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Time-Varying Dependence Between Bitcoin and Gold under Geopolitical Risk and Market Uncertainty

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Abstract. We study the time varying spillover relation between Bitcoin, gold and two variables, geopolitical risk and market uncertainty for the period 2018-2025.The daily data of important event happening in the word are utilized to with respect to the COVID-19 pandemic and the Russia – Ukraine conflict, this paper initially uses the EGARCH and APARCH models for analyzing the dynamic behavior of Bitcoin and gold volatilities. We finally applied the DCC-MGARCH model to estimate their dynamic conditional correlation and use a regression to find out what are the macro-financial determinants of spillover intensity. Our empirical evidence shows that Bitcoin has much more volatility, more pronounced asymmetry, and more speculatory features than the latter while gold still preserves its relatively steady-state safe-haven property. The dynamics of correlation between Bitcoin and gold are also shown to be very persistent and time-varying. Moreover, geopolitical risk severely dampens the co-movement of both assets while market uncertainty, proxied by the VIX index enhances their correlation. The effect of realized geopolitical acts appears to be more negative in terms of their impact on spillover strength than geopolitical threat. In total, these results indicate that the role of gold, which is considered a conventional safe-haven asset, is not completely substituted by Bitcoin. This research adds to the body of knowledge about digital assets and safe-haven markets and has practical implications in portfolio diversification and risk management amidst a world full of uncertainties.

Keywords: Bitcoin, Gold, DCC-MGARCH, Dynamic correlation, Geopolitical risk

1. Introduction

Since the global financial crisis, increasing macroeconomic uncertainty, geopolitical shocks, and changes in monetary policy have renewed interest in safe-haven assets. Gold has long been known to be a good hedge against market turbulence and extreme financial risk [1, 2], while Bitcoin gained popularity as "digital gold" due to its decentralization and fixed supply [3]. Nevertheless, Bitcoin's high volatility and growing integration with the rest of the world economy make it hard to know if Bitcoin may safely act as a refuge for investors. Existing literature points out that the relationship between Bitcoin and gold is not static but rather dynamic: they move together in some markets, but not others; their co-movement could be different when facing financial or geopolitical shocks [4, 5]. Accordingly, static correlation models can be inadequate in modeling their dynamic dependence.

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Following Engle's DCC model [6] and related works of connectedness recently proposed in TVP-VAR type models [7], this work studies the time varying dependence between Bitcoin and gold for the period from 2018 to 2025, a time frame that includes theCOVID-19 pandemic, the Russia-Ukraine war and global financial tightening. In particular, it uses GARCH-family models for modeling volatility features of both assets and applies the DCC-MGARCH model in order to estimate their dynamic dependence, and in addition analyzes the effect that geopolitical risk, the VIX index and the real interest rate have over their spillover link.

2. Methodology

This study employs a combination of univariate and multivariate GARCH-family models to investigate the volatility dynamics and time-varying dependence between Bitcoin and gold. In addition, regression analysis is conducted to examine the macro-financial determinants of dynamic spillover effects.

2.1. Univariate GARCH models

Financial asset returns usually exhibit volatility clustering, persistence, and asymmetric responses to market shocks. To capture these characteristics, this study employs the EGARCH [8] and APARCH models [9] to analyze the volatility behavior of Bitcoin and gold returns.

The EGARCH models proposed in [8] allow positive and negative shocks to have asymmetric effects on conditional volatility and avoids the non-negativity restrictions required in standard GARCH models. The conditional variance equation is expressed as:

$$\ln(h_t) = \omega + \alpha\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| + \gamma\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta\ln(h_{t-1}) \tag{1}$$

To further account for nonlinear volatility structures and varying shock responses, the APARCH model proposed in [9] is also employed:

$$h_t^{\delta} = \omega + \alpha(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^{\delta} + \beta h_{t-1}^{\delta} \tag{2}$$

where δ represents the power parameter that allows the model to flexibly capture different forms of volatility dynamics. Compared with conventional GARCH models, APARCH is more suitable for describing financial time series characterized by heavy tails and leverage effects.

Prior to estimate the GARCH-family models, we conduct Augmented Dickey-Fuller (ADF) test for verifying whether the return series are stationary or not. Besides, we apply the ARCH-LM test to confirm the existence of conditional heteroskedasticity and provide a statistical basis for using GARCH type models.

2.2. Dynamic Conditional Correlation (DCC) model

In order to explore the time varying correlation/spillover effect of Bitcoin and Gold, this paper uses Dynamic Conditional Correlation (DCC) MGARCH model introduced in [6] compared with constant-correlation models, where the dynamic evolution of correlations is allowed, which makes this model suitable when we consider that markets are affected by a crisis or political events in which relations change during periods of uncertainty.

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The DCC-MGARCH model is estimated in two stages. In the first stage, univariate GARCH-family models are used to estimate the conditional variances of Bitcoin and gold returns. In the second stage, the standardized residuals obtained from the first stage are used to estimate the dynamic conditional correlation matrix. The conditional covariance matrix is defined as:

$$H_t = D_t R_t D_t \tag{3}$$

where D_t is a diagonal matrix containing the conditional standard deviations of each asset, and R_t denotes the time-varying conditional correlation matrix.

The dynamic correlation process follows:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha\varepsilon_{t-1}\varepsilon_{t-1}^{'} + \beta Q_{t-1} \tag{4}$$

where $\bar{Q}$ is the unconditional covariance matrix of standardized residuals, α captures the short-run effects of shocks on correlations, and β measures the persistence of dynamic correlations. A larger β coefficient indicates that the correlation process is highly persistent and evolves gradually over time.

Based on the estimated conditional covariance matrix, the dynamic conditional correlation coefficient between Bitcoin and gold is calculated as:

$$\rho_{ij,t} = \frac{h_{ij,t}}{\sqrt{h_{ii,t}h_{jj,t}}} \tag{5}$$

where $\rho_{ij,t}$ represents the time-varying correlation between Bitcoin and gold at time t.

3. Data

3.1. Data resources

In this paper, we use intradaily financial data to analyze the volatility properties of Bitcoin and Gold markets as well as their time varying dependence relationship. To do so, BTC/USD exchange rate for Bitcoin price while gold spot and derivatives data is used to proxy the performance of Gold markets ,, including gold ETF s and gold futures contracts. The employment of several gold related assets permits us to perform a robustness check over various parts of the gold market. In particular, gold ETF prices are capturing the behavior of the spot market available for general investors while gold futures prices reflect expectations and hedging demand on derivatives markets.

The sample spans over a few years of data (from 2018to the end of 2025) covering some significant world economy and finance episodes. The wide range allows for analyzing distinct market regimes, from fairly tranquil times to periods with increased uncertainty or turbulence.

All the prices come from publically available financial databases such as Yahoo Finance, the choice of daily frequency data is appropriate to model short term volatility dynamics and time varying correlations. That we consider in this work.

3.2. Data processing

Before the empirical analysis, all raw price series are processed through a few steps in order to make them comparable with each other.

First of all, we transform all the price series into log-return defined as:

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$$r_t = \ln(P_t) - \ln(P_{t-1}) \tag{6}$$

where P_t denotes the closing price at time t. Logarithmic returns are chosen for their ability to stabilize the variance, ease of interpretation and which are popularly used in finance econometric applications.

Second, as the calendar of trade for Bitcoin differs from that of gold, data alignment is done. Bitcoin trades every day (i.e., 24/7), noting that we use daily frequency including weekend/holidays while gold is traded only in the business hours during weekdays (weekends closed). To make them comparable with each other, we drop Bitcoin observations that correspond to non-gold trading days so as to ensure the same time index for each of the return series.

Third, missing values and possible inconsistency of original datasets are removed by a routine data-cleaning process. Only those observations with complete price information will be used for further analysis.

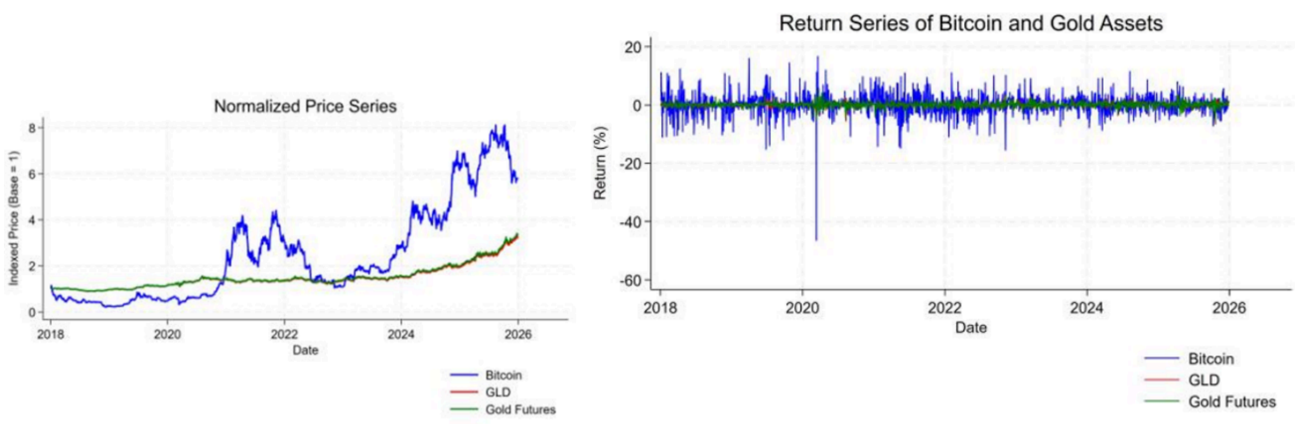
3.3. Descriptive statistics

The descriptive statistics of the return series of Bitcoin, GLD and gold futures in the sample period are reported Table 1.

Table 1. Descriptive statistics of the return for Bitcoin, GLD, and gold futures

variable	mean	std.dev.	Min	Max	Skewness	Kurtosis	JB	p-value
BTC_RET	0.073	3.678	-46.473	16.710	-1.280	21.049	22000	<0.001
GLD_RET	0.057	0.934	-6.643	4.739	-0.462	6.872	1035	<0.001
FUT_RET	0.062	0.972	-5.906	5.778	-0.371	6.873	1016	<0.001

Table 1 and Fig 1 clear demonstrate the distinct statistical properties across the three assets. Bitcoin exhibits a much higher standard deviation (3.678) compared to GLD (0.934) and gold futures (0.972), reflecting its high volatility and speculative nature. All series display negative skewness and high excess kurtosis (especially Bitcoin at 21.049), indicating heavy tails and significant downside risks. The non-normality and volatility clustering observed across all assets provide strong empirical justification for employing the GARCH-family frameworks.



(a) (b)

Figure 1. (a)Normalized price series of Bitcoin, GLD, and gold futures.(b)return series of Bitcoin, GLD, and gold futures, showing volatility clustering

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4. Empirical results

4.1. Volatility dynamics of Bitcoin and gold

Before estimating the dynamic spillover effects between Bitcoin and gold, this study first examines the individual volatility characteristics of Bitcoin, the SPDR Gold Shares ETF (GLD), and gold futures through univariate volatility models. Specifically, the Augmented Dickey–Fuller (ADF) test, ARCH-LM test, EGARCH model, and APARCH model are employed to investigate the stationarity, volatility clustering, asymmetry, and persistence of each return series.

The ADF test results indicate that all return series are stationary at the 1% significance level. The null hypothesis of a unit root is strongly rejected for Bitcoin, GLD, and gold futures returns. Also, the ARCH-LM tests show that there is significant heteroskedasticity for all returns series. The null hypothesis of no ARCH effect is rejected at 1% level for all assets, suggests that there is evidence of volatility clustering and time varying conditional variance which justifies using asymmetric GARCH-family models like EGARCH or APARCH.

The results of EGARCH and APARCH in respect to BTC, GLD and gold future are shown at Table 2. The EGARCH and APARCH estimations for Bitcoin show significant volatility persistence as well as asymmetric volatility behavior. In EGARCH, the ARCH parameter(α) is positive and statistically significant, which indicates a direct influence of the new shock in markets to Bitcoin volatility. The persistence parameter (β = 0.8945) is also quite significant which indicates that there are strong volatility persistence and volatility clustering effects present in Bitcoin return. The asymmetrical parameter (γ) of EGARCH specification is negative but not significant. Suggesting some weak evidence for leverage effects in the EGARCH specification. The APARCH, on the other hand, does provide more compelling evidence for asymmetry. In particular, the APARCH asymmetry coefficient is positive and significant, indicating that positive and negative shocks have a different impact on the conditional volatility.

Furthermore, the estimate of the power parameter (δ=1.943) is significantly different to the standard GARCH restriction indicating that the volatility process for Bitcoin is nonlinear in nature and best described with the more general APARCH specification. The superiority of the APARCH model over the EGARCH for Bitcoin is also confirmed by lower AIC and values, and is in line with the findings reported in [10], which shows the presence of power transformed asymmetric volatility process and fat tail in crypto market which are not well captured by simple GARCH model.

Table 2. Results of EGARCH and APARCH models about BTC, GLD and gold futures

Asset	Model	α	γ	β	δ	Log-likelihood	AIC
Bitcoin	EGARCH	0.270***	-0.071	0.895***		-5752.20	11516.4
Bitcoin	APARCH	0.101**	0.201**	0.836***	1.943***	-5745.72	11505.4
GLD	EGARCH	0.164***	0.062***	0.961***		-2622.21	5256.4
GLD	APARCH	0.087***	-0.333**	0.891***	1.416**	-2622.21	5258.4
Gold Futures	APARCH	0.066***	-0.423**	0.914***	1.349***	-2710.06	5434.1

For the gold market, both GLD and gold futures exhibit strong volatility persistence (β is 0.961 and 0.914, respectively). In contrast to Bitcoin, the asymmetry parameters (γ) are significantly negative in the APARCH specification, confirming the "inverse leverage effect" typical of traditional

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safe-haven assets, where bad market news drives up gold demand and volatility [11]. The power terms (δ) are also statistically significant, validating the nonlinear structure of gold volatility.

4.2. Time-varying dependence between Bitcoin and gold

To further explore the dynamic relation between Bitcoin and gold, in this paper we adopt the Dynamic Conditional Correlation Multivariate GARCH (DCC-MGARCH) model proposed in [6]. Table 3 reports the DCC-MGARCH estimation result. The estimated unconditional correlation between Bitcoin and gold is positive and significantly different from zero ($\rho=0.146$, $p<0.01$), indicating that the two assets have a moderate level of co-movement during the sample period.

More important, the DCC parameters show that there is a high level of persistence for the dynamic correlation process. The short-run adjustment parameter (λ_1 =0.010) is positive and not statistically significant, suggesting that these shocks are having only little impact in the short-run correlations, discouraging to see them as one and the same asset class [12]. Compared to the latter, the persistence parameter (λ_2 =0.970) is quite significant and very close to one which means that changes of the Bitcoin-gold correlation are highly persistent and change slowly over time.

The relatively high level of persistence for the conditional correlation indicates that the time varying dependence between BTC and gold stems mainly from long-lasting market states instead of short-term shocks, which is coherent with the fact that crypto-asset and conventional financial markets are increasingly integrated over the last few years.

Table 3. Results of DCC-MGARCH concerning returns of BTC and GLD

btc_ret gold_ret	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Constant	.115	.08	1.43	.153	-.043	.272	
L	.127	.021	6.09	0	.086	.168	***
L	.806	.028	28.42	0	.75	.862	***
Constant	1.289	.254	5.07	0	.79	1.788	***
Constant	.034	.019	1.81	.071	-.003	.071	*
L	.101	.016	6.16	0	.069	.133	***
L	.852	.026	32.42	0	.801	.904	***
Constant	.045	.013	3.44	.001	.019	.071	***
corr(btc_ret,gold_ret)	.146	.034	4.24	0	.079	.214	***
lambda1	.010	.008	1.26	.209	-.006	.026	
lambda2	.970	.029	33.93	0	.914	1.026	***

*** p<.01, ** p<.05, * p<.1

The estimated dynamic conditional correlation series for Bitcoin and gold is shown in Figure 2. The correlation varies substantially over time, which suggests that the link between both assets varies and several episodes with high correlations are detected in times when higher levels of market uncertainty prevail, for example, during the COVID-19pandemic or times of geopolitical tension. But the correlation is significantly lower in other periods which indicates that there are some special circumstances when Bitcoin behaves differently from gold.

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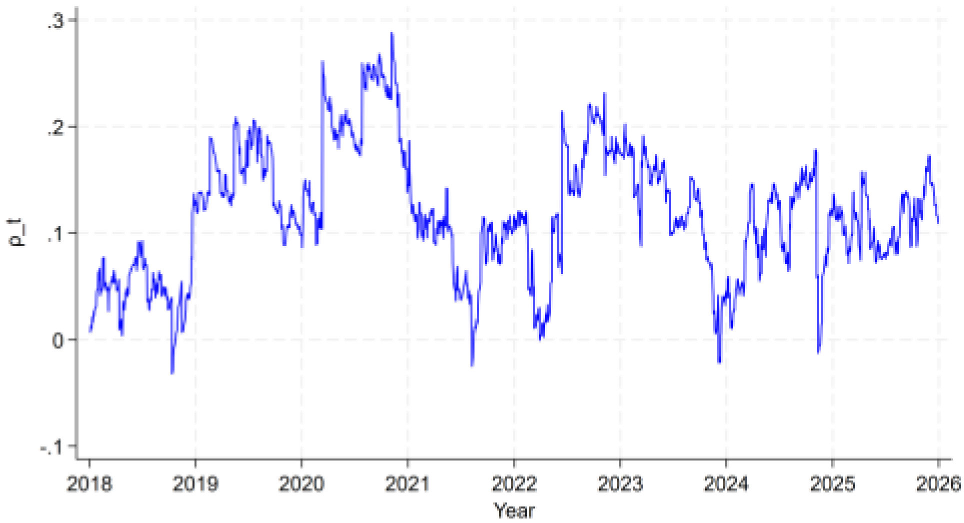

Figure 2. Dynamic conditional correlation series between BTC and gold

4.3. Macro-financial determinants of dynamic dependence

To further explore the driving forces behind the dynamic spillover relation of Bitcoin with gold, this paper further regresses the dynamic conditional correlation series (ρ_t) obtained by DCC-MGARCH model onto geopolitical risk, market uncertainty, and macro-financial conditions. In particular the Geopolitical Risk Index (GPRD) [13], the CBOE Volatility Index (VIX), where the inflation and the real interest rate are used as regressors.

4.3.1. Baseline regression results

Table 4 reports the baseline regression results. The coefficient on GPRD is negative, and it is very significant at 1%. This means that an increase in geopolitical uncertainty will reduce the dynamic correlation between BTC and GOLD. During periods with more geopolitical tensions, the two assets are less correlated, suggesting that Bitcoin's safe-haven properties could be different from those of gold. Gold still acts more like the old safe haven, but Bitcoin seems to be more of a speculation and risk-on asset.

Table 4. Baseline regression results

rho_t	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
GPRD	-.00023	.00002	-10.67	0	-.00027	-.00019	***
vix	.00311	.00021	14.66	0	.00269	.00352	***
rate	.00113	.00123	0.92	.358	-.00129	.00355	
Constant	.08448	.00491	17.19	0	.07485	.09412	***
*** p<.01, ** p<.05, * p<.1							

In comparison, the impact of VIX index on the DCC-based dynamic correlation coefficient is much more significant and positive. The positive sign implies higher level of market fear and financial uncertainty intensifies the degree of co-movement between Bitcoin and gold; This may be attributed to the fact that investors turn their eyes to other alternatives at the same time when facing with financial turmoil, thus raising the correlation between both markets [14]. The sign of the

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coefficient on the real interest rate, though insignificantly positive, implies that there is not much influence from macro-financial yield condition directly to the dynamics in the degree of dependence between Bitcoin and gold over our sample period.

4.3.2. Mechanism analysis: geopolitical act and threat

To shed more light on the underlying channel via which geopolitical risk influences the Bitcoin-gold spillover, we decompose the aggregate GPR index to geopolitical acts (GPRD_ACT) and geopolitical threats (GPRD_THREAT). The results are shown in Table 5.

Geopolitical act and geopolitical threat have a significant negative impact of the dynamic correlation between Bitcoin and gold at the 1% significance level, but indeed, we observe that the coefficient corresponding to geopolitical acts has a higher absolute value compared to the geopolitical threat one showing that the realization of geopolitical events reduces more strongly the co-movement between the two assets than geopolitical tensions/geopolitical expectation only.

Table 5. Results of mechanism analysis regression

rho_t	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
GPRD_ACT	-.00014	.00002	-6.57	0	-.00018	-.00010	***
GPRD_THREAT	-.00009	.00001	-5.61	0	-.00012	-.00006	***
vix	.00314	.00021	14.71	0	.00272	.00356	***
rate	.00242	.00136	1.78	.075	-.00024	.00509	*
Constant	.08213	.00485	16.95	0	.07262	.09163	***
*** p<.01, ** p<.05, * p<.1							

These results indicate that real world geopolitical warfare amplifies the deviation of Bitcoin from gold. During these events, that gold is reinforcing itself back towards being the classic safe-haven asset while Bitcoin has continued to exhibit characteristics of a risky asset that is correlated with investor optimism and risk-taking behavior.

5. Conclusion

The objective of this paper is to explore the volatility characteristics and the time varying dependence between Bitcoin and gold by taking advantage of daily data in the period 2018- 2025. By using EGARCH/APARCH models and the DCC-MGARCH framework, in this paper, we investigate the individual volatility dynamics of the two assets and estimate their dynamic conditional correlation. We also explore the macro-financial determinants of Bitcoin – gold dependence by introducing geopolitical risk, real interest rates, and the VIX index.

These findings suggest that Bitcoin is more volatile, asymmetric and speculative than the gold related assets. Whereas gold continues to be rather constant as a conventional safe-haven asset. The DCC-MGARCH findings suggest that the correlation of Bitcoin with gold is time-varying and extremely persistent, proving that there is a dynamical dependence between both markets. In addition to this, geopolitical risk considerably dampens the Bitcoin – gold correlation while market uncertainty as proxied by the VIX amplifies their co-movement.

In general, the empirical evidence indicates that Bitcoin responds differently from gold to external shocks, suggesting that Bitcoin did not completely replace the role of gold in serving as a conventional safe haven. Asset investors can draw some useful implications regarding their portfolio

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allocations and risk management based on our findings, noting that investors would do well to avoid assuming any fixed relationship exists between the digital asset class and more traditional safe-haven assets. Future research may employ nonlinear, regime-switching, or connectedness models to further examine complex cross-market dependence and potential volatility spillovers.

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