

Explaining Bitcoin Volatility with GARCH Models and SHAP: A Human Centered XAI Approach to Financial Analytics

Menjelaskan Kemeruapan Bitcoin dengan Model GARCH dan SHAP: Pendekatan XAI Berpusatkan Manusia kepada Analitis Kewangan

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ABSTRACT

This paper investigates Bitcoin (BTC) volatility dynamics using a GARCH (1,1) model supplemented with major financial regressors to better understand the causes that drive market variations. Initially, a baseline GARCH (1,1) model with a normal distribution was used to estimate volatility in weekly BTC log returns from January 2016 to May 2025. The model was then improved by adding three regressors, and the fitted sigma values were used as a dependent variable. We use external factors like Google Trends data on the term "Bitcoin crash" as a proxy for public fear and sentiment, the CBOE VIX (market-wide risk sentiment), and Bitcoin trade volume (market activity intensity) to capture behavioral, macro-financial, and transactional influences on extracted volatility. The enhanced GARCH model performed better, with a log-likelihood of 499.94 and significantly improved information criteria values (AIC = -2.02, BIC = -1.96). The SHAP (SHapley Additive exPlanations) analysis was used to interpret the regressors' contributions to BTC volatility. The results showed that Bitcoin crashes (public fear) had the greatest impact on volatility, followed by BTC trading volume and the VIX. BTC crash incidents increased and decreased volatility based on market conditions, although trade volume constantly contributed positively. VIX had the least effect but offered a stabilizing influence. Diagnostic tests confirmed the model's adequacy and robustness, revealing no autocorrelation or heteroscedasticity in the residuals. This study shows how statistical modeling and explainable AI can be combined to generate interpretable insights about Bitcoin market dynamics, with an emphasis on human-centered, data-driven analysis.

Keywords: Bitcoin Volatility; GARCH; Explainable AI (XAI); VIX; Google Trends; SHAP values

ABSTRAK

Kertas kerja ini menyiasat dinamik kemeruapan Bitcoin (BTC) menggunakan model GARCH (1,1) yang digabungkan dengan peregresi kewangan utama untuk lebih memahami punca yang mendorong variasi pasaran. Pada mulanya, model paras dasar GARCH (1,1) dengan taburan normal digunakan untuk menganggarkan kemeruapan dalam pulangan log BTC mingguan dari Januari 2016 hingga Mei 2025. Model itu kemudiannya ditambah baik dengan menambah tiga peregresi, dan nilai sigma yang disuai digunakan sebagai pembolehubah bersandar. Kami menggunakan faktor luaran seperti data Google Trends pada istilah "Bitcoin crash" sebagai proksi untuk ketakutan dan sentimen awam, CBOE VIX (sentimen risiko seluruh pasaran) dan volum dagangan Bitcoin (intensiti aktiviti pasaran) untuk menangkap pengaruh tingkah laku, makro-kewangan dan transaksi terhadap kemeruapan yang diekstrak. Model GARCH yang dipertingkatkan menunjukkan prestasi yang lebih baik, dengan kebolehdarian log 499.94 dan nilai kriteria maklumat yang bertambah baik dengan ketara (AIC = -2.02, BIC = -1.96). Analisis SHAP (SHapley Additive exPlanations) digunakan untuk mentafsir sumbangan peregresi kepada kemeruapan BTC. Keputusan menunjukkan bahawa kejatuhan Bitcoin (ketakutan awam) mempunyai kesan yang paling besar terhadap kemeruapan, diikuti oleh volum dagangan BTC dan VIX. Insiden kejatuhan BTC meningkat dan menurun kemeruapan berdasarkan keadaan pasaran, walaupun volum dagangan sentiasa menyumbang secara positif. VIX mempunyai kesan paling sedikit tetapi menawarkan pengaruh yang menstabilkan. Ujian diagnostik mengesahkan kecukupan dan keteguhan model, mendedahkan tiada autokorelasi atau heteroskedastisiti dalam reja. Kajian ini menunjukkan cara pemodelan statistik dan AI boleh jelas boleh digabung untuk menjana cerapan yang boleh ditafsir tentang dinamik pasaran Bitcoin, dengan penekanan pada analisis berasaskan data yang berpusatkan manusia.

Kata kunci: Kemeruapan Bitcoin; GARCH; AI boleh dijelaskan (XAI); VIX; Tren Google; Nilai SHAP

INTRODUCTION

Cryptocurrencies move from specialized digital assets to well-known financial instruments. Their decentralized structure, high return, and limited regulation have attracted financial investments. However, cryptocurrencies are also known for their significant price volatility and remains poorly understood compared to traditional assets (Frank *et al.* 2025; Malladi & Dheeriyaa 2021). Modeling and forecasting of this volatility accurately are crucial not only for risk management and investment decisions but also for developing effective regulatory framework.

Traditional econometric models have been used to analyze Bitcoin volatility, the first digital asset, and the link between Bitcoin and macroeconomic uncertainty has also been investigated. For example, Akyildirim *et al.* (2020) found significant spillover effects from cryptocurrency returns to implied volatility indicators such as the VIX. These links grow significantly during times of serious financial market stress. This suggests that these new financial products have been influenced by the spread of significant financial market worries. likewise, López-Cabarcos *et al.* (2021) showed that both investor mood and the VIX have a considerable impact on Bitcoin volatility, particularly during speculative bubbles. Ghorbel and Jeribi (2021) have demonstrated that the volatility of digital assets is significantly correlated with that of traditional assets, highlighting their interconnection.

On the other hand, the incorporation of non-traditional indicators including such as public attention and emotions, alongside conventional financial indicators, into the Volatility models has evolved. Google Trends and social media sentiment can predict digital asset volatility (Said *et al.* 2023; Rutkowska & Kliber 2021). This underscores the influence of investor behavior and attention cycles. In addition, dynamic searches for Bitcoin exhibit asymmetric effects on price volatility (Georgiou *et al.* 2020), while Cankaya *et al.* (2019) assessed the impact of media tone and source on cryptocurrency price movements.

Regarding the incorporation of macroeconomic indicators into volatility modeling, Tzeng and Su (2024) and Lawuobahsumo *et al.* (2024) found that US Treasury yields, inflation, and unemployment rates improved volatility forecasts for cryptocurrency. In addition to that Climate policy uncertainty (CPU) has been introduced into GARCH-type models, and results show that volatility prediction was improved (Ding *et al.* 2025). Furthermore, Benammar *et al.* (2025) examined the impact of the Russo-Ukrainian war, demonstrating that geopolitical risk and economic policy uncertainty (EPU) have varied effects on cryptocurrencies, with some functioning as hedges during periods of crisis.

Three gaps in the research on GARCH-type models persist: the lack of clear comparisons of their performance with external regressors, the lack of interpretability in volatility modeling, minimal interpretability of predictors in black-box models, and insufficient study of Explainable Artificial Intelligence (XAI) in interpreting the effects of public fear, attention, trade volume, and VIX on bitcoin volatility. Despite the modeling of cryptocurrency volatility using macro-financial indicators, there is a need to understand the interactions between uncertainty-based external regressors and these models, as well as to leverage human-centered AI tools for interpretation.

The objective of this study is to investigate Bitcoin volatility using a GARCH-X framework. The study also considers external regressors and compares their estimation performance with the benchmark GARCH-family models by employing Shapley Additive Explanations (SHAP) to explain the impact of each external regressor on volatility forecast, thereby enhancing model transparency. The study employs a hybrid econometric-XAI approach, beginning with a GARCH-X model estimated using weekly Bitcoin log returns and external regressors to explain conditional variance. Its performance is compared to that of the standard GARCH. The fitted model's sigma value is then analyzed using SHAP values to assess the contribution of each input variable to predicted volatility. Hence, the paper proposes a hybrid novel GARCH-X model for modeling, predicting, and interpreting BTC volatility. The explanation is conducted and illustrated using XAI tools, and finally, the results aim to assist investors, governments, and researchers in navigating the evolving digital asset market.

The paper is structured as follows: Section 2 reviews the existing literature on Bitcoin volatility; Section 3 details the data sources and econometric models; Section 4 presents the empirical findings; and Section 5 summarizes the key findings and suggests future research areas.

LITERATURE REVIEW

Cryptocurrencies exhibit higher volatility than other financial market indicators; therefore, the causes, patterns, and determinants of cryptocurrency volatility have been increasingly investigated. For example, the relationship between digital assets and financial market indicators has also been analyzed. According to Akyildirim *et al.* (2020) and Ghorbel and Jeribi (2021), there is a significant link between crypto asset volatility and the VIX, particularly

during periods of financial stress due to spillover effects. On the other hand, Bitcoin volatility reacts strongly to investor sentiment and VIX fluctuations during the same periods (López-Cabarcos *et al.*, 2021).

Regarding the importance of macroeconomic variables in enhancing volatility projections, many studies have highlighted this. US macroeconomic variables such as Inflation and Treasury yields may improve the performance of GARCH models (Tzeng and Su, 2024). In addition, the predictive capacity of the US dollar exchange rate and treasury yields has also been confirmed by Lin *et al.* (2025). Likewise, economic policy uncertainty (EPU) influences the stock prices of blockchain, demonstrating time-varying effects across markets (Su *et al.*, 2024).

The literature also considers nontraditional indicators, including public sentiment and digital attention. For example, Google search interest is substantially correlated with bitcoin price swings, suggesting dynamics in investor attention (Rutkowska and Kliber, 2021; Said *et al.*, 2023). The sentiment of both positive and negative news has been examined by Georgiou *et al.* (2020) and Cankaya *et al.* (2019), revealing that there are varying effects of different emotional words and the type of media on price volatility.

The focus was also on the geopolitical and climate-related risks. As in some studies, the incorporation of climate policy uncertainty (CPU) improved the volatility predictions (Ding *et al.*, 2025). In contrast, Benammar *et al.* (2025) highlight how EPU and geopolitical risk stemming from the Russian-Ukrainian war affect digital asset returns, with some altcoins exhibiting hedging characteristics. Similarly, Gherghina and Constantinescu (2025) demonstrate that major global events, such as COVID-19 and the Ukraine conflict, increase volatility in top-market-cap cryptocurrencies.

Empirical results show that GARCH-type models performed well in both in-sample and out-of-sample after comparing them with TGARCH models (Chi and Hao, 2021; Frank *et al.*, 2025). Time series models are effective at handling highly volatile events such as Bitcoin 2028 (Malladi and Dheeriya, 2021). Meanwhile, Mittal and Subramanian (2024) note that decentralized markets, such as Bitcoin and Ethereum, exhibit more pronounced and frequent price volatility than traditional markets.

Regarding the emergence of machine learning and the natural dynamics of the market, both external shocks and internal market dynamics significantly influence cryptocurrency volatility, showing asymmetric responses to positive and negative shocks (Ahmed *et al.*, 2023; Sapuric *et al.*, 2022). However, traditional models remain the baseline despite the rise of machine learning and explainable AI, which integrate interpretable AI capabilities. This opened the door to researchers to compete by merging traditional models with AI models.

Lastly, this underscores the need to incorporate traditional financial indicators alongside non-traditional indicators, such as public opinion and geopolitical threats, into volatility models. This is to say that incorporating external regressors into GARCH models enhances the accuracy of volatility estimates. Furthermore, SHAP analysis is encouraged because it aligns with the growing desire for openness and interpretability in financial modeling, providing insights into the contributions of some aspects to volatility prediction.

METHODOLOGY AND DATA

DATA DESCRIPTION

The study used weekly data from January 3rd, 2016, to May 4th, 2025, totaling 488 weeks, for all variables considered. The dependent variable is Bitcoin volatility, which is modeled using the GARCH (1,1) and GARCH (1,1)-X frameworks. The explanatory variables are: BTC crash, VIX, and Bitcoin trade volume. To verify stationarity, all variables were transformed into log returns, which were then confirmed using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. Descriptive statistics and pre-estimation diagnostics were used to better understand the distributional features and volatility clustering in the data. The log returns from weekly prices were determined as the natural logarithm of the current price divided by the previous week's price, as stated in Equation 1.

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

The study considered the BTC Crash indicator, based on Google Trends data for the search term "Bitcoin crash," which captures public concern or fear during rapid price declines. The VIX indicator indicates traditional market fear and uncertainty, whereas Bitcoin Trade Volume measures market activity and liquidity demands. These characteristics are thought to influence Bitcoin volatility by either amplifying shocks or signaling changes in investor behavior.

OVERALL FLOWCHART

As an overall flowchart of the proposed methods, this study employs a two-stage hybrid methodology that integrates econometric volatility modeling with AI interpretation to analyze the drivers of Bitcoin volatility. The process first estimates conditional volatility using a GARCH framework and then uses a surrogate model to explain the non-linear relationships captured by the econometric model. The complete procedural pipeline is illustrated in Figure 1.

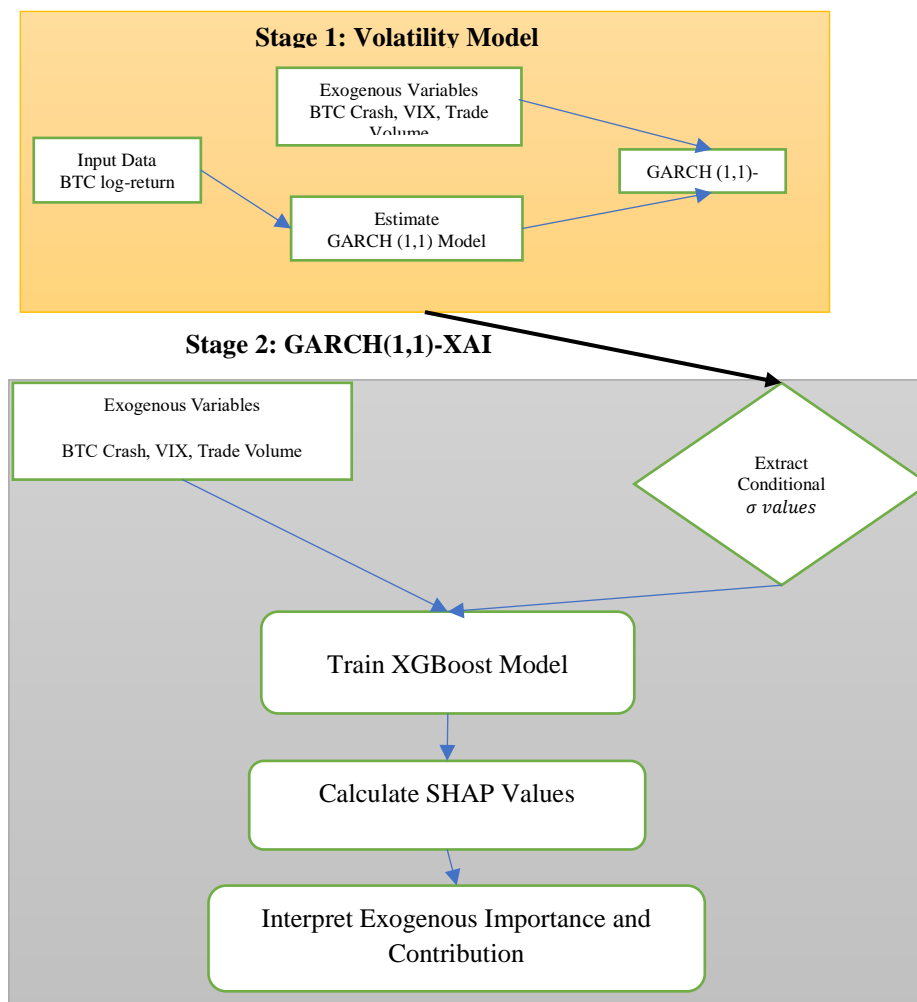


FIGURE 1. Overall Flowchart

ECONOMETRIC STRATEGY

The GARCH (1,1) model is used to estimate conditional variance using only previous shocks and variances. It is then extended to GARCH (1,1)-X by incorporating the previously described external regressors into the variance equation. The goal is to see if integrating exogenous factors improves volatility forecasts and model fit. To improve interpretability, SHAP (SHapley Additive exPlanations) values for the GARCH-X model are calculated using an XGBoost surrogate model, allowing the expected volatility to be decomposed into contributions from each regressor.

TABLE 1. Variables Used in the Analysis

Variable Name	Description	Source
BTCR	Weekly log returns of Bitcoin closing price	Investing.com
BTCR Crash	Google search interest for "Bitcoin crash"	Google Trends
VIXR	CBOE Volatility Index (global market risk indicator)	Investing.com
BTCR Trade Volume	Weekly log returns of BTC trading volume	Investing.com
BTCR Volatility (σ)	Conditional volatility from GARCH-X model	Derived

MODEL AND EQUATIONS

The study used the basic GARCH (1,1) model and its extension, the GARCH (1,1)-X model, which includes exogenous variables. These models were selected because they effectively capture volatility clustering and time-varying conditional variance in financial time series.

GARCH (1,1) Model

Bollerslev's (1986) Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model defines the return process (r_t) and conditional variance (σ_t^2) as:

$$r_t = \mu + \epsilon_t, \quad \epsilon_t = \sigma_t z_t, \quad z_t \sim i.i.d. N(0,1) \quad (2)$$

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

Where μ is the constant mean of the return process, $\omega > 0$ is a constant term, $\alpha \geq 0$ captures the impact of previous squared shocks (ARCH effect), $\beta \geq 0$ captures the persistence of prior conditional variance (GARCH effect), and σ_t^2 is the conditional variance (volatility) at time t . The GARCH (1,1) model assumes that volatility changes as a result of previous innovations and volatility.

GARCH (1,1)-X Model (with Exogenous Regressors)

To account for external causes of volatility, we modify the conventional GARCH model by including exogenous regressors X_t in the variance equation:

$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \delta' X_t \quad (4)$$

X_t is a vector of exogenous variables at time t , such as BTC Crash, VIX, and BTC Trade Volume, and δ is a vector of coefficients indicating their effect on volatility. This extended model allows us to determine whether information other than Bitcoin price fluctuations helps market volatility prediction and understanding. Model adequacy is tested using a variety of statistical criteria, including LL (a measure of model fit) and comparison metrics such as AIC and BIC. The ARCH-LM Test, which checks for residual ARCH effects, and the Q² Statistics Test for autocorrelation in squared residuals were also investigated.

Explainable Artificial Intelligent (SHAP)

Including XAI in a financial dataset is logical and empirically supported. It also overcomes logistics and linear regressions that require linear datasets (Ncube 2024). Furthermore, XAI can handle nonlinear data, as is common in real-world circumstances (Ali *et al.* 2023). This is because, XAI was defined as a machine learning approach that can generate human-readable explanations for AI-powered information systems (Ahmed *et al.* 2022).

We also considered a machine learning model called Extreme Gradient Boosting (XGBoost), and to explain its predictions, we use SHAP (SHapley Additive ExPlanations). this is all to evaluate the contribution of each external regressor to Bitcoin volatility. This approach provides us with human-interpretable insights into how each input variable influences anticipated volatility. The SHAP methodology is model-agnostic, which means it makes no assumptions about the algorithms employed in black-box models. As a result, it may be used to analyze any machine learning model, regardless of type or structure (Bhattacharya 2022; Ncube 2024). SHAP values are calculated as:

$$\varphi_i = \sum_{S \subseteq \{X_1, X_2, X_3\} \setminus \{X_i\}} \frac{|S|! (3 - |S| - 1)!}{3!} [f(S \cup \{X_i\}) - f(S)] \quad (5)$$

In this equation, X_1 represents the Bitcoin crash, X_2 represents the VIX, and X_3 represents the Bitcoin trade volume. The φ_i is the SHAP value of feature X_i and its contribution to the anticipated volatility ($\hat{\sigma}$). The $f(S)$ represents the XGBoost model's prediction utilizing only the features in subset S . The summation covers all subsets of characteristics except X_i .

In summary, our empirical strategy employs a mixed-methods approach. The qualitative insights derived from time-series plots and SHAP visualizations are systematically validated with rigorous statistical tests to ensure the robustness of our findings regarding Bitcoin volatility.

RESULTS AND DISCUSSION

TIME SERIES PLOT ANALYSIS

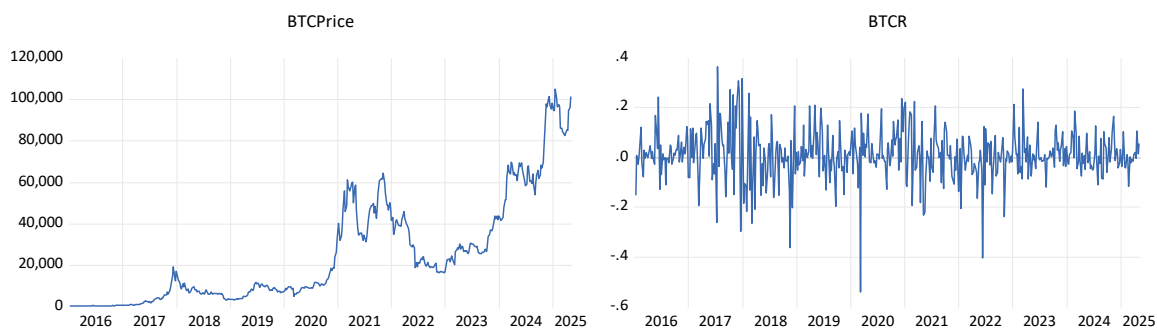


FIGURE 2. TS plot of BTC Prices vs Log return

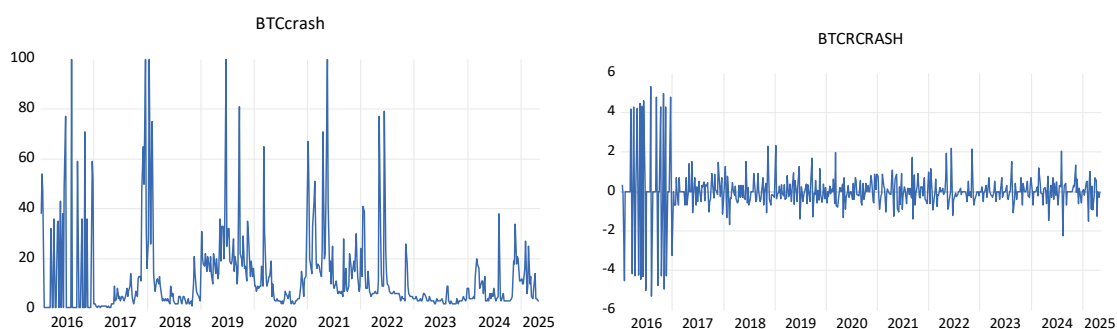


FIGURE 3. TS plot of BTC Crashes vs Log return

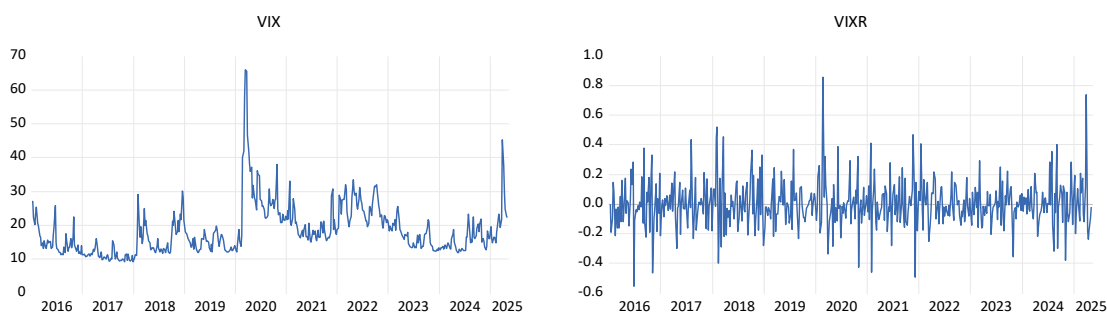


FIGURE 4. TS plot of VIX Prices vs Log return

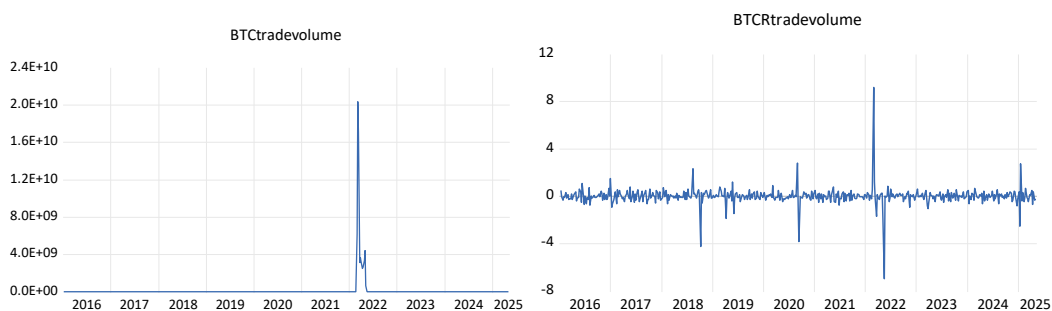


FIGURE 5. TS plot of BTC Trade Volume vs Log return

The BTC prices along with market indicators from 2026 to 20265 have been shown in Figures 2 to 5. The figures show significant price and volatility growth, due to the market stress period, there is a notable collapse. The BTCR figure demonstrates frequent oscillations, highlighting the volatility clustering observed in Bitcoin returns.

As can be depicted from the figures of VIX and VIXR there is a significant market anxiety and volatility expectations aligned with Bitcoin's fluctuations. The BTC trade volume demonstrates sharp spikes in activity, indicative of high kurtosis and positive skewness, likely due to stress events. These trends, combined with volatility clustering in BTCRCRASH and BTCR trade volume, highlight the necessity of accounting for behavioral, sentiment, and trading dynamics in volatility modeling, as detailed in the GARCH-X framework in TABLE 3.

DESCRIPTIVE STATISTICS ANALYSIS

In the descriptive analysis, the descriptive statistics for all variables are presented in TABLE 2. The table indicates that each variable has an almost zero mean, suggesting the absence of long-term trends. There is variability in expectations for public fear and market volatility, as evidenced by the significant standard deviations of 1.18 and 0.16 for BTCR Crash and VIXR, respectively. There is a very high kurtosis (74.42) and positive skewness (1.74) for BTCR Trade Volume, suggesting substantial trading activity spikes, likely linked to high-stress market events. The null hypothesis of normality was rejected for each variable based on JB statistics, and unit root tests confirm the data's stationarity, confirming their suitability for a GARCH-X model.

TABLE 2. Descriptive Statistics of BTCR and Regressors

Variable	BTCR	BTCR Crash	VIXR	BTCR Trade Volume
Mean	0.011131	-0.0052	-0.0004	-0.0008
Max	0.361952	5.298317	0.853717	9.189830
Min	-0.5394	-5.2983	-0.5562	-6.9729
Std. Dev.	0.100122	1.177735	0.157559	0.730729
Skewness	-0.3748	0.020731	0.684592	1.742181
Kurtosis	6.113027	11.80491	6.363693	74.41546
JB	208.0494***	1573.176***	267.6288***	103737.3***
ADF	-7.328***	-10.82***	-9.302***	-8.1915***
PP	-514.04***	-588.42***	-476.53***	-430.97***
ARCH-LM	28.45***	209.22***	8.838	73.869***
Obs	487	487	487	487

Most of the variables display volatility clustering, shown by significant ARCH-LM test results, indicating ongoing heteroskedasticity. The GARCH-X model is suitable for modeling time-varying volatility influenced by market sentiment (VIXR), behavioral indicators (BTCR Crash), and market participation (BTCR Trade Volume). SHAP is utilized on an XGBoost surrogate model to enhance interpretability based on GARCH volatility estimates.

VOLATILITY MODELING ANALYSIS

The parameter estimates presented in Table 3 show significant differences between the standard GARCH (1,1) and the extended GARCH (1,1)-X model after including exogenous regressors such as VIX, BTC Trade Volume, and BTC Crash (Google Trends) as volatility drivers. This improved the model's explanatory power due to the increase in log-likelihood from 449.55 to 499.94 and lower AIC and BIC values despite both models having high persistence $\alpha + \beta = 0.99$. This number, which is very close to one, shows that volatility is very persistent. This means that big changes in Bitcoin's price take a long time to settle down.

The result also shows that the GARCH-X model yielded a higher α coefficient of 0.116 than the traditional GARCH model, which has an α of 0.037. This demonstrates that including regressors also improves the model's response to recent market shocks by capturing short-term volatility dynamics. This is consistent with the descriptive statistics analysis that revealed volatility clustering via ARCH effects and heavy tails in variables such as BTC Trade Volume and BTC Crash. On the other hand, the increase of the volatility half-life from 60.30 to 66.58 implies that these shocks last longer, possibly reflecting the ongoing influence of external factors such as market sentiment and trading activity.

The significance of the external regressors' parameters with positive coefficients indicates that growing market anxiety (VIX), spikes in Bitcoin-related search interest (BTC Crash), and increases in trading volume are all correlated with increased Bitcoin volatility. This motivated the objective of this paper: to explain financial market behavior using statistical modeling and human-centered artificial intelligence. The diagnostic measures, such as ARCH-LM and Q^2 , confirm the efficacy of these explanatory factors because the absence of ARCH effects indicates improved model fit. Overall, these findings reaffirm the desire to use GARCH-X for modeling and then apply explainable AI (SHAP) to analyze volatility drivers more transparently.

TABLE 3. Estimation Results of GARCH (1,1) and GARCH (1,1)-X model.

Model	GARCH (1,1)	GARCH (1,1)-X
Parameters	Panel A: Parameters Estimates	
Constant (μ)	0.0011 (0.00)	0.0013 (0.00)
Omerga (ω)	0.00 (0.47)	0.00 (0.00)
Alpha (α_1)	0.037 (0.01)	0.116 (0.00)
Beta (β_1)	0.951 (0.00)	0.978 (0.00)
VIX	-	0.0005 (0.00)
BTC TV	-	0.0027 (0.00)
BTC crash	-	0.0016 (0.00)
Persistence	0.989	0.989
Half-life	60.30	66.58
LL	449.554	499.939
AIC	-1.829	-2.024
BIC	-1.795	-1.964
ARCH LM (7)	0.225 (0.99)	0.7991(0.94)
Q^2 (9)	0.982 (0.90)	4.821(0.46)
Obs.	487	487

Numbers in parenthesis show p-value

SHAP ANALYSIS OF EXTERNAL REGRESSORS' IMPACT

Extreme Gradient Boosting (XGBoost) was employed to model Bitcoin volatility, achieving exceptional predictive accuracy with an R^2 of 0.995. This exceptional explanatory power, accounting for over 99.5% of the variation volatility (σ), validates the subsequent interpretation of the model. We decompose the marginal contribution of each regressor using SHAP (SHapley Additive ExPlanations) to the fitted conditional volatility, to clarify their interpretability and influence. External regressors considered include BTC crash indicators, trading volume, and VIX to BTC volatility.

We employed SHAP summary plots to interpret the complex Shapley values. These plots give global model explainability by providing each feature's significance and effect on the variable being explained. On the horizontal axis, each point shows a feature instance and its position

show the magnitude and the sign (positive or negative influence on the output) of Shapley values, while it is color corresponds to the feature's raw values) as discussed by Ncube (2024).

The mean absolute SHAP values, which rank the importance of features in predicting BTC volatility, are presented in Figure 5. Regarding the results, the most significant regressor (mean $|\text{SHAP}| \approx 0.012$) was BTC Crash, suggesting a considerable influence. However, the direction of the effect such as positive or negative was context-dependent. Trading Volume had a modest influence (≈ 0.009), whilst the VIX had the least mean impact (≈ 0.005), indicating a minimal or stabilizing function in the model.

We also considered SHAP visualizations to interpret the models that detail both local and global feature contributions. The results show that features like BTC Crash and Trading Volume increase the output from the base value, while the VIX marginally lowers it, as shown in the waterfall plot in Figure 7, which deconstructs a single prediction. The global perspective in Figure 8 also complements the local explanation, which shows a beeswarm plot of the distribution of SHAP values across all instances. The distribution of red dots and blue dots is also explained. For example, red dots (high feature values) and blue dots (low values) are distributed along the SHAP value axis, revealing consistent patterns of influence. Figure 9 depicts a force map of a single prediction, tracing the path from the base value to the final output and clearly measuring each feature's positive or negative push.

Overall, our findings demonstrate that BTC crash indicators are the key drivers of volatility, which is consistent with descriptive statistics that reveal these indicators have significant kurtosis and volatility, indicating frequent extreme values. For example, the BTC crash indicators exhibit high **kurtosis**—a statistical measure of tailedness, and high volatility, together indicating a propensity for frequent and extreme market movements. This obvious interpretability is crucial to politicians, investors, and analysts who must make educated decisions in highly speculative markets.

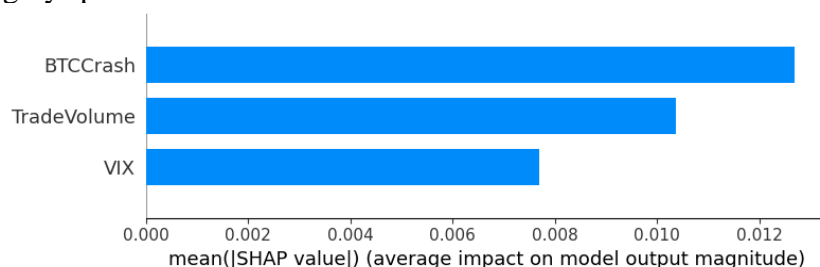


FIGURE 6. Mean SHAP Values Across Features

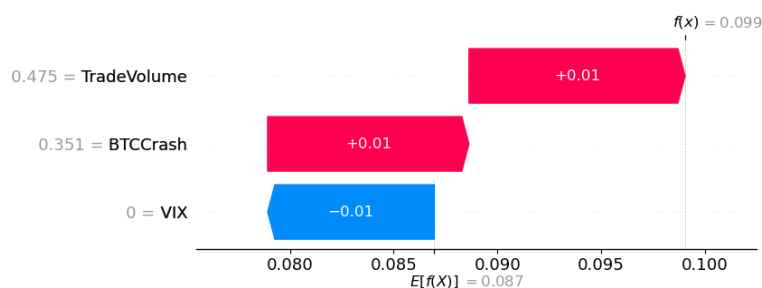


FIGURE 7. SHAP Waterfall Plot for One Instance

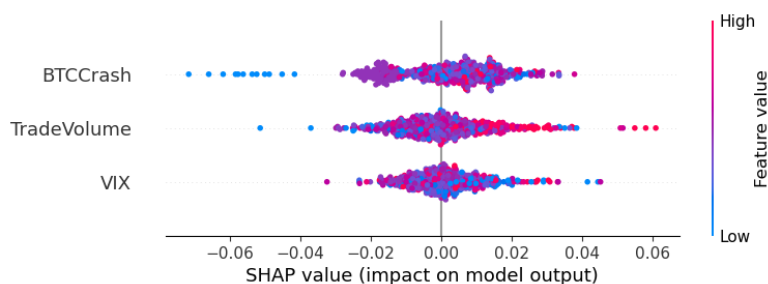


FIGURE 8. SHAP Summary Plot of Feature Impacts (Beeswarm)



FIGURE 9. SHAP Feature Contribution Force Plot

Comparative Analysis with the Current Studies

Table 6 compares our results with the results of the current literature. We have considered Google Trends data using Bitcoin crash phrase, VIX, BTC, sigma, and BTC trade volume as external regressors in a GARCH-X model to estimate the Bitcoin volatility, followed by explainable AI (XAI) interpretation with SHAP.

TABLE 4. Comparative Analysis

Study	Data/ Variables Used	Methodology	Main Findings	Comparison with Our Study	Remarks
Rutkowska and Kliber (2021)	Google Trends for multiple financial assets	VAR and sentiment analysis	Bitcoin prices are responsive to investor interest via Google searches.	Our analysis also makes use of Google Trends, with an emphasis on Bitcoin-related phrases.	We enhance their technique by incorporating GARCH-X and XAI interpretation.
Said <i>et al.</i> (2023)	Google search data and social media	VAR estimation	Google search activity significantly influences Bitcoin volatility.	Similar to our use of Google Trends for the 'Bitcoin crash.	We differ by incorporating these into a GARCH-X model and utilizing XAI.
Georgiou <i>et al.</i> (2020)	Google Trends with positive/negative sentiment	GARCH and EGARCH	Public awareness results in an unbalanced volatility response.	We support using search interest as a volatility driver.	We emphasize interpretability when employing SHAP values.
Cankaya <i>et al.</i> (2019)	News sentiment across categories	ARCH family models	News sentiment led to significant and varying effects on volatility.	We consider Google Trends rather than direct sentiment but similarly model	We include specific terms and interpret SHAP effects.

Our Study	Bitcoin crash, BTC, VIX, BTC trade volume	GARCH-X + SHAP (XAI)	Interpretation of role of regressors in driving volatility.	Innovative integration between volatility modeling and explainability.	Provides more human-understandable insights than traditional GARCH.
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Based on the comparisons in Table 4, our findings have important ramifications for comprehending and predicting cryptocurrency volatility using explainable AI. Through the use of Google Trends' search-based sentiment indicators like Bitcoin crash, BTC, VIX, sigma, and BTC trade volume, the model exhibited good prediction performance of $R^2 = 0.9947$ and outputs that are easy to understand through SHAP analysis. This demonstrates the importance of publicly accessible investor attention data in gauging market sentiment and influencing predictions for volatility. In addition to improving model clarity, the method gives analysts, regulators, and investors a more understandable and practical tool for assessing risk in real time in extremely volatile cryptocurrency markets.

CONCLUSION

This study investigates BTC volatility drivers by integrating traditional econometric models with modern explainable AI (XAI). We first employ a GARCH (1,1) model and its extension with exogenous variables (GARCH-X) to show that incorporating relevant external regressors such as the CBOE VIX, Bitcoin trading volume, and Google Trends-based BTC crash indicators will significantly improve model performance. The enhanced model increased sensitivity to recent shocks, and long volatility half-life that collectively indicate that these variables play an important role in shaping Bitcoin's risk profile.

The paper used SHAP analysis to decompose the contributions of each regressor to the expected volatility. This is to improve model transparency and interpretability. The most powerful driver, was shown to be BTC crash emotion, followed by trading activity, with the VIX having a rather minor and stabilizing effect. Therefore, to understand cryptocurrency market behaviour clearly, the paper proposes this innovative, human-centered approach that combines GARCH-X and SHAP, reconciling statistical rigor with model interpretability. These insights are useful for investors, analysts, and policymakers who want to navigate and manage risk in the quickly evolving digital asset field. Future research could look into time-varying or nonlinear links, as well as apply the explainable AI method to different asset classes. In addition, while the insights from the SHAP analysis are robust and intuitively clear, future research could benchmark these results against other interpretability methods, such as LIME to further validate the findings.

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