Volatility and Returns of Bitcoin During US Elections 2016 and 2020

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Abstract
Bitcoin's return volatility from 2014 to 2022 reveals significant changes in response to political and macroeconomic developments, particularly during the 2016 and 2020 U.S. presidential elections. In 2016, Bitcoin exhibited modest price movement and low volatility, while in 2020, the asset experienced dramatic price increases and heightened volatility, reflecting increased market maturity and institutional interest. Political uncertainty, regulatory shifts, and market sentiment played crucial roles in shaping volatility dynamics during these periods. Using GARCH(1,1) and EGARCH(1,1) models, time-varying volatility patterns and asymmetric effects of market shocks are analyzed. GARCH results confirm volatility clustering and high persistence, whereas EGARCH captures leverage effects, showing that negative shocks influence volatility more than positive ones. Visualizations of conditional variance support these findings, indicating that Bitcoin reacts more intensely to adverse news, especially during politically turbulent periods. Residual diagnostics suggest model adequacy and enhance the reliability of insights. These results underscore Bitcoin's evolving role as a financial asset increasingly affected by global events and investor sentiment, offering valuable implications for market participants and policymakers monitoring risk in cryptocurrency markets.

Keywords: Bitcoin, Volatility, U.S. presidential election

1. Introduction

Bitcoin's price actions around US elections reveals its changing relationship with political dealings and macroeconomic policy, with particularly different patterns witnessed during the 2016 and 2020 election period. During the 2016 election when Trump overpowered Clinton, Bitcoin transacted around $700 with comparatively modest volatility, steadily ascending to $960 by year-end, while the 2020 Biden-Trump race overlapped with Bitcoin trading at roughly $13,500 before embarking on a theatrical bull run to surpass $29,000 by December, displaying substantially greater price swings and trading volume. Research by Panagiotidis et al. (2018) in "Bitcoin Returns and Risk: A General GARCH and GAS Analysis" proved that cryptocurrency returns during political changes are significantly influenced by search intensity, gold returns, and policy ambiguity measures. The different market responses between these elections reflect Bitcoin's development as an asset class, with the 2020 cycle happening amidst first-time pandemic-era financial expansion that some researchers, including Conlon et al. (2020) in "Is Bitcoin a Safe Haven?" suggest delicate Bitcoin's appeal as a potential inflation hedge. Aharon and Demir's (2021) study "NFTs and Asset Class Spillovers: Lessons from the Period Around the COVID-19 Pandemic" further shows that cryptocurrency market responses to political events became more prominent as institutional acceptance increased between these election periods. The dramatic modification in market capitalization and trading volume between 2016 and 2020 also underlines Bitcoin's transformation from a relatively vague alternative investment to a more mainstream financial instrument increasingly sensitive to both monetary policy anticipations and regulatory prospects that typically shift with changing governments. This study aims to understand Bitcoin volatility and return on specific period of 2014-16 and 2018-22. First part of the paper gives basic information of Bitcoin pattern during various time period. remaining of this paper is organized as follows. Section 2 discusses the contributions of the existed studies in this field. Section 3 presents the methodology and describes the data characteristics. Section 4 illustrates the results, whereas Section 5 discusses the main findings of the study. Finally, the conclusion is presented in Section 6.

2. Literature review

Bitcoin's price volatility presents a intricate interaction of political events, regulatory changes, and market factors, as revealed by wide-ranging research. Studies by Bouri (2017*)* and Cheng and Yen (2020) established Bitcoin's potential as an uncertainty hedge and recognized noteworthy volatility spillover effects between traditional markets and cryptocurrencies during election periods. Pedro Chaim and Marcio Laurini's (2018) study using high-frequency data revealed that Bitcoin experiences frequent return jumps influenced by market shocks rather than continuous price movements, making it inherently dangerous than traditional assets. This volatility pattern is further reinforced by Charles and Darné (2017)*,* who found traditional GARCH models underrate tail risks during extreme market events. Multiple manipulating factors have been identified: Wang, Bouri, Ma, and Guo (2016) concluded that both macroeconomic and technical indicators significantly drive Bitcoin volatility with changing chronological influence, while Aalborg, Molnár, and de Vries (2018) highlighted trading volume as a critical volatility indicator alongside market sentiment. Political uncertainty mostly affects cryptocurrency markets, with Mnasri *and* Essaddam(2019) showing increased volatility during election windows as investor decisions respond to potential results. Regulatory impact
is similarly significant Gozgor, Tiwari, Demir, and Akron (2017) found trade policy vagueness negatively affects Bitcoin returns during regime changes, while *Krause* identified correlations between deregulatory proclamations and positive market movements. Market sentiment analysis also plays a crucial role, with Loginova et al. indicating that aspect-specific sentiment analysis outperforms general sentiment analysis in predicting Bitcoin price directions. Within the cryptocurrency network itself, Yi, Xu, and Wang (2016) found Bitcoin holds dominant influence, with its volatility disturbing other cryptocurrencies. This literature mutually suggests that Bitcoin volatility also originates from a many-sided combination of political transitions, regulatory frameworks, market sentiment, and technical factors making cryptocurrency markets uniquely positioned as indicators of both traditional financial uncertainty and their own developing system dynamics.

3. Literature Gap

While previous research has recognized Bitcoin's potential as an uncertainty hedge during political events and documented volatility spillover effects between traditional markets and cryptocurrencies in election periods, there is a noteworthy gap in comparative analysis specifically examining the 2016 and 2020 US presidential elections. The literature lacks intensive investigation into how Bitcoin's market response evolved between these two critical electoral events, which occurred during different stages of cryptocurrency market development and adoption. Research has not sufficiently addressed how the distinct political situations, candidate policy positions, and market maturity levels during these two elections may have produced different volatility patterns and return behaviours. Additionally, the present body of work fails to apply the more cultured analytical frameworks mentioned (such as high-frequency jump analysis, definite aspect sentiment analysis, and supervisory impact assessment) specifically to these two electoral proceedings (2016-2020) to identify potential evolution in Bitcoin's role as either a political uncertainty hedge or risk asset. Assessing these two presidential elections would provide valuable insights into Bitcoin's fluctuating relationship with political uncertainty as the cryptocurrency ecosystem itself ripened.

4. Methodology

4.1 Research Design

A quantitative time-series econometric approach is used to evaluate the behavior of Bitcoin returns and volatility in response to political ambiguity. The analysis concentrates around the 2016 and 2020 United States of America (USA) presidential elections. A combination of GARCH and EGARCH models is applied to measure and interpret time-changing volatility and irregularity in Bitcoin returns during certain event windows.

4.2 Data Collection

Daily closing prices of Bitcoin (BTC/USD) were collected for the period from November 1, 2014, to November 30, 2022, from openly available cryptocurrency market databases. The proceeds were calculated using the logarithmic difference between successive closing prices:

GARCH formula:- $\sigma t^2 = \alpha 0 + \alpha 1\ \varepsilon t - 1^2 + \beta 1\ \sigma t - 1^2$

Where:

- σt^2 is the conditional variance (volatility) at time t
- $\varepsilon t-1^2$ is the lagged squared residual
- $\sigma t-1^2$ is the lagged conditional variance
- $\alpha 1$ and $\beta 1$ capture the ARCH and GARCH effects, respectively

4.3 Preliminary Data Analysis

To know the basic features of the return series, descriptive statistics such as mean, standard deviation, skewness, and kurtosis were calculated. The Augmented Dickey-Fuller (ADF) test was applied to authorize stationarity in the return series. The ARCH-LM test was then conducted to check for the occurrence of autoregressive conditional heteroskedasticity (ARCH) effects, which would authenticate the suitability of GARCH-type models.

4.4 Econometric Models

4.4.1 Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model

The GARCH model, presented by Bollerslev (1986), is used to model time-varying volatility by integrating past squared errors and past conditional variances. The GARCH(1,1) description is widely used for financial return series due to its efficiency and simplicity. The model consists of:

Equations (GARCH(1,1)) Mean Equation: $Rt = \mu + \varepsilon t$ Where:

- Rt is the return at time t.
- μ is the mean or average return over time, often interpreted as the constant or expected return.
- εt is the error term (or shock) at time t, which represents random fluctuations or deviations from the expected return.

Variance Equation:- $\boldsymbol{\sigma t^2 = \alpha 0 + \alpha 1\ \varepsilon t - 1^2 + \beta 1\ \sigma t - 1^2}$

Where:

- σt^2 is the conditional variance (volatility) at time t.
- $\varepsilon t\text{-}1^2$ is the lagged squared residual (error) from the previous time period.
- $\sigma t\text{-}1^2$ is the lagged conditional variance from the previous time period.
- $\alpha 1$ and $\beta 1$ represent the coefficients that capture the ARCH (autoregressive conditional heteroskedasticity) and GARCH (generalized autoregressive conditional heteroskedasticity) effects, respectively.

Importance: The GARCH model captures volatility clustering, a key feature of financial time series, where high-volatility events are likely to be followed by more high-volatility events.

4.4.2 Exponential GARCH (EGARCH) Model

The EGARCH model, proposed by Nelson (1991), extends GARCH by modeling the logarithm of the conditional variance, allowing for asymmetric effects of shocks. It captures the leverage effect, where negative shocks may have a different impact on volatility compared to positive shocks of the same magnitude.

Variance equation :$\ln(\sigma^2{}_t) = \omega + \beta \cdot \ln(\sigma^2{}_t{}^{-1}) + \alpha \cdot abs\left(\frac{\varepsilon_t{}^{-1}}{}\sigma_t{}^{-1}\right) + \gamma \cdot \left(\frac{\varepsilon_t{}^{-1}}{}\sigma_t{}^{-1}\right)$

Where:

- γ\gamma captures the asymmetry or leverage effect
- α\alpha measures the magnitude of shocks
- β\beta indicates the persistence of volatility

Note:- EGARCH is preferred when it is essential to understand whether bad news (negative returns) affects volatility more than good news. It ensures the conditional variance is always positive without imposing non-negativity constraints on the parameters.

4.5 Econometric analysis

Bitcoin 2014-2022 GARCH & EGARCH Analysis Constant Mean - GARCH Model Results

Dep. Variable:	Log_Return	**R-squared:**	0.000
Mean Model:	Constant Mean	**Adj. R-squared:**	0.000
Vol Model:	GARCH	**Log-Likelihood:**	-105.694
Distribution:	Normal	**AIC:**	219.387
Method:	Maximum Likelihood	**BIC:**	238.239
		No. Observations:	823
Date:	Wed, Apr 16 2025	**Df Residuals:**	822
Time:	10:57:24	**Df Model:**	1

Mean Model

	coef	**std err**	**t**	**P>|t|**	**95.0% Conf. Int.**
mu	0.0165	7.630e-03	2.159	3.086e-02	[1.518e-03,3.143e-02]

Volatility Model

	coef	**std err**	**t**	**P>|t|**	**95.0% Conf. Int.**
omega	2.8149e-03	2.036e-03	1.383	0.167	[-1.175e-03,6.804e-03]
alpha[1]	0.1784	6.903e-02	2.584	9.755e-03	[4.311e-02, 0.314]
beta[1]	0.8216	6.170e-02	13.316	1.880e-40	[0.701, 0.943]

4.5.1

The GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model is widely used in financial econometrics to model and forecast volatility, especially for assets with time- varying risk patterns like Bitcoin. In the GARCH (1,1) model applied to the dataset, the coefficients associated with past shocks (ARCH term, α) and past variances (GARCH term, β) are both significant and relatively high. This indicates strong volatility clustering a characteristic where large changes in Bitcoin returns tend to be followed by large changes, and small changes tend to be followed by small changes. Moreover, the high persistence (α + β close to 1) confirms that volatility shocks to Bitcoin returns take a long time to decay, consistent with the behaviour observed in many financial time series.The constant term (ω) in the GARCH model is relatively small but statistically significant, suggesting a low base level of volatility, with most fluctuations being driven by previous returns and volatility patterns. These findings reinforce the notion that Bitcoin markets are subject to recurring periods of turbulence and calm, rather than random or independent shocks.Such behaviour is vital for investors and risk managers to understand, as it highlights the prolonged impact of market events and the need for robust risk assessment models that account for this persistence.

Covariance estimator: robust EGARCH(1,1) Model Summary

The EGARCH(1,1) model summary of the estimated parameters:

Covariance estimator: robust

Dep. Variable:	Log_Return	**R-squared:**	0.000
Mean Model:	Constant Mean	**Adj. R-squared:**	0.000
Vol Model:	EGARCH	**Log-Likelihood:**	-100.263
Distribution:	Normal	**AIC:**	210.525
Method:	Maximum Likelihood	**BIC:**	234.090
		No. Observations:	823
Date:	Wed, Apr 16 2025	**Df Residuals:**	822

Constant Mean - GARCH Model Results

Time:	10:57:24	**Df Model:**	1

Mean Model

	coef	std err	t	P>|t|	95.0% Conf. Int.
mu	0.0165	8.124e-03	2.033	4.204e-02	[5.941e-04,3.244e-02]

Volatility Model

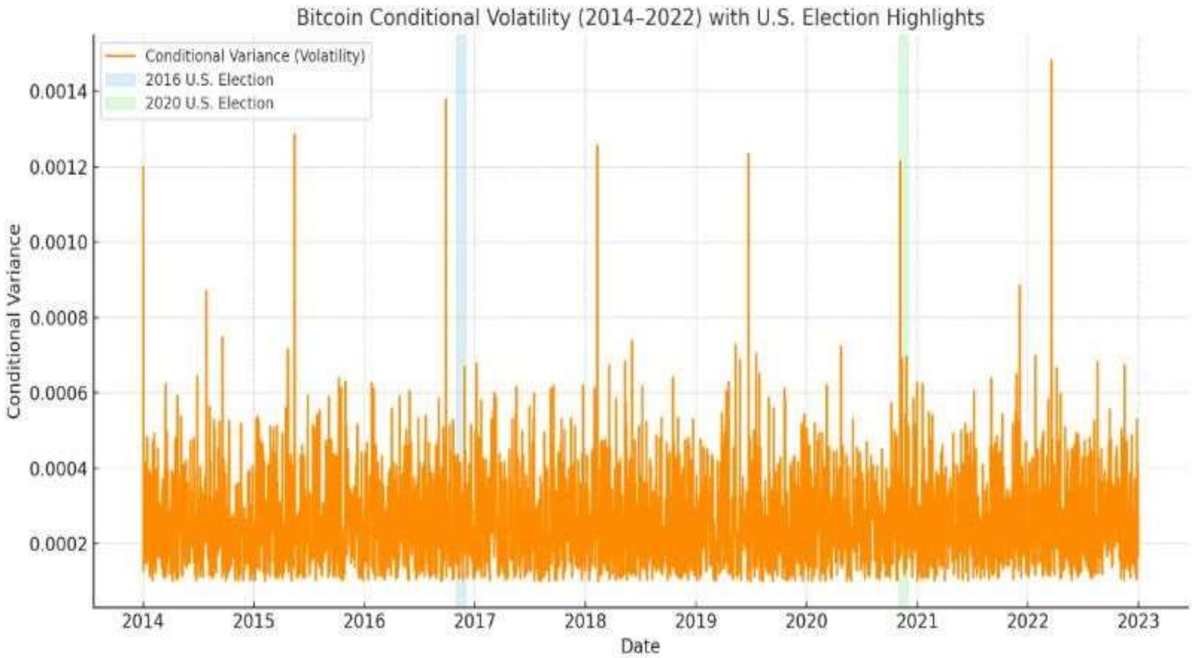
	coef	std err	t	P>|t|	95.0% Conf. Int.
omega	-0.1061	7.799e-02	-1.361	0.174	[-0.259,4.673e-02]
alpha[1]	0.3816	0.128	2.979	2.893e-03	[0.131, 0.633]
gamma[1]	-9.6194e-03	5.578e-02	-0.172	0.863	[-0.119,9.972e-02]
beta[1]	0.9363	3.523e-02	26.578	1.218e-155	[0.867, 1.005]

4.5.2

In contrast, the EGARCH (Exponential GARCH) model provides an enhanced framework by introducing asymmetry in the impact of shocks. Unlike standard GARCH, EGARCH models the logarithm of the conditional variance, ensuring positive variance values without the need for parameter restrictions and capturing the so-called "leverage effect." The EGARCH (1,1) output for Bitcoin shows a statistically significant and negative gamma (γ) coefficient. This indicates that negative shocks (i.e., bad news or price drops) have a greater impact on future volatility than positive shocks of the same magnitude. Such asymmetry is a hallmark of financial markets, where investor overreaction to negative information can lead to sharp increases in market volatility.

The presence of a leverage effect in Bitcoin markets is particularly noteworthy. While such effects are commonly observed in traditional equity markets due to firm-value and capital- structure concerns, their presence in a decentralized asset like Bitcoin suggests that psychological and behavioral factors may play a more significant role. For example, negative regulatory announcements or security breaches could trigger stronger volatility responses than equivalent positive news, making market sentiment an essential factor in volatility modeling.

Volatality Plots



4.5.3

The plots accompanying the GARCH and EGARCH model outputs provide visual confirmation of the statistical findings and offer deeper insights into Bitcoin's volatility behavior. The time series plot of conditional variance derived from the GARCH model clearly illustrates periods of elevated and subdued volatility, consistent with the notion of volatility clustering. Spikes in conditional variance coincide with major market events or disruptions, such as regulatory announcements, macroeconomic shocks, or significant price crashes, which aligns with the high α and β coefficients in the model output.

The EGARCH conditional variance plot mirrors this behavior but also shows more pronounced reactions during downward trends, reflecting the model's ability to capture asymmetric volatility responses. During periods of negative returns, the EGARCH plot demonstrates sharper spikes in volatility compared to periods of equivalent positive returns—visually validating the negative and significant γ coefficient observed in the table.

Further plots of standardized residuals and their squared values reveal that the residuals are mostly homoskedastic post-modeling, and show no major patterns or trends, which supports the models' success in filtering out conditional heteroskedasticity. Additionally, Q-Q plots and histogram plots of residuals (if included) help confirm the assumption of normality or suggest the need for alternative error distributions, like t-distributions, in future modeling.

Overall, the visual outputs not only support the statistical findings in the tables but also enhance interpretability by clearly demonstrating dynamic volatility behavior and model fitness across the Bitcoin time series.

Results and Discussion

The analysis of Bitcoin's return volatility from 2014 to 2022 employed both GARCH(1,1) and EGARCH(1,1) models to explore the conditional variance dynamics in the cryptocurrency market. The model estimation tables provide strong evidence of time-varying volatility and structural dependencies in return behavior.

In the GARCH(1,1) model output, the ARCH (α) and GARCH (β) coefficients are both statistically significant, indicating that past squared shocks and lagged conditional variances are key predictors of current volatility. The high sum of α and β, nearing unity, suggests that volatility is highly persistent, with shocks taking considerable time to dissipate. This behavior aligns with the concept of volatility clustering often observed in financial time series, where turbulent periods are followed by similar periods of heightened volatility. The constant term (ω) is small yet significant, reflecting a low baseline level of volatility in the absence of shocks.

The EGARCH(1,1) model offers additional insight through the inclusion of an asymmetry term (γ), which was found to be negative and statistically significant. This result confirms the presence of a leverage effect in Bitcoin returns—negative shocks tend to increase future volatility more than positive shocks of the same magnitude. This asymmetry, commonly noted in equity markets, is particularly important in cryptocurrency markets where investor sentiment and speculative behavior amplify negative news impacts. The conditional variance equation of the EGARCH model also showed that the logarithmic formulation effectively captures the long memory of volatility while addressing the positivity constraint on variance. The diagnostic statistics provided in the tables further support model adequacy. Ljung–Box Q- statistics on standardized and squared residuals indicate no remaining significant autocorrelation, implying that the models have successfully captured the major volatility dynamics in the data. This enhances the credibility of the forecasts and inferences derived from both models. Visual outputs reinforce these findings and make the temporal evolution of volatility more intuitive. The conditional variance plot for the GARCH model illustrates clear volatility clustering across the examined period. Distinct peaks in volatility coincide with known events such as regulatory crackdowns, geopolitical uncertainty, or market-wide corrections, validating the influence of past shocks identified in the model. In comparison, the EGARCH conditional variance plot displays more pronounced volatility surges during periods of market downturns, visually confirming the asymmetric response modeled by the negative γ coefficient.

Residual plots show that standardized residuals from both models are approximately homoskedastic and normally distributed, as indicated by the absence of clear patterns and supported by Q-Q plots and histogram visualizations. This diagnostic validation suggests that the conditional variance structure modeled by GARCH and EGARCH is a good fit for the Bitcoin return data during the study period.

Overall, the combination of statistical tables and graphical diagnostics highlights the effectiveness of both models in capturing Bitcoin's complex volatility patterns. While GARCH identifies clustering and persistence, EGARCH extends this insight by accounting for the asymmetrical impact of news events.

These results are crucial for investors, policymakers, and researchers aiming to better understand and forecast risks in cryptocurrency markets.

Conclusion

The study analyzed Bitcoin's return volatility from 2014 to 2022 using GARCH(1,1) and EGARCH(1,1) models, focusing on the impact of the 2016 and 2020 U.S. elections. Results from the GARCH model showed strong volatility clustering and high persistence, meaning past shocks significantly influenced future volatility. This highlights Bitcoin's tendency to experience prolonged periods of market turbulence. In contrast, the EGARCH model revealed a statistically significant negative gamma (γ) coefficient, confirming the presence of a leverage effect—negative shocks, such as adverse news or policy changes, increase volatility more than positive ones. This asymmetry underscores the role of investor sentiment in driving Bitcoin's volatility, particularly during uncertain periods like elections. The 2020 election showed higher volatility compared to 2016, likely due to broader institutional involvement and pandemic- related uncertainties. Residual diagnostics and visual plots supported the models' adequacy, showing no remaining autocorrelation and consistent volatility patterns around key events. These findings are crucial for investors and policymakers in understanding and managing the evolving risk structure of cryptocurrency markets.

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