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Analysis of the Dynamic Co-movement Mechanism Between Cryptocurrencies and Traditional Assets

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Abstract:

This paper selects the data of Bitcoin, Gold, and the S&P 500 index from 2018 to 2025, utilizing GARCH(1,1) and DCC-GARCH models to depict the dynamic conditional correlations among assets. By incorporating the Global Geopolitical Risk Index, the 10-year breakeven inflation rate, and the VIX panic index, it constructs daily and monthly cross-frequency regression models to examine their macro-driving mechanisms. The results show that whether at the high-frequency daily level or the smoothed monthly level, macroeconomic variables exhibit extremely significant driving effects on the co-movement of Bitcoin. Under the liquidity squeeze concerns triggered by intensified global panic or high inflation expectations, Bitcoin fails to act as a haven alongside gold. Instead, it exhibits a stronger synchronous crash with the US stock market. This empirical study rejects the hypothesis of Bitcoin as "digital gold," revealing its essence as a "risk amplifier" highly dependent on traditional liquidity, and provides quantitative support for international investors in asset allocation under extreme macroeconomic scenarios.

Keywords: Cryptocurrency; safe-haven asset; geopolitical risk; inflation expectation.

1. Introduction

In recent years, in response to the shock of the COVID-19 pandemic, major global economies have experienced severe inflation and aggressive rate hike cycles. Meanwhile, frequent geopolitical crises in regions such as Russia-Ukraine and the Middle East have led to continuously elevated global risk aversion. Under these dual macroeconomic shocks, cryptocurrencies, characterized by a fixed total supply and decentralization, are commonly regarded by some investors as “digital gold” to hedge against systemic risks. However, with the approval of Bitcoin spot ETFs and the deepening of market institutionalization, whether cryptocurrencies will play a safe-haven role or act as risk amplifiers under extreme shocks has become a pressing question.

Recent academic research sparks heated academic debates regarding the asset properties of cryptocurrencies under extreme macroeconomic environments. Regarding geopolitical conflicts, Ustaoglu points out, by comparing the performance of major assets during

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the Russia-Ukraine conflict, that physical gold remains the optimal safe-haven asset for absorbing market panic [1]. Conversely, cryptocurrencies encountered severe sell-offs during the short-term window of the war's outbreak. Furthermore, Singh verified that the spillover effect of geopolitical risk on the crypto market has time-varying characteristics that lead to the collapse of its safe-haven properties [2]. Academic opinion is divided regarding how to navigate a high-inflation environment. Research by Klein and Conlon indicates that cryptocurrencies are driven by speculation and expectations of monetary tightening, rather than serving as short-term inflation hedges [3, 4]. Conversely, Choi and Shin find that cryptocurrencies positively anchor inflation expectations over the long term [5].

A review of the latest literature reveals significant limitations in existing studies. First, the studies mostly treat geopolitical panic or stagflation as isolated phenomena — without looking at them simultaneously. Second, they make use of static dummy variables, which do not reflect well the gradual, continuing nature of the connection between cryptocurrencies and traditional assets. Moreover, these analyses tend to omit the " time-frequency asymmetry " that is part of macroeconomic pricing, hence failing to separate with certainty high-frequency noise from low-frequency macro-trends [6].

Therefore, this paper utilizes daily data on core assets from 2018 to 2025 and employs the DCC-GARCH model to measure the dynamic conditional correlation coefficients (ρ_t) between assets. It then introduces the Global Geopolitical Risk Index (as defined mostly by Caldara and Iacoviello) and the 10-year breakeven inflation rate, which is treated as an approximate indicator of expected inflation [7]. Finally, concerning a " lagged level " setup that leaves macroeconomic trends intact, the paper proposes, for the first time, daily or monthly cross-frequency multivariate OLS attribution models.

The present paper goes beyond a static binary cognition and uses empirical means to reject the " digital gold " hypothesis by means of cross-frequency macro pricing tests, thus uncovering the basic character of Bitcoin's dependence on traditional liquidity. From a methodological standpoint, the repeated use of lagged levels in cross-frequency regressions prevents unnecessary signal loss due to over-differencing, and gives numerical backing to cross-border investors' planning of portfolios amid stagflation or wartime uncertainty.

2. Data and Methodology

2.1 Data Source and Processing

To comprehensively characterize the dynamic interlinkages among major asset classes amidst the dual shocks of high inflation and geopolitical conflicts, this study utilizes daily time-series data spanning from January 1, 2018, to December 31, 2025. The years covered include a large number of macroeconomic phenomena, among them the COVID–19 pandemic, the worldwide high–inflation phase (2021–2023), the Federal Reserve's sharp rise in interest rates, and the Russia-Ukraine or Israel-Palestine conflicts, which together form an ideal " natural experiment " setting for empirical work. Definitions and data sources for the main variables appear in Table 1.

Table 1. Core data selection

Variable Category	Variable Name	Code/ Abbreviation	Variable Description and Economic Meaning	Data Source
Basic Assets (Used for constructing the dynamic correlation coefficient dependent variable)	Bitcoin	BTC-USD	Core subject of this study, representing emerging cryptocurrency assets	Yahoo Finance
	SPDR Gold ETF	GLD	Internationally recognized proxy for traditional safe-haven assets	Yahoo Finance
	S&P 500 Index	S&P 500	Globally most representative traditional high-risk equity asset	Yahoo Finance
Core Explanatory Variables (Macro driving mechanism)	Global Geopolitical Risk Index	GPRD	Built on text mining of global mainstream media, quantifying short-term panic shocks caused by sudden wars and geopolitical conflicts	Researchers' official website (Caldara & Iacoviello)
	10-Year Breakeven Inflation Rate	T10YIE	Ingeniously avoids the low-frequency defect of CPI data, serving as a high-frequency daily proxy for market long-term inflation expectations	Federal Reserve Economic Data (FRED)

Variable Category	Variable Name	Code/ Abbreviation	Variable Description and Economic Meaning	Data Source
Control Variable (Market sentiment)	CBOE Volatility Index	VIX	Measures systemic panic and overall sentiment volatility in global financial markets	Yahoo Finance

Given the mismatch between the trading calendars of cryptocurrency markets and traditional financial markets, and following the standard conventions established by Corbet and Bouri, this study aligns the data for all assets using the U.S. stock market (S&P 500) trading calendar as the benchmark [8,9].
Furthermore, to eliminate the issue of "spurious regression" arising from potential non-stationarity in price series, the logarithmic differencing method is applied to convert asset prices (or indices) into percentage returns, as shown in Equation (1).

$$R_{i,t}=\ln(\frac{P_{i,t}}{P_{i,t}-1})\times 100 \tag{1}$$

Where $R_{i,t}$ represents the percentage log return of asset i at time t, and $P_{i,t}$ is the closing price on that day. After processing, all sequences must pass the ADF unit root test to ensure stationarity.

2.2 Empirical Model Construction

2.2.1 Phase One: DCC-GARCH Model Construction

DCC-GARCH, proposed by Engle, has the core advantage of being able to capture the volatility clustering characteristics of assets while simultaneously measuring the dynamic evolution of correlation coefficients over time [10]. The model is estimated in two steps.
First, a univariate AR(1)-GARCH(1,1) model is constructed to fit the marginal distribution of the returns of each asset to extract standardized residual sequences. The mean equation and variance equation are shown in Equation (2) and Equation (3), respectively, and Equation (4) presents the conditional variance (i.e., volatility) of asset i at time t.

$$R_{i,t}=\mu_i+\phi_i R_{i,t-1}+\epsilon_{i,t} \tag{2}$$

$$\epsilon_{i,t}=z_{i,t}\sqrt{h_{i,t}},\ z_{i,t}\quad \text{i.i.d}(0,1) \tag{3}$$

$$h_{i,t}=\omega_i+\alpha_i\epsilon_{i,t-1}^2+\beta_i h_{i,t-1} \tag{4}$$

Where α_i measures the impact of external shocks on variance (ARCH term), and β_i measures the persistence of its own volatility (GARCH term).
Cryptocurrencies such as Bitcoin display obvious leptokurtic features and strong volatility clustering in high-frequency daily trading. For this reason, this paper employs the multivariate Student-t distribution to estimate GARCH marginal distributions. This setting is not only supported by the Jarque-Bera test in earlier descriptive statistics but also highly consistent with Katsiampa's classic empirical findings on the optimal volatility measurement models for cryptocurrencies, effectively avoiding the underestimation of tail extreme risks [11].
After obtaining the standardized residual sequence $z_t=(z_{BTC,t},z_{GLD,t})'$ this paper utilizes the DCC-GARCH model to construct the dynamic conditional correlation structure. This structure is shown in Equation (5).

$$Q_t=(1\text{-}a\text{-}b)\bar{Q}+a(z_{t-1}z_{t-1}')+bQ_{t-1} \tag{5}$$

Where $\bar{Q}$ is the unconditional covariance matrix of standardized residuals, Q_t is the dynamic covariance matrix, and a and b are non-negative parameters satisfying $a+b<1$.
Ultimately, the dynamic conditional correlation coefficient (ρ_t^{BG}) between Bitcoin (B) and Gold (G) at time t is calculated as shown in Equation (6).

$$\rho_t^{BG}=\frac{q_t^{BG}}{\sqrt{q_t^{BB}q_t^{GG}}} \tag{6}$$

2.2.2 Phase Two: Macro-Driving Mechanism Test

To further explore the underlying causes of dynamic co-movement, this paper uses the dynamic conditional correlation coefficient (ρ_t) extracted in the first phase as the dependent variable. For the selection of explanatory variables, this paper introduces the daily Global Geopolitical Risk Index, the 10-year breakeven inflation rate, and the panic index. In the econometric setting, to mitigate endogeneity, this paper lags all macro explanatory variables by one period. More importantly, to isolate the micro-speculative white noise in daily trading, this paper constructs a cross-frequency comparative test of daily and monthly data [12]. Through data frequency reduction processing, it matches the true functional cycles of macroeconomic variables.
The final baseline regression model is set as shown in Equation (7).

$$\rho_t^{BTC,i}=\gamma_0+\gamma_1 GPRD_{t-1}+\gamma_2 T10YIE_{t-1}+\gamma_3 VIX_{t-1}+\epsilon_t \tag{7}$$

Where $\rho_t^{BTC,i}$ represents the dynamic correlation coeffi-

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cient between Bitcoin and gold/US stocks at time t, respectively. ϵ_t is the random error term.

3. Empirical Results

3.1 Descriptive Statistics and Preliminary Analysis

Table 2. Descriptive statistics and preliminary analysis results

Asset	BTC	GLD	GSPC
Mean	0.08841418	0.05985749	0.04677677
Std. Dev	4.122754	0.9954831	1.238941
Skewness	-0.921078	-0.3533551	-0.6550683
Kurtosis	14.50901	6.892386	17.71161
J-B Test p-value	<0.001***	<0.001***	<0.001***
ADF Test p-value	<0.001***	<0.001***	<0.001***
ARCH Effect Test p-value	<0.001***	<0.001***	<0.001***

(Note: Values in parentheses are p-values. ***, **, * indicate significance at the 1%, 5%, and 10% confidence levels, respectively.)

With a view to applying DCC-GARCH modeling, the present paper starts by analyzing the daily log returns of all assets. From Table 2 it is clear that Bitcoin's daily standard deviation is much greater than that of ordinary equities or of gold, and so it has strong " high-risk " properties. Every one of the assets studied here has negative skewness and kurtosis, both much above the standard normal value of 3, thus showing distinct " leptokurtic and fat-tailed " behavior. The very significant Jarque-Bera tests make it evident that the Student-t distribution is necessary for modeling purposes.

In addition, ADF tests tell that all of the return series are stationary (at the 1%significance level), with no serious spurious regression. Ljung-Box tests applied to squared returns yield significance at the 1% level, and strongly support a " volatility clustering " form of asset return behavior. Such evidence gives direct backing to the idea of applying GARCH models to heteroskedasticity.

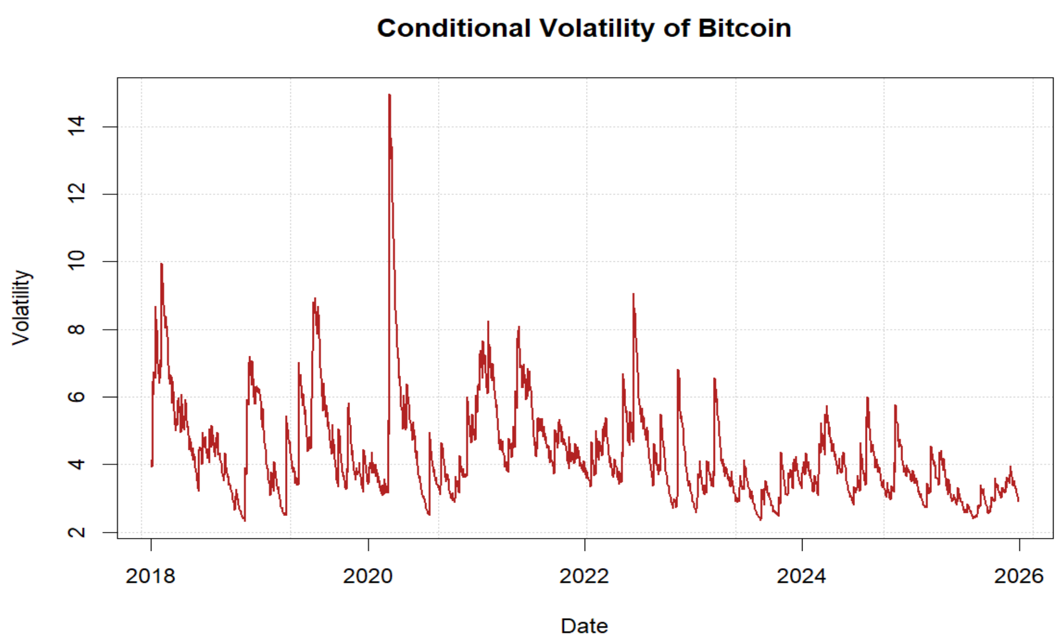

Fig. 1 Time series evolution of bitcoin volatility

Figure 1 illustrates the daily conditional volatility of Bitcoin derived from ARMA-GARCH(1,1) marginal distributions. Bitcoin's conditional volatility has gone up sharply, sometimes quite suddenly, at moments of grave macroeconomic disturbance, namely the liquidity crisis caused by the COVID-19 pandemic in early 2020 or the outbreak of the Russia-Ukraine conflict in early 2022. Such preliminary data seem to show that, with extreme panic present, crypto assets fail to be safe havens and do not help to stabilize volatility.

3.2 Core Chart Display: Time Series Evolution of Dynamic Correlation

Table 3. DCC-GARCH(1,1) model parameter results

Parameter	Estimate	Std. Error	t Statistic	p-value
Marginal Distribution Variance Equation				
α_{BTC}	0.093	0.020	4.600	< 0.001***
β_{BTC}	0.906	0.016	55.109	< 0.001***
α_{GLD}	0.047	0.013	3.513	< 0.001***
β_{GLD}	0.942	0.019	48.690	< 0.001***
α_{SP500}	0.171	0.024	7.114	< 0.001***
β_{SP500}	0.816	0.022	36.993	< 0.001***
Dynamic Conditional Correlation Equation				
α_{DCC}(dcca1)	0.024	0.005	4.467	< 0.001***
β_{DCC} (dccb1)	0.958	0.010	90.811	< 0.001***
Distribution Shape Parameter				
v(mshape)	4.837	0.218	22.201	< 0.001***

(Note: Values in parentheses are p-values. ***, **, * indicate significance at the 1%, 5%, and 10% confidence levels, respectively.)

In this study, the DCC-GARCH model is estimated using a two-step Quasi-Maximum Likelihood Estimation (QMLE) approach combined with a multivariate Student-t distribution. The estimation results for the model's core parameters are detailed in Table 3.

Regarding the variance equations of the marginal distributions, the coefficients for the ARCH terms (α) and GARCH terms (β) for the assets are highly significant, further confirming the strong volatility clustering effect characteristic of financial time series.

Among the estimation results of the dynamic conditional correlation equation, both α_{DCC} and β_{DCC} are highly significant at the 1% level, and their sum is strictly less than 1 (approaching 0.982), fully meeting the requirements of mean-reversion and stationarity for the DCC model. That conclusion shows clearly that the three main asset classes, when taken as a group, exhibit substantial time-variation and long memory effects. Moreover, the degrees of freedom parameter of the multivariate t-distribution is 4 . 837 and very significant, which implies the necessity of this model for extreme risk analysis.

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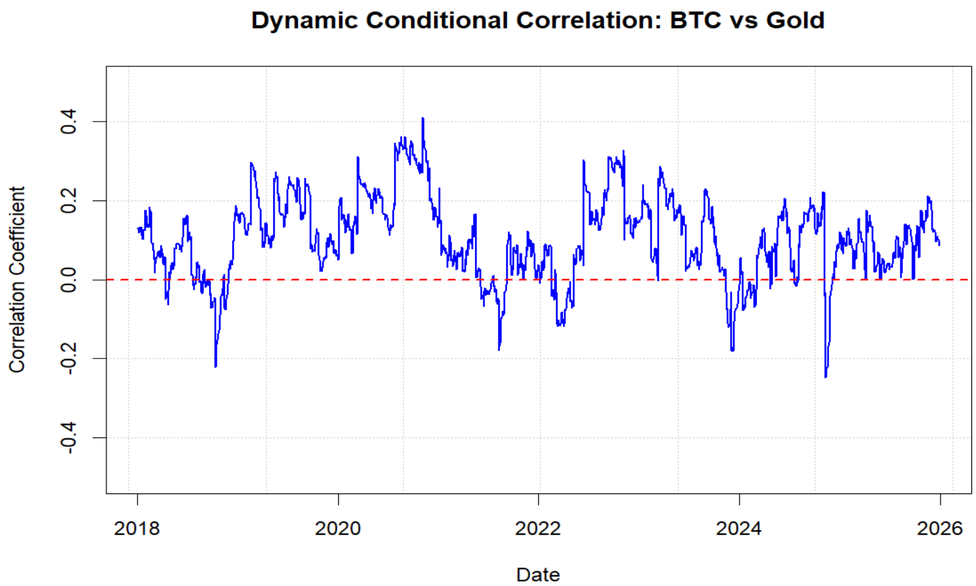

Fig. 2 Dynamic conditional correlation: comparative analysis of bitcoin and gold

Figure 2 visually presents the development path taken by the dynamic conditional correlation coefficient ($\rho_{BTC,GLD}$) between Bitcoin and gold over the sample period. Judging by the figure itself, the co-movement of the two is associated with very extreme cross-state regime shifts. First, in the short-term window corresponding to macro shocks of extreme intensity, the correlation coefficient drops suddenly, almost in a cliff-like fashion, into the negative region. That suggests a similarity between Bitcoin and standard risky assets when liquidity runs occur briefly in panic sales. On the other hand, for the 2021–2023 era of high inflation and of sharply rising rates, the central axis of the correlation coefficient rises quite steadily. Such divergences and convergences will be causally clarified—on a macro level—in the model analyzed in the following section.

3.3 Regression Results

Table 4. Macro-driving mechanism test of cryptocurrency dynamic correlation (daily)

Explanatory Variables (Lagged level series)	Model 1 (Dependent Variable: BTC-Gold Correlation)	Model 2 (Dependent Variable: BTC-US Stocks Correlation)
Lagged Geopolitical Risk ($GPRD_{t-1}$)	-0.00015*** (<0.001)	-0.00014*** (<0.001)
Lagged Inflation Expectation ($T10YIE_{t-1}$)	-0.09967*** (<0.001)	0.21150*** (<0.001)
Lagged Panic Index (VIX_{t-1})	0.00293*** (<0.001)	0.01060*** (<0.001)
Constant	0.27810*** (<0.001)	-0.39000*** (<0.001)
Sample Size	2007	2007
Adjusted R^2 (Adj. R^2)	0.2411	0.4388
F-Statistic p-value	< 0.001***	< 0.001***

(Note: Values in parentheses are p-values. ***, **, * indicate significance at the 1%, 5%, and 10% confidence levels, respectively.)

Table 4 reports the OLS lagged level series regression results at the daily level. The adjusted R^2 of Model 1 and

Model 2 reach 24.11% and 43.88%, respectively, and all macro variables are highly significant at the 1% level. These highly explanatory empirical results completely tear off Bitcoin's safe-haven disguise of being "digital gold", and their coefficient signs deeply reveal Bitcoin's risk asset nature tied to traditional liquidity.

First, geopolitical panic and systemic risk expose Bitcoin's vulnerability. Whether it is lagged geopolitical risk or the panic index, both exert heterogeneous shocks on the BTC-Gold correlation (Model 1), while the coefficient for VIX is significantly positive on the BTC-US Stocks correlation (Model 2). This demonstrates that when global systemic risk surges, Bitcoin not only fails to exhibit independent safe-haven characteristics but rather forms a stronger "synchronous crash" (positive correlation surge) with US equities, solidifying its role as a "risk amplifier."

Second, stagflation expectations drive cryptocurrencies to thoroughly degenerate into an appendage of US stocks. The model results show that inflation expectations are significantly negative for the BTC-Gold correlation and significantly positive for the BTC-US Stocks correlation. These heterogeneous correlation patterns outline a complete macro liquidity transmission mechanism. When rising inflation expectations trigger market worries over Federal rate hikes, gold retains its value-preserving advantage as a zero-coupon safe-haven asset. Conversely, Bitcoin, sharing the long-duration risk asset profile, has its pricing logic highly synchronized with US tech stocks, suffering from indiscriminate capital withdrawals. Therefore, the high inflation era did not endow Bitcoin with safe-haven value, but instead tied it more tightly to the chariot of US stock market volatility.

4. Robustness Checks

Table 5. Cross-frequency macro-driving mechanism test of cryptocurrency dynamic correlation (monthly)

Explanatory Variables (Lagged level series)	Model 3 (Dependent Variable: BTC-Gold Correlation)	Model 4 (Dependent Variable: BTC-US Stocks Correlation)
Lagged Geopolitical Risk ($GPRD_{t-1}$)	-0.0003 (0.229)	-0.0001 (0.749)
Lagged Inflation Expectation ($T10YIE_{t-1}$)	-0.0836*** (0.006)	0.2118*** (<0.001)
Lagged Panic Index (VIX_{t-1})	0.0033** (0.014)	0.0111*** (<0.001)
Constant	0.2519*** (<0.001)	-0.4083*** (<0.001)
Sample Size	94	94
Adjusted R^2 (Adj. R^2)	0.2443	0.4449

(Note: Values in parentheses are p-values. ***, **, * indicate significance at the 1%, 5%, and 10% confidence levels, respectively.)

To strip away the interference of micro-speculative "white noise" in daily high-frequency trading, this paper aggregates the data by calendar month for the data frequency reduction process and constructs cross-frequency models to perform robustness checks. As the results in Table 5 show, the direction of impact and the significance ($p < 0.01$) of inflation expectations and the panic index on correlation coefficients remain highly consistent with the daily baseline models, and the explanatory power (Adj. R^2) of the monthly models further improves to over 44%. This fully proves that this paper's empirical conclusion regarding Bitcoin as a "US stock risk amplifier" is cross-frequency robust.

5. Conclusion

Under the dual shocks of frequent high inflation and exacerbated geopolitical conflicts in the post-pandemic era, this paper uses the DCC-GARCH model to depict the dynamic conditional correlation among assets, and innovatively constructs daily and monthly cross-frequency level regression models.

This paper finds that during sudden geopolitical crises, the volatility extracted by the GARCH model shows that Bitcoin's risk undergoes pulse-like surges, and its correlation with gold drops cliff-like, failing to play a short-term safe-haven role.

In addition, the cross-frequency macro test thoroughly rejects the "macro decoupling theory" for the crypto market. Bitcoin's underlying pricing is strongly anchored by panic sentiment and inflation expectations. The liquidity

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tightening triggered by high inflation significantly severs the link between Bitcoin and gold, while deepening its synchronized fluctuations with traditional stocks.

The previous conclusions suggest definite practical consequences. For an investor, the illusion of buying " anti-inflation digital gold " should no longer be entertained. During stagflation or extreme macroeconomic turmoil, Bitcoin allocation does not help to limit losses of standard equity portfolios. Rather, it experiences steeper drawdowns and proves itself to be a high-volatility alternative risk asset. From the standpoint of financial regulators, one needs to consider how leveraged capital may trigger extreme cross-market risk spillovers. With macroeconomic conditions worsening sharply, the crypto and traditional stock markets often behave in unison. Such a state of affairs calls for a cross-market liquidity analysis (or early warning) and for rules that help isolate cross-asset risks in practice.

This paper only adopts lagged levels of macro indicators to analyze linear co-movement patterns among different assets, which inevitably leaves certain limitations in the research framework. In real-world financial markets, price and volatility responses to macro shocks are typically marked by prominent asymmetric features. Follow-up research can adopt the asymmetric DCC-GARCH model (ADCC-GARCH) for empirical estimation, and incorporate indicators tracking global US dollar liquidity to conduct more comprehensive and in-depth extended analysis on the underlying mechanisms of asset co-movement.

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