Dean&Francis

ISSN 2959-6130

From Diversifier to Amplifier? Investigating the BTC–NDX Linkage and the Modulating Role of VIX

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Abstract:

The growing interconnection between cryptocurrencies and traditional financial markets such as US equities has attracted increasing scholarly attention, with important implications for risk management and asset allocation. This study aims to quantitatively assess the volatility spillover and dynamic correlation between Bitcoin and major US technology stock indices, specifically the Nasdaq-100 (NDX), and to examine the moderating role of investor sentiment in this relationship. Using a multi-stage econometric framework combining univariate GARCH(1,1), dynamic conditional correlation (DCC-GARCH), and OLS regression models. Since Bitcoin only entered the public spotlight in 2017, this article will focus on daily data from 2017 to 2024. The results reveal significant time-varying correlations between BTC and NDX, which intensify during systemic events such as the COVID-19 crash and the US monetary tightening cycle. This article also detects a weak but notable bidirectional volatility spillover, with increased BTC volatility leading to higher NDX fluctuations. Notably, the regression results show that investor fear, represented by the VIX index in this article, significantly amplifies the BTC-NDX correlation ($\gamma = 0.0106$, $p < 0.001$), suggesting a sentiment-driven trend during stress periods. These findings indicate that Bitcoin is potentially no longer an isolated digital asset but a non-negligible source of volatility for US stock markets, especially for high-volatility tech stocks. Investor sentiment acts as a key amplifier of this connection. The results have a practical contribution to portfolio diversification strategies, systematic risk monitoring by policymakers, and the design of a more advanced risk management structure in financial institutions.

Keywords: Volatility Spillover; Dynamic Conditional Correlation; Investor Sentiment; Market Integration; Investment Diversification.

1. Introduction

Rapid growth of financial technology has reshaped global financial markets, introduced new asset classes, and redefined risk-return dynamics [1]. Among these innovations, Bitcoin (BTC) is the most prominent cryptocurrency. It has grown from a highly contested digital asset to a globally recognized financial instrument with a market valuation of more than 2.3 trillion US dollars as of today. Recent developments, including the approval of spot Bitcoin ETFs and the adoption of Bitcoin as legal tender in certain jurisdictions [2], signal that the digital assets represented by Bitcoin and Ethereum have become more mainstream in financial systems [1, 3]. This increasing integration raises non-trivial concerns regarding the dependence of digital assets on traditional financial markets, particularly US equities. This article will concentrate primarily on the interaction between Bitcoin and the Nasdaq-100 Index, as both represent leaders in the digital asset market and US stocks, respectively [4, 5, 6].
Historically, Bitcoin has been treated as an alternative investment with low correlation to stocks [7], representing a possible diversification benefit. However, recent evidence suggests that during systemic stress events, such as the COVID-19 pandemic and the subsequent tightening of monetary policy, Bitcoin has exhibited a similar movement to major stock indices [5, 7], including the Nasdaq-100 (NDX). If this trend continues, Bitcoin, which has been marketed to diversify one's portfolio, may not be as valuable as people think.
The relationship between Bitcoin and traditional markets has also attracted significant academic attention [1, 7]. This article summarizes three main groups of related work.Early research [8] reported that Bitcoin and stocks had weak, even negative correlations, clarifying their role in diversification. Unlike the early research, a more recent study, which employs time-varying correlation models [9], indicates that correlations have strengthened since 2020, particularly during periods of market volatility [10, 11].Multivariate GARCH models (e.g., BEKK, DCC) and Granger causality tests have yielded mixed evidence regarding volatility transmission. Some studies find unidirectional spillovers from stocks to Bitcoin, indicating that US stocks have an impact on Bitcoin, while others suggest bidirectional effects during crises [1,12].
The VIX (CBOE Volatility Index) and the Crypto Fear & Greed Index are two examples of sentiment indices that have an enormous impact on short-term return volatility [12, 13]. However, only a few studies have incorporated sentiment indicators into dynamic correlation frameworks to determine whether fear in the market magnifies the inter-market relationship [12].
Despite these findings, some questions remain unanswered. Key gaps include: Few studies have addressed the directionality of volatility spillovers, especially whether Bitcoin will affect NDX's volatility [4, 7]. Insufficient attention is given to the Nasdaq-100 (NDX) specifically [4, 14], which should be treated as a high-growth and high-risk section of the market [6], similar to Bitcoin. There is a lack of direct evidence on how investor sentiment, particularly market fear (proxied by VIX), moderates the BTC-NDX correlations [1].
This study addresses these gaps by asking the following research questions:
(i) How does the dynamic conditional correlation between BTC and NDX increase over time and depend on market states (e.g., pre- and post-COVID, monetary tightening)[10]?
(ii) Are volatility spillovers between BTC and NDX unidirectional or bidirectional?
(iii) What is the impact of investor mood (measured by VIX) on the BTC-NDX correlation dynamics [3]?
This research incorporates investor sentiment to investigate the connections between cryptocurrency and equity markets and demonstrates the behavioral effects on cross-market risk transmission. Additionally, the findings will inform portfolio diversification strategies, highlight the smaller hedging benefits of Bitcoin during stress periods, and guide risk managers in assessing the risk of contagion. A multistage econometric framework is used for this study. First, fit univariate GARCH(1,1) models to capture volatility persistence in BTC and NDX returns. Second, apply the DCC-GARCH model to measure time-varying correlations. At last, examine the moderating influence of investor sentiment (VIX) by regression and dynamic correlations on VIX levels.

2. Methodology

2.1 Data Description

The data used in this study are sourced from Binance and Yahoo Finance. The data set consists of daily observations from January 2017 to June 2024:
Bitcoin (BTC): Daily closing prices in USD.
Nasdaq-100 Index (NDX): Daily closing levels.
Investor Sentiment: The CBOE Volatility Index (VIX).
All price series are converted into continuously compounded returns:

$$r_t = ln\left(\frac{P_t}{P_{t-1}}\right)\times 100 \qquad (1)$$

Stationarity is tested using the Augmented Dickey-Fuller (ADF) test, while ARCH-LM tests confirm volatility clustering. VIX is standardized for regression analysis [12].

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2.2 Preliminary Visualization

Figure 1 presents normalized BTC and NDX prices along with major events such as the COVID-19 crash and Federal Reserve tightening (Data retrieved from Binance and Yahoo Finance).

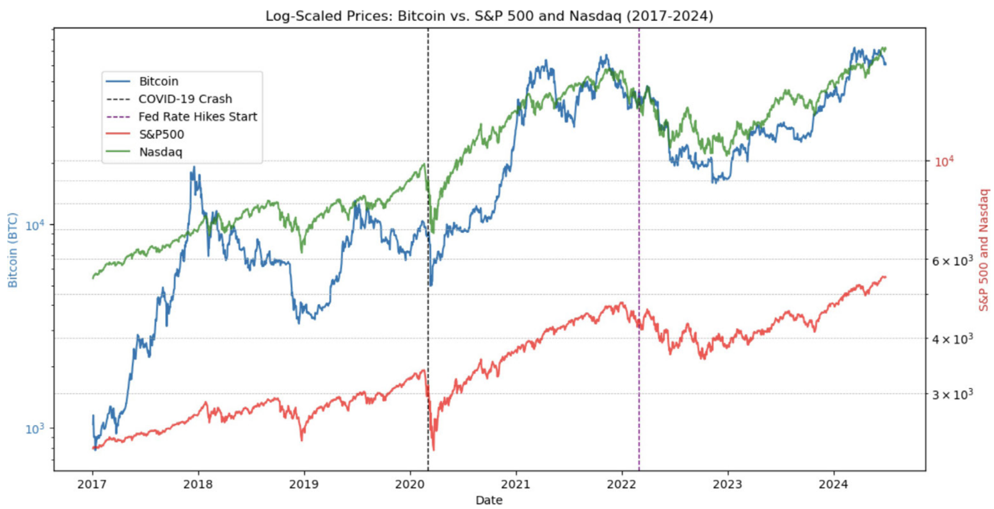

Fig. 1. Normalized Prices of BTC and NDX (2017–2024)

In Figure 1, it is evident that the logarithmic scale prices of BTC and NDX have shown a clear convergence since early 2021.

2.3 Univariate Garch(1, 1) Model

To model volatility clustering in financial returns, apply the GARCH(1,1) model [15]

$$r_t = \mu + \epsilon_t, \epsilon_t | \ \Omega_{t-1} \sim N\left(0, \sigma_t^2\right) \tag{2}$$

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{3}$$

Where rt is the return at time t, μ is the mean return, and σ2 is the conditional variance. Parameters ω > 0, α ≥ 0, and β ≥ 0 ensure positivity and capture volatility dynamics. A higher α reflects sensitivity to shocks, while β indicates volatility persistence.

2.4 Dynamic Condition Correlation (DCC-GARCH)

The DCC-GARCH(1,1) model [16] captures time-varying conditional correlations:

$$H_t = D_t R_t D_t, R_t = \mathrm{diag}\left(Q_t\right)^{-1/2} Q_t \mathrm{diag}\left(Q_t\right)^{-1/2} \tag{4}$$

$$Q_t = \left(1 - \alpha - \beta\right)\bar{Q} + \alpha z_{t-1} z_{t-1}' + \beta Q_{t-1} \tag{5}$$

Where *zt* are standardized residuals from univariate GARCH models, the correlation dynamics are summarized by $\rho^{\mathrm{BTC,NDX}}$.

2.5 VIX Influence Analysis

To assess whether market fear amplifies the BTC-NDX correlation, regress the estimated DCC correlation series on lagged VIX:

$$\rho_t^{BTC,NDX} = \gamma_0 + \gamma_1 \mathrm{VIX}_{t-1} + u_t \tag{6}$$

Where γ_1 captures the sensitivity of the correlation to investor fear. A positive and statistically significant γ_1 implies that higher VIX levels strengthen BTC-NDX linkage during periods of stress.

2.6 Estimation and Diagnostics

Estimation is performed using Maximum Likelihood using Student-t distributions. The adequacy of the model is verified using Ljung-Box and ARCH-LM tests. All computations are implemented in Python using the arch and stats models libraries.

3. Results

3.1 Volatility Dynamics of BTC and NDX

To capture the volatility behavior of Bitcoin (BTC) and the Nasdaq-100 index (NDX), first estimate univariate GARCH(1,1) models for each return series. The results are reported in Table 1.

Table 1: GARCH(1,1) Estimation Results for BTC and NDX

ω	α	β	α + β
BTC 1.5696**	0.1209**	0.8113***	0.9322
NDX 0.0389***	0.1291***	0.8548***	0.9839

Notes: ***p < 0.001, **p < 0.05. Robust standard errors were used. High α + β implies persistent volatility. BTC shows stronger and more unstable volatility compared to NDX.

Both assets exhibit highly persistent volatility (with α + β > 0.9), showing that the market requires longer times to recover from the event, consistent with financial time series properties.

To assess the long-run behavior of volatility, the unconditional variance can be derived as:

$$\sigma^2_{\text{uncond}} = \frac{\omega}{1-\alpha-\beta}, \text{provided that} \alpha+\beta<1. \tag{7}$$

Applying this to the estimated models:

For BTC: ω = 1.5696, α = 0.1209, β = 0.8113, hence α + β = 0.9322, and unconditional variance is around 23.13.

For NDX: ω = 0.0389, α = 0.1291, β = 0.8548, hence α + β = 0.9839, and unconditional variance is around 2.42.

These results suggest that BTC exhibits a larger unconditional variance, which validates its increased risk profile. In addition, the ω value of BTC (1.5696) is significantly higher than the ω value of NDX (0.0389). This means that Bitcoin will be more volatile even when the market is not shocked.

3.2 Time-Varying Correlation between BTC and NDX

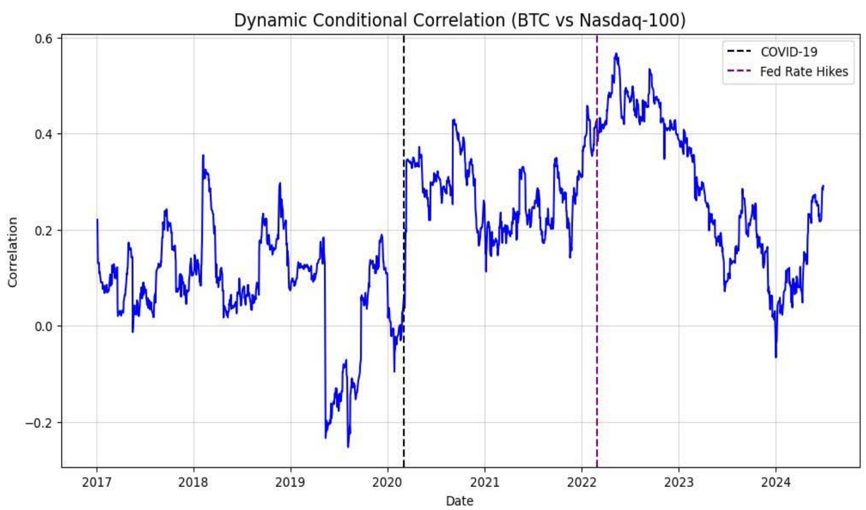

Fig 2: Dynamic Conditional Correlation (BTC vs Nasdaq-100)

Next, this article estimates the dynamic conditional correlation (ρBTC,NDX,t) between the returns of BTC and NDX using the DCC-GARCH model. Figure 2 visualizes the evolution of this correlation from 2017 to 2024.

The correlation remains moderate and fluctuating in the early years, with an average correlation around 0.18, but shows significant spikes during periods of systemic stress. Around March 2020, coinciding with the onset of COVID-19, the correlation rises to 0.4. A second peak occurs in early 2022, coinciding with the monetary tightening implemented by the US Federal Reserve. The data indicate that BTC's correlation with stock markets intensifies during periods of stress, contradicting its assumed function as a diverse asset.

Figure 2 also shows clear co-movements throughout time, especially during systemic shocks, indicating likely bidirectional volatility spillovers, where both markets respond to and influence each other's volatility structure.

3.3 Impact of Market Sentiment on Correlation

To examine whether market fear affects the BTC-NDX linkage, regress the DCC correlation series on the lagged VIX index:

$$\rho_{BTC,NDX,t} = \alpha + \delta \cdot VIX_{t-1} + \epsilon_t \tag{8}$$

The scatter plot and the regression results are shown in Figure 3, Table 2, and Table 3, respectively. Figure 3 presents a scatter plot illustrating the relationship between the lagged VIX index (horizontal axis) and the dynamic

ISSN 2959-6130

conditional correlation (DCC) between BTC and NDX (vertical axis), and Table 2 reports the OLS regression results investigating how investor sentiment, represented by lagged VIX, affects the correlation between BTC and NDX.

3.3.1 Analysis of Regression Diagnostic Statistics

The Regression Diagnostics from Table 1 confirm the explanatory power of the model. The model's Akaike Information Criterion (AIC) of -2376 indicates good model fit, as lower AIC values imply better trade-offs between explanatory power and complexity. However, the Durbin-Watson score is significantly low (0.043), indicating considerable positive autocorrelation in the residuals, either due to missed dynamics or structural gaps in the correlation series.

Table 2: Regression Diagnostics

Statistic	Value
F-statistic	811.1
AIC	-2376
Durbin-Watson	0.043
Skewness	-0.730
Kurtosis	4.210

The residuals also exhibit negative skewness (-0.730), suggesting a left-tailed distribution. At the same time, the kurtosis value of 4.210 indicates leptokurtic behavior, meaning the distribution is more peaked and has fatter tails than a normal distribution. These results suggest that the residuals diverge from normality, a common occurrence in financial time series. This does not invalidate the model but requires careful analysis of standard errors.

3.3.2 Visualized Analysis of Regression Results

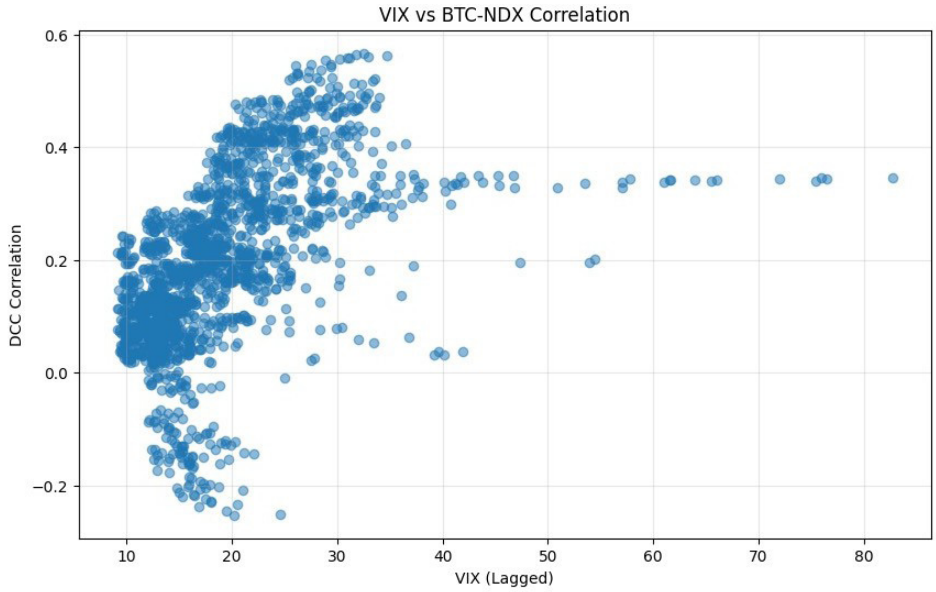

Fig 3: VIX vs BTC-NDX Dynamic Correlation

Visually, there is a clear positive association between investor fear (proxied by higher VIX values) and the BTC-NDX correlation, indicating that increased market uncertainty tends to coincide with stronger correlation between the two markets. This finding is consistent with the regression analysis, supporting the hypothesis that investor sentiment acts as a significant amplifier of the volatility link between cryptocurrency and technology stocks during periods of elevated risk perception.

3.3.3 Numerical Analysis of Regression Results

Table 3: OLS Regression: VIX Predicting BTC-NDX Correlation

	Coef.	Std. Err.	*p*-value
Intercept	-0.0044	0.0077	0.567
VIX (Lagged)	0.0106	0.0004	< 0.001***

R^2 0.301

Notes: The VIX coefficient is highly significant, suggesting that increases in market fear correlate with stronger BTC-NDX linkage.

Numerically, the positive coefficient for the VIX index (0.0106, $p < 0.001$) indicates a highly significant relationship. Specifically, a one-unit increase in VIX is associated with an average increase of approximately 0.0106 in the dynamic conditional correlation, suggesting stronger market integration during periods of increased fear. The intercept is statistically insignificant (−0.0044, $p = 0.567$), indicating no systematic bias in the correlation levels absent increased fear conditions. The model explains about 0.301 of the variation in the BTC-NDX correlation (R2 = 0.301), reinforcing that investor sentiment plays an important role, but also highlighting that other factors likely influence market co-movements. This finding also supports the argument that market fear intensifies volatility links between the cryptocurrency and technology stock markets.

4. Conclusion

This study aimed to quantitatively assess volatility spillovers, dynamic conditional correlations, and the moderating role of investor sentiment between Bitcoin (BTC) and the Nasdaq-100 index (NDX). The research specifically examined whether Bitcoin functions as a diversification asset and how market fear, indicated by the VIX, influences the correlation dynamics between BTC and NDX.

The key findings can be summarized as follows. First, both BTC and NDX exhibited significant volatility persistence, with BTC showing higher volatility magnitude and longer persistence ($\alpha BTC + \beta BTC = 0.9322$, $\alpha NDX + \beta NDX = 0.9839$). Second, the dynamic conditional correlation (DCC) between BTC and NDX was found to be varying over time and was significantly intensified during systematic stress events, such as the COVID-19 crisis and periods of monetary tightening. Third, the evidence suggested a weak yet significant bidirectional volatility spillover, particularly indicating that BTC volatility notably influenced NDX volatility during market stress periods. Fourth, investor sentiment (VIX) was identified as a strong moderator, with the regression results ($\gamma = 0.0106$, $p < 0.001$) clearly showing that increases in market fear significantly amplified the correlation between BTC and NDX.

Theoretically, this paper contributes to the existing literature by explicitly examining the directionality of volatility spillovers between emerging digital assets and established technology stocks. Furthermore, it extends previous research by demonstrating the critical role of investor sentiment as a channel of volatility contagion.

Practically, the findings have significant implications for several parties. Investors, especially those seeking portfolio diversification benefits from cryptocurrencies, should be cautious in depending on Bitcoin during periods of market panic, given its increased co-movement with stock markets under such conditions. For risk management professionals, the results emphasize the need to include sentiment indicators and cross-market spillovers into current risk assessment frameworks. Regulators and policymakers should recognize the potential for increased systemic risk transmission from the crypto market to traditional financial markets during periods of investor panic, and consequently, strengthen monitoring procedures to prevent market instability.

However, this research also has limitations that cannot be ignored. The reliance on daily data and the use of a single sentiment measure (VIX) may not fully capture the intraday volatility dynamics and broader dimensions of investor sentiment. Additionally, the chosen econometric models assume linear relationships, potentially overlooking non-linear contagion channels.

Future research could explore intraday data for more precise volatility transmission insights, consider more sentiment indicators like the Greedy index, and use nonlinear models to reflect complex market realities better.

Acknowledgement

Grateful acknowledgement is extended to Ruiqi Yang, my partner, and Hongwei Lin, my mentor, for their idea and support throughout the study.

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