considerable asymmetry, indicated by a marginally negative γ_1. The Adjusted Pearson Goodness-of-Fit Test for both models indicates possible misspecification for extreme values, shown by low p-values across all groups. The findings indicate that while the models demonstrate general efficacy, they may need more modification to better properly capture severe market fluctuations.

As per Table 4, the EGARCH results reveals that Bitcoin and GOLD USD have unique volatility characteristics, indicative of their divergent functions in financial markets. The pronounced volatility persistence of Bitcoin (β_1 = 0.967052) and the positive leverage impact (γ_1 = 0.108310) underscore its speculative and high-risk characteristics, with significant price variations mostly influenced by market mood and speculative behavior. Conversely, GOLD USD exhibits less volatility (β_1 = 0.911645) and lacks a leverage impact, aligning with its function as a safe-haven asset that remains comparatively steady under economic instability. GOLD USD's pronounced response to historical shocks (α_1 = 0.062843) signifies more sensitivity to global economic occurrences, like fluctuations in interest rates, inflation, or geopolitical conflicts.

News Impact Curve

The EGARCH models' News Impact Curves (NICs) shown in Figure 2 demonstrates that Bitcoin and GOLD USD have different volatility characteristics. In the case of Bitcoin, the NIC reveals a strong leverage effect, in which negative shocks considerably increase volatility at the expense of positive shocks. This highlights the fact that Bitcoin is a high-risk asset, particularly during market downturns, due to its speculative character and susceptibility to negative news. The NIC for GOLD USD, on the other hand, shows positive asymmetry, meaning that positive shocks affect volatility more than negative ones. This demonstrates that gold is a stable asset and a safe-haven, with volatility being more affected by positive than bad economic situations.

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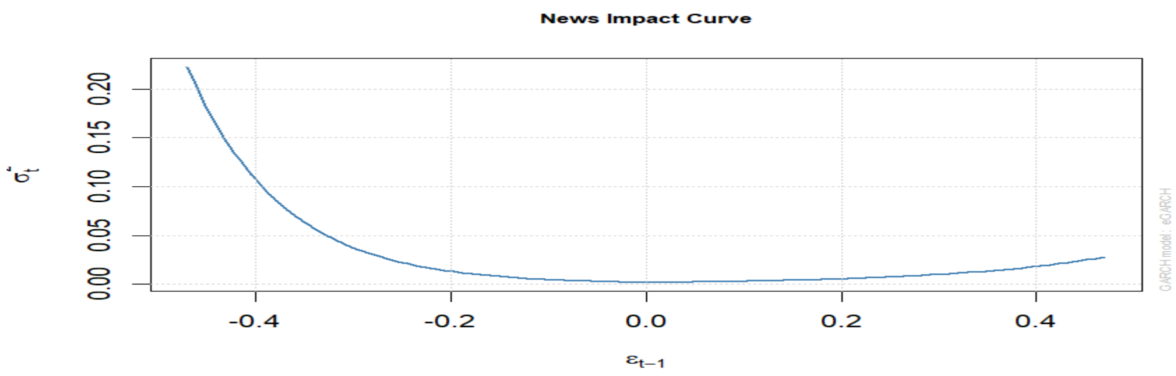
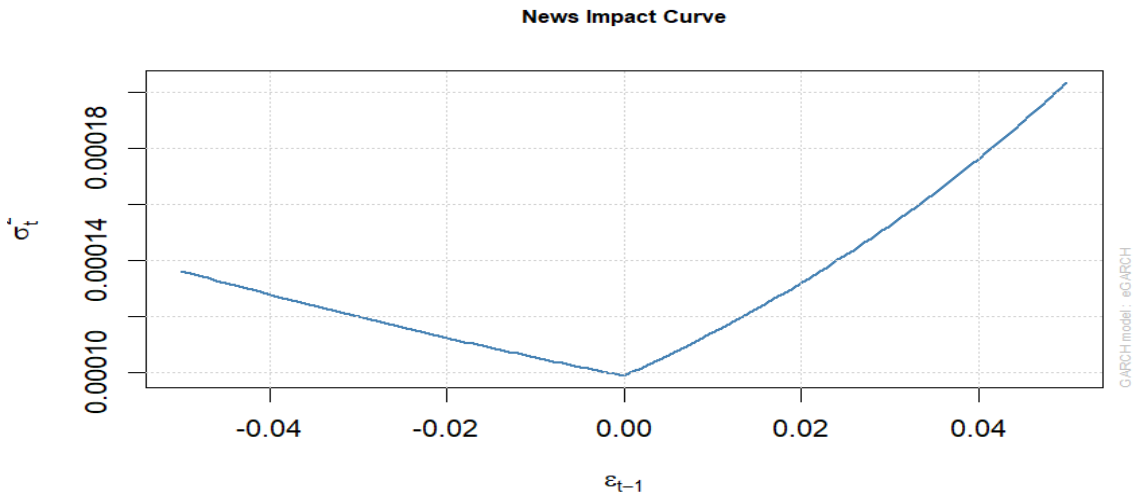


Bitcoin News Impact Curve



Gold USD News Impact Curve

Figure 2 News Impact Curve

The combined research highlights the risk-taking nature of Bitcoin and the safe-haven features of GOLD USD. With Bitcoin being very vulnerable to negative shocks and gold being quite stable, there are chances to diversify and hedge thanks to these opposing tendencies. Investors and policymakers may benefit from better forecasts, risk management, and portfolio optimization tactics when these links are understood.

DCC-GARCH Model

We have employed the GARCH model with dynamic conditional correlation (DCC), developed by Engle (2001). The model incorporates correlation effects in conjunction with the GARCH model. It models the dynamic process of volatile conditions and their interdependencies. These models not only represent the variance and covariance, but they also forecast the flexibility of variance (Yan et al. 2022). The present values in the DCC-GARCH model are associated with their historical values and squared residuals.

Given two time series datasets, r_i,t and r_j,t, and using AR (1) models, two residual time variables, a_i,t and a_j,t, are generated. In this context, Ht denotes the dynamic conditional covariance matrix of the two-time series r_i,t and r_j,t.

R_t: represents the dynamic conditional correlation (DCC) matrix.
D_t: represents the diagonal matrix from the covariance matrix H_t.
D_t^{-1}: the inverse of the D_t Matrix.
Then, the relationship between the matrices of H_t, R_t, D_t, and $D_t^{-1}$is:

$$H_t = D_t\, R_t\, D_t \quad (4)$$

$$R_t = D_t^{-1}\, H_t\, D_t^{-1} \quad (5)$$

After adopting two GARCH (1,1) models, we obtained two normalized residual variables ε_i,t and ε_j,t; the following relationship is obtained by defining the following variables
Q_t indicates Covariance Matrix
$G_t$indicates the diagonal matrix of the covariance matrix Q_t,
G_t^{-1} indicates the inverse matrix of the matrix Q_t.
C_t indicates Correlation Matrix
The relationships between the matrices of Q_t, C_t, G_t, and G_t^{-1} are:

$$Q_t = G_t\, C_t\, G_t \quad (6)$$

$$C_t = G_t^{-1}\, Q_t\, G_t^{-1} \quad (7)$$

For a two-order matrix, R_t, H_t, and Q_t, assume:

$$R_t = \begin{bmatrix} \rho i,t & \rho ij,t \\ \rho ji,t & \rho j,t \end{bmatrix} \qquad H_t = \begin{bmatrix} \sigma i,t & \sigma ij,t \\ \sigma ji,t & \sigma j,t \end{bmatrix} \qquad Q_t = \begin{bmatrix} qi,t & qij,t \\ qji,t & qj,t \end{bmatrix} \quad (8)$$

$$\sigma ij,t = \sigma i,t\rho ij,t\,\sigma j,t \qquad \sigma ji,t = \sigma i,t\ \rho ji,t\ \sigma j,t \quad (9)$$

Using the relationships of $\sigma i,t = \sigma i,t\varepsilon_i,\mathrm{t}$ *and* $\sigma j,t = \sigma j,t\ \varepsilon_j,\mathrm{t}$ from AR (1) and GARCH (1,1) (Engle 1982, 2001).
The dynamic conditional correlations between the two series can be defined as:

$$\rho ij,t = \frac{qij,t}{qi,tqj,t}\ ,\ \ \rho ji,t = \frac{qji,t}{qj,tqi,t} \quad where,\ \ \rho ij,t = \rho ji,t \quad (10)$$

Because the time variable t is considered, the correlation variables $\rho ij,t$ and $\rho ji,t$ are the varying correlation.

The dynamic correlation process is influenced by two parameters: α and β. The estimators derived from the DCC GARCH model are dynamic and fluctuate over time. The variable in the DCC model quantifies the short-term volatility effect in cryptocurrencies, reflecting the persistence of the standardized residuals from the preceding period.

The coefficient in the DCC model quantifies the residual influence of the shock on the conditional correlations. The aggregate of these two values is below one, indicating that the conditional correlation within the models is not time-invariant and the model exhibits stability.

The Dynamic Conditional Correlation GARCH (DCC-GARCH) model offers a comprehensive framework for examining the time-varying correlation and volatility spillovers between financial assets. In this section, we apply the DCC GARCH (1,1) model to analyze the dynamic relationship between Bitcoin and GOLDUSD, shedding light on how volatility in one asset influences the other and how their correlations evolve over time. The DCC-GARCH (1,1) model provides key insights into the joint dynamics of Bitcoin and GOLDUSD.

Table 5 summarizes the optimal parameter estimates

Parameter	Estimate	Std. Error	t-value	p-value
[Bitcoin].μ	0.001608	0.000355	4.5355	<0.0001

[Bitcoin].ar1	0.255846	0.010745	23.8113	<0.0001
[Bitcoin].ma1	-0.281976	0.011294	-24.9674	<0.0001
[Bitcoin].ω	-0.974901	0.301982	-3.2283	0.0012
[Bitcoin].β_1	0.840767	0.050205	16.7466	<0.0001
[GOLDUSD].μ	0.000416	0.000243	1.7113	0.0870
[GOLDUSD].ar1	-0.082500	0.028827	-2.8619	0.0042
[GOLDUSD].β_1	0.967052	0.000525	1842.95	<0.0001
[Joint]dcca1	0.008238	0.003194	2.5792	0.0099
[Joint]dccb1	0.982985	0.004294	228.9414	<0.0001

The high value of **dccb1** indicates that the dynamic correlation between Bitcoin and GOLDUSD evolves smoothly and exhibits strong persistence over time. This suggests a stable relationship that remains consistent across varying market conditions.

Spillover Effects and Volatility Transmission

Table 5 shows that the DCC-GARCH model demonstrates significant spillover effects between Bitc oin and GOLDUSD, indicating how volatility shocks in one market affect the other. The metric dcca 1 (0.008238, p-value = 0.0099) reflects short-term dynamic correlations, indicating that these assets rapidly react to common market shocks. This indicates a simultaneous fluctuation in their volatilities , especially during times of market instability. The enduring nature of this link is shown by the metri c dccb1 (0.982985, p-value < 0.0001), indicating robust long-term correlation dynamics. The signifi cant persistence of connection indicates that fluctuations in the volatility of one asset, such as a rapi d increase in Bitcoin's volatility owing to regulatory developments, may have a lasting influence on the volatility of GOLDUSD and vice versa. This spillover mechanism highlights the interdependenc e of financial markets.

The DCC-GARCH model offers a comprehensive framework for examining the dynamic correlation and volatility spillovers between Bitcoin and GOLDUSD. The pronounced spillover effects and end uring connection underscore the interconnectedness of various assets, especially in times of market volatility. These results underscore the significance of accounting for both individual and combined volatility dynamics in successful risk management and portfolio optimization. Investors and regulat ors may use this information to more effectively traverse the intricacies of financial markets and imp rove decision-making processes.

Discussion and Conclusion

Discussion

This research uses the EGARCH and DCC-GARCH models to reveal Bitcoin and Gold USD volatility dynamics and dependency. Bitcoin showed a leveraging effect, where negative shocks cause far larger volatility than positive shocks of the same amount. Katsiampa (2017) found Bitcoin to be speculative and sensitive to market occurrences. Bitcoin's broad range of returns and huge fluctuation reflect its high-risk, high-reward status, making it appealing to speculative investors but risky for portfolios. However, Gold USD showed positive asymmetry, with positive shocks affecting volatility more than negative shocks. Gold's safe-haven status amid financial turmoil is shown by this behavior (Baur & McDermott, 2010). Gold USD's steady returns and low volatility attract to risk-averse investors looking to hedge against economic downturns.

The DCC-GARCH model showed considerable spillover effects and dynamic correlations between Bitcoin and Gold USD, especially during market uncertainty. The time-varying correlation structure shows that these assets are uncorrelated during stable times but highly linked during market turmoil, similar to Ji et al. (2019). Bitcoin's growing potential and Gold USD's stabilizing impact make them complementing portfolio components.

Conclusion

This study contrasts Bitcoin and Gold USD volatility and dynamic interdependencies. The leverage impact in Bitcoin and positive asymmetry in Gold USD were represented by the EGARCH model. The dynamic correlation and spillover effects between these assets were analyzed using the DCC-GARCH model, showing their changing connection.

The results affect investors and policymakers. The differences between Bitcoin and Gold USD provide investors diversification and greater risk-adjusted returns. However, policymakers may utilize these data to monitor financial stability, especially as cryptocurrencies enter global financial systems. Finally, this paper analyzes Bitcoin and Gold USD volatility and correlation patterns, adding to financial market dynamics literature. To further understand their function in diversified portfolios, future research might examine these patterns over longer time periods or incorporate more assets.

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