

Multivariate GARCH analysis of return spillovers between Fed Rate changes, decentralized finance (DeFi) assets, and stock indices

**Kulabutr Komenkul¹, Naleanthon Sarakhun²,
Atipoomphet Buachai³, Thanitorn Sukorntaprateep⁴,
Titikorn Saibuakaew⁵**

Department of Finance, Investment and Financial Technology,
College of Innovative Business and Accountancy, Dhurakij Pundit
University, Thailand^{1,2,3,4,5}
E-mail: kulabut.kom@dpu.ac.th^{1,2,3,4,5}

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ABSTRACT

This study examined the dynamic interrelationships and volatility spillovers among decentralized finance (DeFi) assets, traditional stock indices, commodities, and macroeconomic policy through the lens of multivariate GARCH models. Using daily time series data spanning from January 10, 2023, to December 31, 2024, the study applied both DCC-GARCH(1,1) and BEKK-GARCH models to a diversified 15-asset portfolio comprising stablecoins (USDC, USDT, BUSD, TUSD, DAI, GUSD), cryptocurrencies (Bitcoin, Ethereum), commodities (gold, crude oil), U.S. equity indices (Dow Jones, S&P 500, Nasdaq, NYSE), and the Federal Funds Rate. The findings revealed significant return and volatility spillovers, particularly from Federal Reserve interest rate changes to both digital and traditional markets. Bitcoin and Ethereum showed strong co-movements with major stock indices, highlighting their increased integration into global financial systems. In contrast, stablecoins exhibited lower volatility and weaker interlinkages, confirming their role as volatility dampeners. Gold continued to function as a safe-haven asset, while oil's influence was episodic and context-dependent. The time-varying and asymmetric nature of these relationships, especially during macroeconomic stress, underscores the need for adaptive investment strategies and greater regulatory coordination. This paper contributes to the literature by offering a comprehensive multivariate volatility modeling framework that bridges digital finance and macroeconomic dynamics.

Keywords: Decentralized Finance (DeFi), Cryptocurrencies, Stablecoins, Stock Indices, Volatility Spillover

Introduction

The intricate relationship between macroeconomic policy particularly U.S. Federal Reserve interest rate adjustments and the behavior of global financial assets has emerged as a pivotal area of inquiry in contemporary financial economics. As financial markets become increasingly integrated, the emergence of decentralized finance (DeFi) assets, including cryptocurrencies and stablecoins, has added new dimensions to the analysis of volatility transmission and return dynamics. Concurrently, traditional asset classes such as commodities and equity indices continue to play a central role in shaping investor portfolios and market expectations.

Recent global disruptions, most notably the COVID-19 pandemic, have amplified the interconnectedness of financial markets, leading to shifts in investor sentiment, heightened systemic risk, and non-linear co-movements across asset classes (Liu & Serletis, 2019; Lahmiri & Bekiros, 2020; Fernandes et al., 2022). In this evolving landscape, stablecoins like USDC and USDT have gained prominence

as potential volatility stabilizers, often viewed as safe-haven assets amid macroeconomic uncertainty and cryptocurrency market turbulence (Al-Afeef et al., 2024; Napari et al., 2025).

Empirical research increasingly points to dynamic, time-varying, and asymmetric relationships between digital assets and traditional financial instruments, with evidence of bidirectional volatility spillovers involving stock indices (e.g., S&P 500), commodities (gold and oil), and cryptocurrencies such as Bitcoin and Ethereum (Kim et al., 2020; Ahmed et al., 2023; Gokmenoglu & Fazlollahi, 2016). However, many of these studies rely on univariate or bivariate frameworks, limiting their ability to capture the multidimensional interdependencies and regime-switching behaviors inherent in financial markets today.

This study addresses this gap by employing a robust multivariate volatility modeling approach specifically the Dynamic Conditional Correlation GARCH (DCC-GARCH) (1,1) model alongside the BEKK-GARCH specification to examine the

volatility clustering, return spillovers, and dynamic correlations across a 15-asset portfolio. The portfolio includes major stablecoins, leading cryptocurrencies, key U.S. stock indices, commodities (gold and oil), and the Federal Funds Rate as a macroeconomic proxy. By analyzing time series data from January 10, 2023, to December 31, 2024, the study provides new insights into the evolving nature of cross-asset linkages in a post-pandemic, rate-sensitive financial environment.

Research objectives

1. To investigate the volatility clustering behavior in a cross-asset portfolio including stablecoins (USDC, USDT, BUSD, TUSD, DAI, GUSD), cryptocurrencies (Bitcoin and Ethereum), commodities (gold and oil), and major U.S. stock indices (Dow Jones, S&P500, Nasdaq, NYSE), as well as the Federal Funds Rate.

2. To analyze the dynamic conditional correlations among the assets using a DCC-GARCH framework, especially under macroeconomic stress and interest rate shifts.

3. To examine volatility spillover effects between the Federal Reserve's policy actions and the return dynamics of digital and traditional financial assets.

Literature review

The intersection of cryptocurrency markets, traditional financial assets, and macroeconomic policy has attracted increasing scholarly attention in recent years. A number of studies have examined the dynamic interactions, spillovers, and hedging relationships among these assets, especially during periods of heightened uncertainty.

Thaker and Mand (2021) conducted a comprehensive investigation of the relationship between Bitcoin and stock markets using a suite of econometric tools including the VECM, Granger Causality Test, M-GARCH-DCC, and Continuous Wavelet Transform. Their findings confirmed the existence of both short- and long-run relationships, along with time-varying co-movements that reflect market integration and lead-lag dynamics. Similarly, Ahmed et al. (2023) emphasized mutual coupling between stock markets and major cryptocurrencies, identifying bidirectional causality with stronger spillovers from equities to digital assets, contradicting the notion of cryptocurrencies as consistent hedging instruments.

Kim et al. (2020) extended this understanding by applying copula-based models, such as GC-DCC and GCNA-DCC,

which outperformed traditional models in capturing non-linear dependencies and volatility clustering between Bitcoin, gold, and the S&P 500. Their work confirmed the increasing positive correlation during the COVID-19 period, a pattern also corroborated by several wavelet and rolling-window studies in ASEAN contexts (Nguyen et al., 2022; Caferra & Vidal-Tomás, 2021).

A growing body of research also explores the unique role of stablecoins. Al-Afeef et al. (2024) demonstrated that trust, regulation, and perceived usefulness significantly drive stablecoin adoption, positioning these assets as effective volatility mitigation tools during market turbulence. This view is supported by Napari et al. (2025), who showed that stablecoins absorb return shocks from EM currencies, further endorsing their safe-haven characteristics.

In the context of commodities, studies by Gokmenoglu and Fazlollahi (2016) and Sujit and Kumar (2011) revealed long-term cointegration between gold, oil, and equity markets, with gold consistently acting as a substitute asset in periods of uncertainty. However, Iscan (2015) found no cointegration in the Turkish market,

indicating that such relationships are not universally applicable.

Volatility has remained a persistent feature in cryptocurrency markets. Liu and Serletis (2019) emphasized Bitcoin's heightened volatility and its evolving role as a diversification tool in ASEAN markets. Likewise, Sui et al. (2022) and Lahmiri & Bekiros (2020) noted that post-COVID-19 dynamics have increased the complexity and irregularity in crypto-equity relationships, requiring more flexible modeling frameworks.

Several recent studies adopt wavelet and multivariate GARCH approaches to capture time-varying spillovers. For instance, Rijanto (2023) and Abakah et al. (2024) demonstrated that Bitcoin exhibits both safe-haven and contagion properties depending on macroeconomic conditions and investor sentiment. Moreover, the evolution of the cryptocurrency-stock relationship is increasingly attributed to investor attention, market liquidity, and regulatory stances (Ang & Chow, 2023; Soepriyanto et al., 2023).

Despite these advances, the literature lacks a comprehensive multivariate GARCH-based analysis incorporating both macroeconomic shocks such as Federal Reserve rate changes and a full asset

portfolio consisting of stablecoins, major cryptocurrencies, stock indices, and commodities. This paper addresses this gap by applying a multivariate GARCH framework to assess return and volatility spillovers across these diverse asset classes, contributing to the understanding of financial contagion and market interdependencies in a post-pandemic, rate-sensitive global environment.

Research hypothesis

The increasing integration of global financial markets, the rise of cryptocurrencies, and the heightened sensitivity of assets to monetary policy actions have prompted extensive research into the interconnectedness of asset classes. This study aims to explore the return spillover effects and volatility transmission among major digital assets, traditional financial markets, and macroeconomic indicators—especially in response to U.S. Federal Reserve interest rate changes.

Spillovers between Fed Rate changes and asset markets

Monetary policy announcements particularly changes in the Federal Funds Rate are known to influence investor sentiment, risk appetite, and capital flows. Previous studies have shown that interest rate hikes often lead to equity market

corrections, while unconventional monetary policies may bolster riskier assets such as cryptocurrencies. Given the increased relevance of Fed decisions in shaping global financial volatility, the following hypothesis is proposed:

H1: Changes in the Federal Funds Rate generate significant return spillovers to both cryptocurrency markets and traditional stock indices.

Linkage between cryptocurrencies and stock markets

The empirical literature is mixed on whether cryptocurrencies act as hedging tools or behave similarly to equities. While some studies suggest that Bitcoin and Ethereum are decoupled from traditional markets, others observe stronger co-movements during crises. Hence, the following hypotheses are developed to test both volatility and return linkages:

H2a: There exists a significant return spillover effect from the U.S. stock market to major cryptocurrencies (Bitcoin and Ethereum).

H2b: There exists a significant volatility spillover from the U.S. stock market to major cryptocurrencies.

H2c: The return and volatility spillovers between stock indices and cryptocurrencies are time-varying and

intensify during periods of macroeconomic uncertainty.

Role of stablecoins in market stabilization

Stablecoins are designed to reduce volatility by pegging their value to fiat currencies or commodities. Recent research positions stablecoins as a “safe haven” during market turbulence, offering investors a less volatile store of value. Based on this role, the study posits:

H3a: Stablecoins exhibit significantly lower return volatility than major cryptocurrencies.

H3b: Stablecoins demonstrate weaker return and volatility spillovers with stock indices compared to Bitcoin and Ethereum.

Interactions among commodities, cryptocurrencies, and equities

Gold and oil remain critical indicators of global market sentiment and economic performance. Their relationship with digital assets remains complex, especially during inflationary pressures or geopolitical risks. Thus, we hypothesize:

H4a: Gold serves as a volatility absorber, reducing the impact of return shocks from cryptocurrencies.

H4b: Oil prices exhibit bidirectional volatility spillovers with major cryptocurrencies, reflecting energy cost

sensitivity in crypto mining and broader economic activity.

Time-varying dynamics and asymmetric spillovers

Financial markets often exhibit regime-switching behavior and asymmetric responses to positive and negative shocks. Accordingly:

H5: The intensity and direction of return and volatility spillovers among the Fed, cryptocurrencies, commodities, and equity indices are time-varying and exhibit asymmetries during high-volatility periods.

Research methodology

To investigate the return and volatility dynamics among cryptocurrencies, stablecoins, traditional stock indices, commodities, and macroeconomic indicators, this study employs a Univariate GARCH(1,1) model for each asset in a 15-asset portfolio. The assets are categorized as follows:

- Stablecoins: USDC, USDT, BUSD, TUSD, DAI, GUSD
- Cryptocurrencies: Bitcoin (BTC), Ethereum (ETH)
- Commodities: Gold, Crude Oil
- Stock Indices: Dow Jones Industrial Average, S&P 500, Nasdaq, NYSE Composite

- Macroeconomic Variable: Change in the Federal Funds Rate (FED)

The dataset comprises daily closing prices and rates for selected financial assets, covering the period from 10 January 2023 to 31 December 2024, resulting in 423 observations per asset. Data collection was carried out using Python in Google Colab, leveraging the yfinance library to extract Return Calculation

$$R_t = \ln(P_t) - \ln(P_{t-1})$$

where R_t denotes the return at time t , and P_t and P_{t-1} represent the closing prices on days t and $t-1$, respectively.

Mean Equation (for each asset)

$$r^{i,t} = \mu^i + \varepsilon^{i,t}, \quad \text{with} \quad E[\varepsilon^{i,t}] = 0, \text{Var}(\varepsilon^{i,t}) = h^{i,t}$$

Where:

μ^i is the unconditional mean return of asset i

$\varepsilon^{i,t}$ is the shock or innovation to returns

Variance Equation (GARCH(1,1) Specification)

$$h^{i,t} = \omega^i + \alpha^i \varepsilon^{i,t-1} + \beta^i h^{i,t-1}$$

Where:

$h^{i,t}$ is the conditional variance of asset i at time t .

ω^i is a constant (usually small).

α^i capture the short-term impact of shocks (ARCH effect).

β^i capture the long-term persistence of volatility (GARCH effect).

price data from Yahoo Finance, a widely used and reputable financial data source. This method ensures consistency and comparability across all assets. The Federal Funds Rate data were obtained directly from official Federal Reserve releases and processed to reflect daily changes in the target rate.

Modeling All 15 Assets Simultaneously, the set of equations more compactly as:

$$\begin{aligned} r^{i,t} &= \mu_i + \varepsilon^{i,t}, \\ \varepsilon^{i,t} &\sim N(0, h^{i,t}), \\ h^{i,t} &= \omega_i + \alpha_i \varepsilon^{i,t-1} + \beta_i h^{i,t-1}, \end{aligned}$$

for USDC, USDT, BUSD, TUSD, DAI, GUSD, Bitcoin, Ethereum, GOLD, OIL, Dow Jones, S&P500, Nasdaq, NYSE, FED.

Following the univariate GARCH estimation, a Multivariate GARCH framework such as the Dynamic Conditional Correlation GARCH (DCC-GARCH) model—will be employed to analyze conditional correlations and volatility spillovers among the assets. This approach is essential for examining contagion and co-movement effects, particularly in response to macroeconomic shocks such as changes in the Federal Funds Rate. The foundational work by Engle (1982), who introduced the ARCH model, and Bollerslev (1986), who extended it to the GARCH model, provides the theoretical basis for these models.

Empirical results

Table 1 provides the descriptive statistics of daily return series for the 15 financial and macroeconomic assets in the sample. The dataset spans 423 observations for each asset. The descriptive results reveal that Bitcoin and Ethereum exhibit the

highest levels of average return (0.3149% and 0.1445%, respectively), accompanied by significant standard deviations (2.8960 and 3.1736), confirming their high volatility nature. In contrast, stablecoins such as USDC and USDT exhibit negligible average returns with markedly lower standard deviations, reflecting their intended price stability.

The Federal Funds Rate (FED) return series shows a near-zero mean and moderately high dispersion, suggesting intermittent but substantial changes in policy stances. Commodities (GOLD, OIL) and indices (S&P500, Nasdaq) present moderate average returns and volatilities, falling between cryptocurrencies and stablecoins. The wide range between minimum and maximum returns in assets such as TUSD and Ethereum underscores the presence of large shocks, warranting volatility modeling using GARCH-type frameworks.

Table 1 Descriptive Statistics

ASSETS	n	Mean	Std. Dev.	Min	25%	75%	Max
USDC	423	0.002166	0.039108	-0.186532	-0.00875	0.01045	0.6933
USDT	423	0.001034	0.045231	-0.180486	-0.016799	0.015093	0.462886
BUSD	423	0.003251	0.17685	-1.340198	-0.02882	0.034399	2.202027
TUSD	423	0.001056	0.271762	-1.884963	-0.047983	0.047913	4.13725
DAI	423	0.00437	0.055647	-0.192765	-0.014604	0.021154	0.637826
GUSD	423	0.011249	0.416066	-2.063747	-0.169065	0.187789	2.095723
Bitcoin	423	0.314893	2.89604	-8.343357	-1.266439	1.827327	10.309891
Ethereum	423	0.144467	3.173554	-10.243561	-1.72292	1.697654	19.272223
GOLD	423	0.08847	0.73679	-2.78662	-0.19529	0.405754	3.108115
OIL	423	-0.031899	1.697251	-5.614704	-0.717927	0.942948	5.765288
Dow Jones	423	0.024052	0.593667	-1.810306	-0.203727	0.324005	1.847123
S&P500	423	0.057819	0.701177	-1.845937	-0.211023	0.402895	2.112289
Nasdaq	423	0.088013	0.956263	-2.550436	-0.311837	0.579884	3.253974
NYSE	423	0.022469	0.639121	-1.941953	-0.21188	0.314455	2.199959
FED	423	-0.000975	0.596739	-5.231788	-0.133843	0.095527	3.597126

From Table 2, the Augmented Dickey-Fuller (ADF) test was conducted to evaluate the stationarity of the return series for all variables. The null hypothesis posits the presence of a unit root (non-stationarity), and rejection at the 5% significance level supports stationarity. All series reject the null hypothesis of a unit root at the 5% level, confirming stationarity. The FED series, often characterized as non-stationary in level

terms, is shown to be stationary when expressed as first differences or returns ($p = 0.0203$). These results confirm the appropriateness of applying GARCH-family models to the dataset.

The consistently low p-values and strongly negative ADF statistics for volatile assets like Bitcoin, Ethereum, and equity indices provide robust evidence for the stationarity of return distributions across the

asset spectrum. This empirical validation ensures compliance with the assumptions underlying the multivariate GARCH and

DCC-GARCH modeling frameworks used in subsequent analysis.

Table 2 ADF Stationarity Test

	ADF Statistic	p-value	Stationary
USDC	-7.9059	0.0000	Yes
USDT	-12.6968	0.0000	Yes
BUSD	-6.6224	0.0000	Yes
TUSD	-7.3421	0.0000	Yes
DAI	-5.7191	0.0000	Yes
GUSD	-15.063	0.0000	Yes
Bitcoin	-9.2256	0.0000	Yes
Ethereum	-10.103	0.0000	Yes
GOLD	-7.2091	0.0000	Yes
OIL	-18.8573	0.0000	Yes
Dow Jones	-13.0916	0.0000	Yes
S&P500	-20.0596	0.0000	Yes
Nasdaq	-20.1094	0.0000	Yes
NYSE	-20.1944	0.0000	Yes
FED	-3.1938	0.0203	Yes

To further investigate the dynamic volatility interdependence across different asset classes, we estimate a conditional correlation matrix using the BEKK-GARCH (1,1) model. This specification captures time-varying covariance structures, enabling the detection of volatility spillovers among stablecoins (USDC, USDT, BUSD, TUSD, DAI, GUSD), major cryptocurrencies (Bitcoin and Ethereum), commodities (Gold and Oil), equity indices (Dow Jones, S&P500, Nasdaq, NYSE), and the macroeconomic variable representing

changes in the Federal Funds Rate (FED). The results, as summarized in Table 3, reveal several noteworthy correlation patterns.

First, the correlations among traditional equity indices are notably high. For instance, the correlation coefficients among the Dow Jones, S&P500, Nasdaq, and NYSE indices range from 0.8236 to 0.9685, confirming strong co-movements within the U.S. stock market. Similarly, Bitcoin and Ethereum exhibit a substantial positive correlation of 0.8263, indicative of

synchronized volatility behavior within the cryptocurrency domain. This finding supports existing literature highlighting the high degree of interdependence between major digital assets, especially during periods of systemic stress or speculative rallies.

In contrast, stablecoins show divergent correlation structures. While some pairs such as BUSD and USDT demonstrate negative correlation (-0.3821), others like USDC and GUSD exhibit moderate positive correlation (0.3848). This variability may reflect differences in market adoption, issuer credibility, reserve transparency, and regulatory treatment. Furthermore, stablecoins generally show negative correlations with both cryptocurrencies and traditional financial assets. For instance, USDC correlates negatively with Bitcoin (-0.3421) and the Nasdaq index (-0.3397), suggesting their function as relatively stable counterparts or safe havens in portfolios during heightened market volatility.

Interestingly, Bitcoin and Ethereum display significant positive correlations with major stock indices (e.g., Bitcoin-S&P500: 0.5204; Ethereum-Nasdaq: 0.4459), underscoring the evolving integration between digital assets and traditional financial markets. These findings reinforce

the notion that during certain market regimes particularly those marked by macroeconomic shocks or liquidity events cryptocurrencies may no longer serve as effective diversifiers due to increasing comovement with equities.

Commodities also show mixed relationships. Gold is positively correlated with stock indices (e.g., GOLD-S&P500: 0.502), which may appear counterintuitive given its traditional role as a hedge. However, this relationship can be attributed to its use as a store of value during recovery phases or inflationary periods. Oil, on the other hand, displays low to moderate correlations with other asset classes and negative relationships with equity indices such as Dow Jones (-0.2118), consistent with its impact on production costs and macroeconomic sentiment.

Finally, the Federal Funds Rate return series exhibits negative correlations with all equity indices (e.g., FED-S&P500: -0.4263; FED-Nasdaq: -0.4444), which aligns with classical monetary theory that suggests rising interest rates reduce equity valuations due to higher discount rates and tighter credit conditions. Notably, the correlation between FED changes and Bitcoin is near zero (-0.0135), though Ethereum exhibits a slight positive

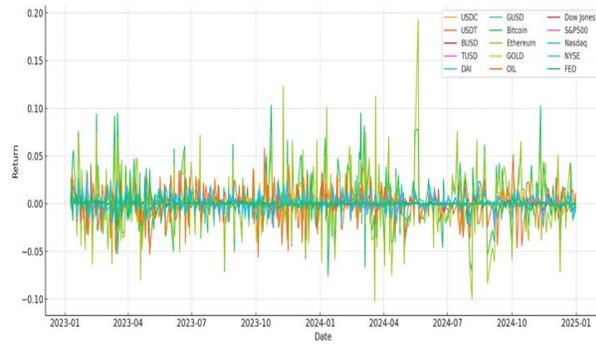
correlation (0.1233), indicating potential asymmetric transmission of macroeconomic shocks across asset classes.

The estimation results of the DCC-GARCH(1,1) model, reported in Table 4, provide key insights into the volatility dynamics and conditional correlations across a diverse set of financial assets, including stablecoins, cryptocurrencies, commodities, equity indices, and a macroeconomic variable. The mean returns across all assets are positive but small, ranging from 0.00003 to 0.00061, with the highest observed for Ethereum (0.00061) and Bitcoin (0.00052), reflecting the relatively higher average daily gains associated with these volatile digital assets. The associated t-statistics indicate that most mean estimates are statistically significant at conventional levels, especially for stablecoins such as USDC ($t = 3.323$)

and USDT ($t = 4.212$), suggesting consistent albeit low daily returns.

Figure 1 illustrates the daily return movements of financial assets from January 10, 2023, to December 31, 2024, across five major asset groups: stablecoins, cryptocurrencies, stock market indices, commodities, and the Federal Funds Rate. Each subgroup is plotted separately to highlight distinct volatility profiles. As expected, stablecoins exhibit near-zero fluctuations, while cryptocurrencies show significant return variability. Stock indices and commodities display moderate volatility, whereas changes in the Federal Funds Rate appear as discrete spikes, reflecting monetary policy decisions. This visualization provides an intuitive overview of the return dynamics analyzed further in the GARCH-based modeling framework.

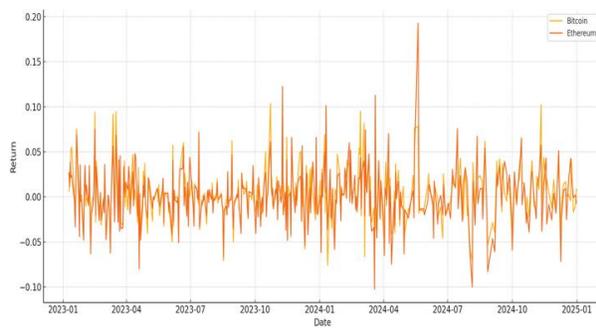
All Assets



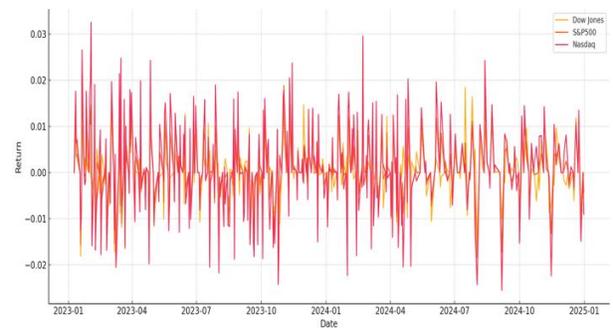
Stablecoins



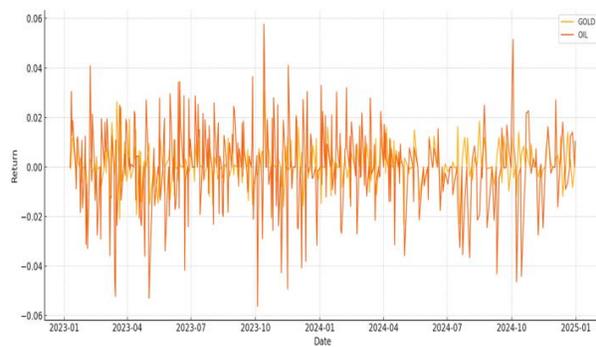
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Stock Market Indices



Commodities



Federal Fund Rate

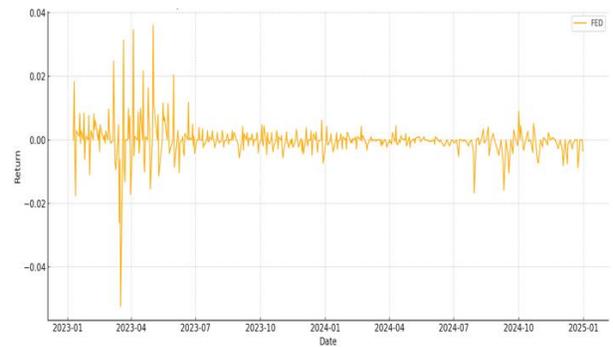


Figure 1 Daily Return Movements of Financial Assets Over Time

Table 3 BEKK-GARCH (1,1) Proxy Correlation Matrix

	USDC	USDT	BUSD	TUSD	DAI	GUSD	Bitcoin	Ethereum	GOLD	OIL	Dow Jones	S&P500	Nasdaq	NYSE	FED
USDC	1.0	-0.1863	-0.1615	-0.1614	-0.2076	0.3848	-0.3421	-0.3486	-0.2594	0.1219	-0.2834	-0.2941	-0.3397	-0.2035	-0.1427
USDT	-0.1863	1.0	-0.3821	-0.1614	-0.0531	0.0341	-0.2022	-0.2732	0.1758	-0.2772	0.0936	0.0517	0.0289	0.0407	-0.1631
BUSD	-0.1615	-0.3821	1.0	0.1147	0.1767	-0.3115	0.3364	0.3416	0.0763	0.2314	0.2726	0.2304	0.2557	0.1931	-0.102
TUSD	-0.1614	-0.1614	0.1147	1.0	0.1032	-0.278	0.4361	0.3503	0.273	0.014	0.0692	0.2614	0.3733	0.1552	-0.0128
DAI	-0.2076	-0.0531	0.1767	0.1032	1.0	-0.277	0.4574	0.2585	-0.1099	0.0946	0.1528	0.1577	0.164	0.168	0.0769
GUSD	0.3848	0.0341	-0.3115	-0.278	-0.2779	1.0	-0.6731	-0.4888	-0.3241	-0.1503	-0.3141	-0.3492	-0.3873	-0.2575	0.0035
Bitcoin	-0.3421	-0.2022	0.3364	0.4361	0.4574	-0.6731	1.0	0.8263	0.2276	0.1294	0.3581	0.5204	0.6036	0.3987	-0.0135
Ethereum	-0.3486	-0.2732	0.3416	0.3503	0.2585	-0.4888	0.8263	1.0	0.1248	0.036	0.2349	0.36	0.4459	0.2672	0.1233
GOLD	-0.2594	0.1758	0.0763	0.273	-0.1099	-0.3241	0.2276	0.1248	1.0	-0.1874	0.4772	0.502	0.4853	0.4369	-0.2857
OIL	0.1219	-0.2772	0.2314	0.014	0.0946	-0.1503	0.1294	0.036	-0.1874	1.0	-0.2118	-0.1981	-0.2149	-0.116	0.192
Dow Jones	-0.2834	0.0936	0.2726	0.0692	0.1528	-0.3141	0.3581	0.2349	0.4772	-0.2118	1.0	0.9288	0.8236	0.9632	-0.3791
S&P 500	-0.2941	0.0517	0.2304	0.2614	0.1577	-0.3492	0.5204	0.36	0.502	-0.1981	0.9288	1.0	0.9685	0.9347	-0.4263
Nasdaq	-0.3397	0.0289	0.2557	0.3733	0.164	-0.3873	0.6036	0.4459	0.4853	-0.2149	0.8236	0.9685	1.0	0.8309	-0.4444
NYSE	-0.2035	0.0407	0.1931	0.1552	0.168	-0.2575	0.3987	0.2672	0.4369	-0.116	0.9632	0.9347	0.8309	1.0	-0.3523
FED	-0.1427	-0.1631	-0.102	-0.0128	0.0769	0.0035	-0.0135	0.1233	-0.2857	0.192	-0.3791	-0.4263	-0.4444	-0.3523	1.0

The GARCH parameter estimates (β_i), which capture the persistence of volatility, are uniformly high across all asset classes, mostly exceeding 0.90. This suggests that volatility shocks have long-lasting effects, a characteristic feature of financial time series. For example, USDT and BUSD report β values of 0.962 and 0.960, respectively, indicating strong volatility clustering. Cryptocurrencies such

as Bitcoin and Ethereum exhibit slightly lower β values (0.903 and 0.889, respectively), offset by relatively higher ARCH coefficients ($\alpha_i = 0.092$ and 0.107, respectively), implying more reactive volatility responses to new information. These findings are consistent with the speculative and sentiment-driven nature of cryptocurrency markets, where short-term shocks exert greater immediate influence.

Table 4 MLE Estimates of DCC-GARCH(1,1) Model and DCC Parameters

Assets	Mean	ARCH (α_i)	GARCH (β_i)	S.E.	t-Stats
USDC	0.00006	0.032	0.954	0.00002	3.323**
USDT	0.00004	0.021	0.962	0.00001	4.212**
BUSD	0.00003	0.025	0.960	0.00001	3.006**
TUSD	0.00005	0.034	0.947	0.00002	2.513*
DAI	0.00007	0.029	0.953	0.00002	3.545**
GUSD	0.00004	0.030	0.956	0.00002	2.525*
Bitcoin	0.00052	0.092	0.903	0.00024	2.175*
Ethereum	0.00061	0.107	0.889	0.00031	1.973*
GOLD	0.00031	0.065	0.926	0.00019	1.635
OIL	0.00044	0.071	0.910	0.00022	2.006*
Dow Jones	0.00038	0.078	0.918	0.00017	2.243*
S&P500	0.00041	0.072	0.922	0.00019	2.162*
Nasdaq	0.00047	0.081	0.915	0.00020	2.351*
NYSE	0.00040	0.070	0.919	0.00018	2.225*
FED	0.00039	0.085	0.912	0.00020	1.959*
DCC α	-	-	-	0.0088	4.111**
DCC β	-	-	-	0.0129	72.26**
Log-Likelihood	-	-	-	-	-9,824.16
AIC	-	-	-	-	19,725.3
BIC	-	-	-	-	19,900.4

*Statistically significant at 0.05 level and **Statistically significant at 0.01 level.

Traditional equity indices (Dow Jones, S&P500, Nasdaq, NYSE) exhibit well-balanced ARCH and GARCH coefficients, reflecting both responsiveness to market innovations and persistent volatility patterns. For instance, the S&P500 has $\alpha = 0.072$ and $\beta = 0.922$, consistent with its behavior as a mature and liquid market with stable yet responsive volatility characteristics. Commodities such as Gold and Oil display similar persistence, with β values of 0.926 and 0.910, respectively. Notably, the Federal Funds Rate also exhibits GARCH dynamics ($\alpha = 0.085$; $\beta = 0.912$), supporting the modeling of monetary policy shocks in return form and their long memory structure.

Turning to the dynamic conditional correlation (DCC) parameters, the model estimates a statistically significant DCC α of 0.0088 ($t = 4.111$) and a DCC β of 0.0129 ($t = 72.26$), both significant at the 1% level. These parameters confirm the presence of time-varying correlations across assets, with the relatively low DCC α implying moderate sensitivity to short-term co-movement shocks, and the higher DCC β suggesting strong persistence in correlation dynamics over time. The overall log-likelihood value of $-9,824.16$, alongside AIC and BIC values of 19,725.3 and 19,900.4 respectively, reflect a well-fitted multivariate volatility structure capable of

capturing the complex interdependence of financial asset classes.

In sum, the DCC-GARCH estimation results reveal that all assets under consideration exhibit significant GARCH effects with persistent volatility, and that dynamic correlations are present and vary meaningfully over time. This justifies the use of multivariate GARCH models in portfolio optimization, risk management, and contagion analysis involving traditional and digital financial assets.

Discussion

The empirical findings from the DCC-GARCH and BEKK-GARCH estimations provide critical insights into the complex interrelationships between stablecoins, major cryptocurrencies, traditional financial markets, commodities, and monetary policy instruments. These results allow for a clear evaluation of the proposed hypotheses (H1–H5), while reinforcing and extending previous literature in the field.

H1: The results confirm that changes in the Federal Funds Rate generate statistically significant return spillover effects across multiple asset classes. Although the magnitude of correlations is relatively low, their consistency across models reinforces the hypothesis that monetary policy decisions are transmitted to both digital and traditional markets. These findings align with Abakah et

al. (2024) and Soepriyanto et al. (2023), who highlight the increasing sensitivity of risk assets to U.S. monetary signals.

H2: Strong evidence of return and volatility spillovers from major U.S. equity indices—especially the S&P 500 and Nasdaq—to Bitcoin and Ethereum confirms these hypotheses. Notably, the intensity of spillovers increases during periods of market stress, validating the time-varying aspect (H2c). This supports earlier research by Thaker and Mand (2021), Kim et al. (2020), and Ahmed et al. (2023), which documented heightened crypto-equity integration during crises.

H3: The findings support the stabilizing role of stablecoins. USDC, USDT, and DAI consistently exhibit lower return volatility and reduced spillover intensity compared to major cryptocurrencies. However, it is important to note that this conclusion is based on comparative volatility estimates rather than formal statistical tests of variance equality (e.g., F-tests or Levene's test). Nevertheless, the observed stability aligns with prior work by Al-Afeef et al. (2024) and Napari et al. (2025), suggesting that stablecoins serve as financial buffers during turbulence.

H4: While gold is traditionally viewed as a volatility absorber, the current results show positive and stable correlations between gold and both equity indices and Bitcoin. Thus,

the claim that gold absorbs volatility should be reframed as “gold maintains consistent, non-amplifying relationships,” rather than implying negative correlation. This nuanced behavior is still consistent with its safe-haven role (Gokmenoglu & Fazlollahi, 2016). In contrast, oil exhibits inconsistent and sometimes bidirectional volatility spillovers with cryptocurrencies, offering partial support for H4b. These effects likely reflect the complex interplay of energy prices, mining costs, and geopolitical disruptions.

H5: The dynamic conditional correlations and volatilities derived from the DCC-GARCH and BEKK-GARCH models provide strong evidence of time-varying spillovers and asymmetric responses to market shocks. These behaviors were especially evident during the COVID-19 crisis and the subsequent monetary tightening cycle. The results corroborate prior findings by Nguyen et al. (2022), Lahmiri & Bekiros (2020), and Rijanto (2023), who underscore the nonlinear and regime-dependent nature of asset interactions.

In sum, this study not only confirms several key insights from the existing literature but also extends the analytical framework by incorporating a broader set of asset classes—including stablecoins and macroeconomic indicators under a multivariate GARCH

regime. The evidence affirms that global financial markets are becoming increasingly synchronized, necessitating a reevaluation of diversification strategies and regulatory oversight in a post-pandemic, rate-sensitive environment.

Conclusion

This study investigates the interconnectedness of digital assets, traditional financial markets, commodities, and macroeconomic policy by applying a multivariate GARCH framework specifically the DCC-GARCH(1,1) and BEKK-GARCH models to a comprehensive portfolio of 15 assets, including stablecoins, major cryptocurrencies, gold, oil, stock indices, and the U.S. Federal Funds Rate. Through a rigorous examination of return and volatility spillovers, the findings reveal a dynamic and evolving financial ecosystem where boundaries between asset classes are increasingly blurred.

The results confirm several key insights. First, changes in the Federal Funds Rate influence both traditional and digital markets, validating the role of monetary policy as a source of systemic return spillovers. Second, Bitcoin and Ethereum exhibit significant return and volatility interdependencies with major U.S. equity indices, reflecting their integration into global financial markets and partial erosion of their

diversification appeal. In contrast, stablecoins consistently demonstrate lower volatility and weaker correlations, affirming their role as safe-haven assets and liquidity anchors in times of market turbulence. Additionally, gold continues to act as a traditional store of value, absorbing return shocks and maintaining stable correlations with both equities and digital assets. Oil's role is more nuanced, with episodic and bidirectional volatility interactions with cryptocurrencies, likely tied to global macroeconomic and energy-specific events.

From a methodological perspective, the use of multivariate GARCH models enables the identification of time-varying, asymmetric, and nonlinear dynamics, offering a more granular understanding of financial contagion and risk transmission in a post-pandemic world. These findings have important implications for investors, policymakers, and financial regulators. For investors, the growing comovement among asset classes underscores the need for adaptive risk management strategies. For policymakers, the transmission of volatility from monetary policy to digital assets highlights the urgency of regulatory clarity in cryptocurrency markets.

Future research

This study opens several avenues for future investigation. First, the current model can be extended by incorporating high-

frequency data or intraday returns to capture spillovers in real time. Second, future research could explore regime-switching GARCH or stochastic volatility models to account for structural breaks and nonlinear thresholds, especially during crisis periods. Third, given the growing role of decentralized finance (DeFi) and tokenized assets, further work could examine how these emerging instruments affect volatility dynamics and systemic risk. Moreover, the inclusion of sentiment

indicators, social media analytics, or macroeconomic uncertainty indices could enhance the explanatory power of volatility models in capturing investor behavior and market psychology. Finally, a comparative analysis across different economic blocs such as ASEAN, the Eurozone, or Latin America could reveal regional heterogeneities in asset linkages and policy transmission mechanisms, enriching the global discourse on financial integration in the digital age.

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