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BEYOND THE PRICE: HOW TRADING ACTIVITY SHAPES BITCOIN VOLATILITY

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ABSTRAK

Bitcoin memiliki kecenderungan volatilitas harga yang jauh lebih tinggi dari asset cryptocurrency lainnya, ini membuat perbedaan yang sangat signifikan dari aset keuangan lainnya yang dapat melampaui logika pasar konvensional sehingga menciptakan hambatan besar dalam manajemen risiko. Studi ini bertujuan untuk membedah anomali ekstrem volume perdagangan bitcoin terhadap volatilitas pengembalian Bitcoin. Menggunakan pendekatan deret waktu kuantitatif studi ini menganalisis data bulanan harga dan volume perdagangan bitcoin menggunakan harga Bitcoin pada periode Februari 2015 hingga Desember 2025. Kami menilai volatilitas menggunakan model GARCH-X untuk memperkenalkan volume perdagangan sebagai variabel eksogen. GARCH dasar menunjukkan persistensi volatilitas yang signifikan, menunjukkan pengelompokan volatilitas tinggi dalam pengembalian Bitcoin. Temuan ini menghasilkan bahwa volume perdagangan bukan hanya sekedar angka transaksi yang statis tetapi mencerminkan sebuah proxy informasi yang sangat krusial. Setiap pergerakan aktivitas perdagangan menghasilakn sinyal baru dalam memicu rekasi harga yang agresif. Volume perdagangan juga sangat berkorelasi dengan volatilitas pengembalian, meskipun ketidakstabilan model menunjukkan perlunya interpretasi yang cermat. Volatilitas Bitcoin tidak semata-mata karena dinamika volatilitas historis, tetapi juga adanya dorongan dari aktivitas perdagangan, menyoroti perlunya mempertimbangkan pemodelan volatilitas yang akurat di pasar aset digital. Penelitian ini menambah nilai dengan menyematkan volume perdagangan ke dalam model GARCH untuk mengevaluasi kontribusinya dalam menjelaskan volatilitas Bitcoin melalui wawasan empiris untuk keputusan investasi dan manajemen risiko di pasar cryptocurrency.

Kata kunci: *Bitcoin, Volatilitas, Volume Perdagangan, GARCH, Mata Uang Kripto*

ABSTRACT

Bitcoin has a tendency of price volatility that is much higher than other cryptocurrency assets, this makes a very significant difference from other financial assets that can go beyond conventional market logic thus creating a major obstacle in risk management. This study aims to dissect the extreme anomalies of bitcoin trading volume against the volatility of Bitcoin returns. Using a quantitative time series approach, the study analyzed monthly data on bitcoin price and trading volume using Bitcoin prices in the period February 2015 to December 2025. We assess volatility using the GARCH-X model to introduce trading volume as an exogenous variable. The basic GARCH shows significant volatility persistence, indicating a clustering of high volatility in Bitcoin's returns. This finding results that trading volume is not just a static transaction number but reflects a very crucial information proxy. Every movement of trading activity generates new signals in which aggressive price react. Trading volume is also highly correlated with the volatility of returns, although the volatility of the model indicates the need for careful interpretation. Bitcoin's volatility is not solely due to historical volatility dynamics, but also the impetus from trading activity, highlighting the need to consider accurate volatility modeling in the digital asset market. This research adds value by embedding trading volumes into the GARCH model to evaluate its contribution in explaining Bitcoin's volatility through empirical insights for investment decisions and risk management in the cryptocurrency market.

Keywords: Bitcoin, Volatility, Trading Volume, GARCH, Cryptocurrency.

INTRODUCTION

Crypto assets and their volatility attributes employed as an alternative investment tool have been investigated in academia and financial industry widely over the last decade. As the first and largest crypto, Bitcoin has enormous fluctuations in asset prices, so a model of volatility has to be developed that accurately reflects the risk behaviour (Baur et al., 2018 ; Katsiampa, 2017). Several earlier investigations reported that Bitcoin returns do not follow standard distributions, exhibit conditional heteroscedasticity, and display the clustering of volatility. Because of this, the ARCH/GARCH model is the most commonly used approach in estimating the price volatility in crypto markets (Dyhrberg, 2016; Katsiampa, 2017; Chu et al., 2017). Furthermore, the GARCH model shows empirically more effective performance of volatility estimation than standard methods (Katsiampa, 2017). The studies demonstrate the time-varying and market shock sensitivity of Bitcoin's volatility.

The literature has developed, and not only historical volatility has received attention in research, but also the factors contributing to volatility. According to the Mixture of Distributions Hypothesis (MDH), increasing trading volumes indicate new information which leads to higher price volatility (Clark, 1973; Tauchen et al., 1983). The correlation between trading volume and Bitcoin volatility returns, given the crypto market, has been well studied empirically and is observed to have substantial results (Balcilar et al., 2017; Ciaian et al., 2016). However, majority of studies study volume and volatility relationship independently or static. Trading volume has a significant predictive potential with regard to volatility for Bitcoin, particularly when quantiles are very high (Balcilar et al., 2017). Other results imply that high trading levels are a reflection of speculative investors' behavior that drives up price volatility on crypto (Bouri et al., 2019). Similar research also confirms an asymmetrical relationship between Bitcoin's volume and volatility (Kristoufek, 2018).

Based on this gap, this study contributes to the literature of returns by incorporating a GARCH model using trading volumes as an exogenous variable to conduct empirical investigations into the dynamics of Bitcoin return volatility. The GARCH-MIDAS model provides insight into how market factors exert a large influence on crypto volatility (Conrad et al., 2018). Logarithmic or differentiated trading volumes explains Bitcoin's fluctuations in a more orderly and meaningful way (S Kumar & Ajaz, 2019; Mensi et al., 2021). Bitcoin volatility is also impacted by global market trends. The relationship is further supported by the relationship of the volume of the trading with the volatility of the crypto market due to uncertainty, which may be caused globally as well as by economic crises (Corbet et al., 2020; Goodell et al., 2021). This shows in greater and greater numbers as Bitcoin has been incorporated into the overall global financial system, and retains its high volatility characteristics.

The impact of trading volume on Bitcoin's return volatility is relevant for further analysis of financial accounting and digital capital markets. Accordingly, this study formulates a more explicit research question to guide the empirical analysis, namely to what extent does trading volume, as a proxy for information flow, contribute to improving the estimation and prediction of Bitcoin return volatility beyond traditional volatility models based solely on historical data.

LITERATURE REVIEW

Volatility Characteristics and Modeling Approaches

Early research on Bitcoin's price changes mainly looked at its statistical features, like extreme price swings, groups of high volatility, and how volatility tends to continue over time. These features show that volatility changes over time and has different levels of variation depending on the situation, which means models like ARCH or GARCH are especially good for analyzing it. The creation of the ARCH model by Engle in 1982 and its later improvement by Bollerslev in 1986 set up a basic way to understand and describe these kinds of changes. Later research showed that models from the GARCH family work better than older methods when it comes to measuring Bitcoin's volatility and they are good at showing how its volatility tends to cluster together (Katsiampa, 2017; Chu et al., 2017)

Trading Activity as a Driver of Volatility

While early literature emphasized statistical modeling, more recent research shifts focus toward the determinants of volatility, particularly trading activity. Trading volume has been widely recognized as a critical factor influencing price dynamics, serving as a proxy for information flow in financial markets. According to the Mixture of Distributions Hypothesis (MDH), increased trading activity reflects the arrival of new information, which leads to higher uncertainty and price fluctuations (Clark, 1973).

Beyond Internal Dynamics: Market Integration and External Influences

As Bitcoin becomes increasingly integrated into the global financial system, its volatility is also influenced by external market factors. Recent literature highlights the role of spillovers from equity, commodity, and macroeconomic markets in shaping Bitcoin volatility. For example, shocks from major financial markets such as equities and gold have been found to significantly affect Bitcoin's volatility, reflecting its growing interconnectedness with traditional financial systems.

Hyphotheses

Bitcoin's high price volatility reflects the complex characteristics of the market, where price dynamics are determined not only by historical patterns, but also by the trading activity that represents the flow of information. Within the framework of the Mixture of Distributions Hypothesis (MDH), trading volume is seen as a proxy of new information entering the market, which ultimately increases uncertainty and drives price fluctuations (Clark, 1973).

In addition, the results of the GARCH model estimation show the existence of clustering volatility, which indicates that past volatility has a strong influence on current volatility. However, the GARCH-X approach allows the integration of external variables, such as trading volume, to capture additional dynamics that cannot be explained by historical data alone.

The Direct Effect of Trading Volume on Volatility

Trading volume not only reflects transaction activity, but also reflects the intensity of information circulating in the market. Increased trading volume is associated with increased uncertainty and more aggressive price reactions.

H_1: Trading volume has a positive and significant effect on the volatility of Bitcoin's returns.

Volatility Dynamics in the GARCH Model

Bitcoin's volatility is persistent in nature and is influenced by internal factors (historical volatility) and external factors (trading volume).

H_2: Bitcoin's return volatility is significantly influenced by historical volatility and trading volume in the GARCH-X model.

METHODS

Data Types and Sources

This study employs a quantitative time series approach using secondary data consisting of Bitcoin closing prices and trading volumes obtained from Yahoo Finance. The observation period runs from February 2015 to December 2025, resulting in 131 monthly observations. The study adopts a census method, combining all available data within the specified timeframe. The use of monthly data was deliberately chosen to reduce excessive short-term noise and extreme fluctuations commonly observed in daily or intraday cryptocurrency data. This frequency allows for a more stable representation of volatility dynamics and is better suited to capturing the medium- to long-term relationship between trading activity and volatility. However, the study acknowledges that the relatively limited number of observations can limit model complexity, justifying the use of a parsimonious specification such as GARCH(1,1). Bitcoin returns are calculated using logarithmic returns, while trading volumes are transformed into natural logarithms and first differences (DLNVOL) to address scale differences and ensure stationarity. Formally, the model incorporates Lagged conditional variance (GARCH effect) to capture volatility persistence Trading volume (DLNVOL) as an exogenous variable representing information flow. Thus, the framework links internal market dynamics (historical volatility) with external information factors (trading activity) in explaining Bitcoin volatility.

Model Specification and Justification

The choice of GARCH-X was motivated by the research objective of explicitly evaluating the role of trading activity in influencing volatility. Unlike the standard GARCH model, GARCH-X allows the inclusion of external variables, making it particularly suitable for testing the MDH framework. However, the study acknowledges that alternative models may offer additional advantages: EGARCH and TGARCH: capable of capturing asymmetric effects in volatility. GARCH-MIDAS: suitable for disentangling long-term and short-term volatility components. These models are recognized as potential extensions for future research, particularly given indications that Bitcoin volatility may exhibit non-linear and asymmetric behavior.

Data Analysis Methods

The data analysis process started with a stationarity test based on the Augmented Dickey-Fuller (ADF) Test, with a 5 percent significance level. If the probability value is less than 0.05 then the data is said to be stationary. In addition, we performed volatility analysis using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The GARCH(1,1) model is used as a base model because it is useful for modeling conditional volatility, and volatility persistence has an effect also. For this purpose, the residual is derived from an estimate of the mean, and is used for obtaining variance. The change in the trading volume log in the GARCH variance equation was included in order to predict the impact of trading volume on Bitcoin's return volatility. Parameter estimation was performed with the Maximum Likelihood Estimation (MLE) approach (assumes normal distribution). The testing of the model includes residual autocorrelation tests (Breusch–Godfrey LM Test) and ARCH effect testing to check residual heteroscedasticity. All data handling and analysis are performed in Eviews software.

Research Framework

In summary, the flow of this research can be described as follows

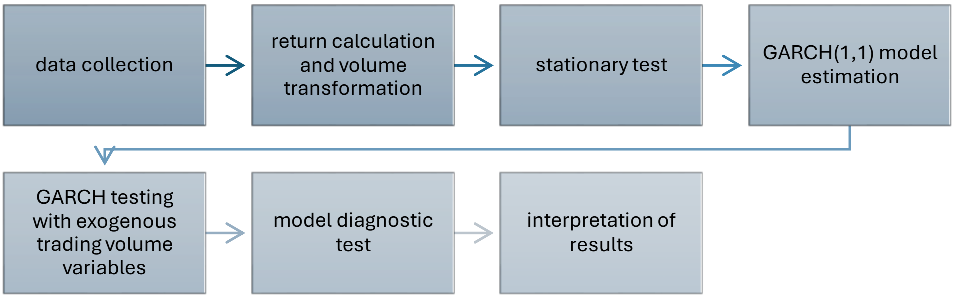

Figure 1. Research Framework

RESULT AND DISCUSSION

Stasioneritas Test

Table 1. Augmented Dickey-Fuller test statistic (RET)

			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-9.539374	0.0000
Test critical values:	1% level		-2.582872	
	5% level		-1.943304	
	10% level		-1.615087	

Source: Processed Data (2026)

The stationarity test is performed using the Augmented Dickey-Fuller (ADF) test to determine whether or not Bitcoin's return data (RET) contains root units. The hypotheses used in this test are:

H_0: Bitcoin returns have root units (not stationary)
H_1: Bitcoin returns do not have root units (stationary)

Based on the test results, the ADF statistical value for the Bitcoin return variable is -9.539374 with a probability value of 0.0000. The statistical value of ADF is smaller (more negative) compared to the critical values at the significance levels of 1%, 5%, and 10%, of -2.582872, -1.943304, and -1.615087, respectively. Since the probability value is less than 0.05 and the statistical value of ADF is smaller than the entire critical value, the null (H_0) hypothesis is rejected. Thus, it can be concluded that Bitcoin's returns are stationary at the level. These results show that Bitcoin's return data has met the stationarity assumption and is feasible for use in volatility analysis using the GARCH model without the need for additional differentiation. The stationarity of returns also indicates that Bitcoin's price fluctuations are mean-reverting in the short term, although its volatility can change over time. The value of the RET(-1) coefficient that is significant and negatively values indicates a correction to the deviation of returns in the previous period, which reinforces the indication that Bitcoin's returns do not contain root units. In addition, the statistical Durbin-Watson value of 2.021902 indicates the absence of serious residual autocorrelation in the ADF test model.

Table 2. Bitcoin Return (RET) Stationary Test (ADF)

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
RET(-1)	-0.824986	0.086482	-9.539374	0.0000
R-squared	0.413616	Mean dependent var		-0.001452
Adjusted R-squared	0.413616	S.D. dependent var		0.255888
S.E. of regression	0.195948	Akaike info criterion		-0.414273
Sum squared resid	4.953029	Schwarz criterion		-0.392215
Log likelihood	27.92777	Hannan-Quinn criter.		-0.405311
Durbin-Watson stat	2.021902			

Source: Processed Data (2026)

Based on the results of the Augmented Dickey-Fuller (ADF) test equation, RET(-1) is a coefficient of -0.824986, a t-statistic of -9.539374 and a probability value of 0.0000. Probability is considered below the threshold criterion that is to say, it is statistically significant. This negative and substantial coefficient denotes the possibility of a correction mechanism for the departure of returns in the previous interval, thereby supporting the conclusion that Bitcoin returns are not root units and stationary. The R-squared value of 0.413616 indicates that approximately 41.36% of the variance in Bitcoin return variation is explained by return values obtained in the previous period, as captured in the ADF test equation. The determination coefficient is not the target variable in the stationarity test, but it does suggest that the model has an adequate explanatory capacity. The statistical Durbin-Watson value of 2.021902 is close to 2, which suggests no serious residual autocorrelation problem in the model. Moreover, the Akaike Information Criterion (AIC) -0.414273 and Schwarz Criterion (SIC) -0.392215 are good evidence of compatibility of the model. All in all we can see that Bitcoin is stationary when we consider the return data, and it is easily explicable (via advanced estimation tools, for instance GARCH).

Table 3. Augmented Dickey-Fuller test statistic (LNVOL)

			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-10.93945	0.0000
Test critical values:	1% level		-2.582872	
	5% level		-1.943304	
	10% level		-1.615087	

Source: Processed Data (2026)

The Augmented Dickey-Fuller (ADF) test is utilized to conduct a stationarity assessment, aimed at identifying whether the Volume (VOL) data includes unit roots. The hypotheses used in this test are:

H_0: Volume has root unit (not stationary)

H_1: Volume does not have root unit (stationary)

The findings from the Augmented Dickey-Fuller (ADF) test indicated that the ADF statistic was -10.93945, accompanied by a probability value of 0.0000.

This ADF statistic is lower (more negative) than the critical values at significance thresholds of 1%, 5%, and 10%.

Since the probability value < 0.05 and the ADF statistic < critical value, the null (H_0) hypothesis stating that the variable contains the root unit is rejected. Thus, it can be concluded that the voltage variable tested is stationary.

These results indicate that the data has met the stationarity assumptions and is suitable for use in advanced analysis, including as a variable in econometric models such as GARCH, VAR, or time series regression, without the need for additional transformations. Based on the ADF test, the VOL variable is declared stationary because the statistical value of ADF (-10.93945) is smaller than the critical value and the probability is 0.0000 (< 0.05).

Table 4. DLNVOL Stationary Test (ADF Test) Trade Volume

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLNVOL(-1)	-0.960382	0.087791	-10.93945	0.0000
R-squared	0.481242	Mean dependent var		0.000615
Adjusted R-squared	0.481242	S.D. dependent var		0.472402
S.E. of regression	0.340247	Akaike info criterion		0.689370
Sum squared resid	14.93404	Schwarz criterion		0.711428
Log likelihood	-43.80906	Hannan-Quinn criter.		0.698333
Durbin-Watson stat	1.962846			

Source: Processed Data (2026)

Based on the findings from the Augmented Dickey-Fuller (ADF) test, the coefficient for DLNVOL(-1) was recorded at -0.960382, accompanied by a t-statistic of -10.93945 and a probability of 0.0000. The absolute value of the ADF statistic exceeds the critical values at significance levels of 1%, 5%, and 10%, while the probability is significantly lower than $\alpha = 0.05$.

So the null hypothesis (H_0) that the DLNVOL variable has unit roots is rejected which means DLNVOL has stationary characteristic. This implies that the root unit problem is resolved by 1st differentiation transformation in the trade volume log. The Durbin-Watson analysis shows the absence of a significant autocorrelation with the residuals, yielding a value of 1.962846, indicating reliability to our estimates. The value of R-squared= 0.481242 implies that approximately 48.12% of the variation of the change of DLNVOL could be explained by its lagged point, i.e. relatively strong temporal dependence of the variation of the trading volume. Methodologically, these results confirm that DLNVOL satisfies the stationarity condition and may serve as an exogenous variable in the GARCH analysis for the computation of how trading volume affects the return volatility of Bitcoin.

Normality Test

The findings from the mean equation estimation indicate that the constant (C) has a coefficient of 0.045782, accompanied by a t-statistic of 2.710071 and a probability value of 0.0076. Since this probability value is lower than the 5% significance threshold, it suggests that the constant holds statistical significance. A positive constant coefficient indicates that Bitcoin's average return during the observation period tends to be positive, although the fluctuations are relatively high. The R-squared value of 0.000000 indicates that the mean model only uses constants without including other explanatory variables, so it is not intended to explain the variation in returns, but rather solely to capture the average value of the return. The Durbin-Watson value of 1.738020 indicates the absence of a strong autocorrelation in the residual, so the mean equation is acceptable as the basis for the development of a volatility model. Thus, this mean equation is suitable for use as an input in the estimation of the GARC model, because the main focus of the next analysis is on the dynamics of variance (volatility) returns, not on the movement of the average return.

Table 5. Estimating the Mean Equation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.045782	0.016893	2.710071	0.0076
R-squared	0.000000	Mean dependent var		0.045782
Adjusted R-squared	0.000000	S.D. dependent var		0.193354
S.E. of regression	0.193354	Akaike info criterion		-0.440987
Sum squared resid	4.860136	Schwarz criterion		-0.419038
Log likelihood	29.88462	Hannan-Quinn criter.		-0.432068
Durbin-Watson stat	1.738020			

Source: Processed Data (2026)

Table 6. Uji Autokorelasi (Breusch-Godfrey LM Test)

F-statistic	2.189391	Prob. F(1,129)	0.1414
Obs*R-squared	2.186230	Prob. Chi-Square(1)	0.1392

Source: Processed Data (2026)

Table 7. Test Equation Breusch-Godfrey LM

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-7.72E-05	0.016817	-0.004590	0.9963
RESID(-1)	0.129267	0.087363	1.479659	0.1414
R-squared	0.016689	Mean dependent var		5.51E-18
Adjusted R-squared	0.009066	S.D. dependent var		0.193354
S.E. of regression	0.192475	Akaike info criterion		-0.442549
Sum squared resid	4.779027	Schwarz criterion		-0.398653
Log likelihood	30.98696	Hannan-Quinn criter.		-0.424712
F-statistic	2.189391	Durbin-Watson stat		2.006557
Prob(F-statistic)	0.141402			

Source: Processed Data (2026)

The findings from the Breusch-Godfrey Serial Correlation LM Test indicated an F-statistic of 2.189391 alongside a probability of 0.1414, as well as an Obs*R-squared value of 2.186230 with a corresponding probability of 0.1392. Both probability values exceed the 5% significance threshold. Thus, the null hypothesis

(H_0) suggesting the absence of autocorrelation up to the first lag remains unrefuted. This suggests that the residuals of the model do not exhibit issues related to autocorrelation, thereby confirming that the employed model satisfies one of the fundamental assumptions in time series analysis. The absence of autocorrelation in the residual indicates that the specification of the mean equation is adequate and does not require the addition of additional autoregressive or moving average components. Therefore, the residual of the mean equation is suitable for use as a basis in GARCH model estimation to further analyze return volatility.

Based on the outcomes from estimating the Test Equation with RESID as the dependent variable, a coefficient of 0.129267 for RESID(-1) was calculated, accompanied by a t-statistic of 1.479659 and a probability value of 0.1414. Since this probability exceeds the 5% significance threshold, it indicates that the residual lag coefficient lacks statistical significance. This shows that the previous period residual has no significant effect on the residual of the current period, which indicates the absence of autocorrelation in the residual until the 1st lag. Thus, the null (H_0) hypothesis that there is no autocorrelation cannot be rejected. The F-statistical value of 2.189391 with a probability of 0.141402 further strengthens the conclusion that the model does not contain autocorrelation problems. In addition, the Durbin-Watson value of 2.006557 is close to the number 2, which also indicates a residual condition that is free of positive and negative autocorrelation. A very small R-squared value (0.016689) is normal in autocorrelation test equations, since the purpose of this model is not to explain residual variations, but rather to detect the presence of serial correlations.

Table 8. GARCH-X Model Estimation with DLNVOL

Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.038688	0.012590	3.072916	0.0021
	Variance Equation			
C	0.000640	0.000397	1.611433	0.1071
RESID(-1)^2	-0.066836	0.016229	-4.118203	0.0000
GARCH(-1)	1.038593	2.32E-14	4.48E+13	0.0000
DLNVOL	0.013977	0.003052	4.580157	0.0000
R-squared	-0.001357	Mean dependent var		0.045782
Adjusted R-squared	-0.001357	S.D. dependent var		0.193354
S.E. of regression	0.193485	Akaike info criterion		-0.581632
Sum squared resid	4.866730	Schwarz criterion		-0.471892
Log likelihood	43.09692	Hannan-Quinn criter.		-0.537040
Durbin-Watson stat	1.735665			

Source: Processed Data (2026)

GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1) + C(5)*DLNVOL

The GARCH(1,1) model with the exogenous variable DLNVOL was estimated using the Maximum Likelihood (ML) method assuming a normal distribution. However, the estimation results show a "Failure to improve likelihood (non-zero gradients)" message, which indicates that the model has not reached optimal convergence, so the estimated results need to be interpreted carefully.

Mean equation

The constant coefficient (C) in the mean equation is 0.038688 with a probability value of 0.0021, which indicates that Bitcoin's average return is significant and has a positive value at a significance level of 5%. This indicates a positive average return during the observation period. According to the variable statistics in the table for the variance equation, the value for DLNVOL is positive and significant. It seems that trade volume (ΔLnVOL) changes increase the volatility of Bitcoin returns. Such findings reaffirm that larger trading volume is related to more market uncertainty, and increased volatility. Empirical evidence demonstrates that changes in trading volume (DLNVOL) significantly affect the volatility of Bitcoin's returns. But owing to the GARCH-X model not achieving convergence and violating the stationary variance assumption, these findings are inconclusive and may require an alternative modeling approach to test. Although significant influence of the volume of trading on return volatility of Bitcoin is indicated by the estimates, optimal convergence and non-stationarity should be considered based on the assumptions of variance stationarity that the GARCH-X model fails to conform to. Accordingly, these results are given some caution and must be investigated more thoroughly with alternative volatility modeling methods.

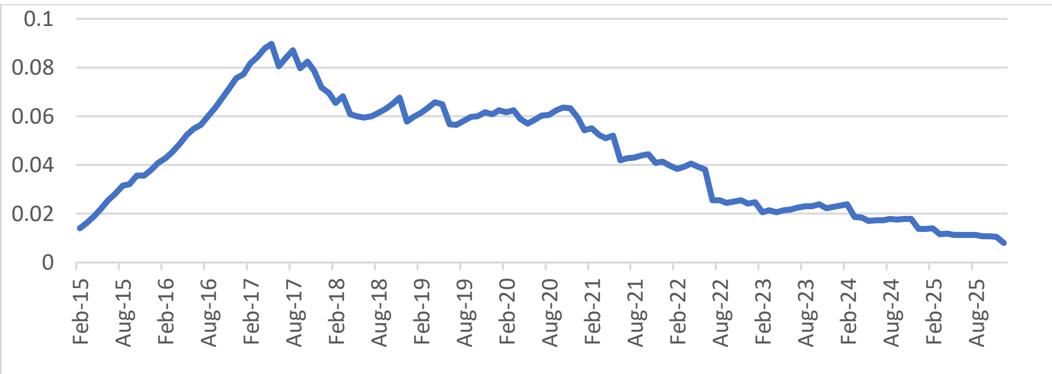

Figure 2. GARCH–VAR

The GARCH–VAR results confirm that Bitcoin's volatility is persistent and clustered, with a peak of risk in a given period and a stabilizing tendency at the end of the sample. It supports the use of GARCH to dynamically model crypto risk.

CONCLUSIONS

Our aim in this study has been to investigate how the volume of trading affects the volatility of Bitcoin returns in the form of a time series methodology using a GARCH model. Results of the Augmented Dickey-Fuller (ADF) stationarity test show that both Bitcoin returns and the log change in trading volume (DLNVOL) are stationary and are therefore suitable for further research. The estimation results with GARCH(1,1) without the exogenous variables show a high level of volatility persistence, proving that previous volatility influences the high level of volatility in the present period. This observation highlights volatility clustering in Bitcoin returns. When trading volume variation (DLNVOL) is included as an external factor in the variance equation of the GARCH-X model, the estimation results indicate that DLNVOL significantly affects the volatility of Bitcoin returns. It shows that when there is more trading activity in the Bitcoin market, what we get is more price volatility. However, the main contribution of this study lies in the evaluation of the integration of trading volumes in the volatility model. Although theoretically trading volumes are seen as a proxy for relevant information flows, the results of this study show that the linear GARCH-X model has not been able to adequately capture these influences stably and consistently.

Thus, this study does not use the results of the GARCH-X estimation as the basis for the main inferential conclusion. Conversely, the model's volatility provides important insights that the relationship between trading activity and Bitcoin's volatility is likely to be more complex than assumed in a linear framework, encompassing potential non-linearity, asymmetry, and dependence on market conditions. Therefore, these findings not only confirm the volatility characteristics of Bitcoin, but also challenge the adequacy of conventional modeling approaches in the context of the digital asset market. The implications of this study are two-way. Theoretically, the study confirms the need to develop more flexible volatility models to understand the dynamics of the crypto market. In practical terms, these results indicate that investment decision-making and risk management in the Bitcoin market cannot rely solely on historical indicators or a simple linear approach. As a further direction of research, it is recommended to adopt a more adaptive approach, such as non-linear, asymmetric, or regime-based volatility models, in order to obtain a more stable and representative estimate of the unique characteristics of the Bitcoin market.

RECOMMENDATIONS

Based on the results of the research and the limitations found, related to the development of a research model for future researchers, alternative volatility models such as EGARCH or TGARCH can be used which are able to capture asymmetric effects and tend to be more stable when including exogenous variables. In using distribution assumptions, it is possible to use non-normal distribution assumptions, such as Student-t or Generalized Error Distribution (GED), to accommodate the characteristics of Bitcoin's returns that tend to have fat tails as well as additional relevant variables such as global crypto market volatility, economic uncertainty indices, or market sentiment, to obtain a more comprehensive picture of the factors that affect Bitcoin's volatility. Data Periods and Frequencies with higher frequencies (daily or intraday) as well as longer observation periods are expected to improve the accuracy of volatility analysis. For investors and market participants, the results of this study can be a consideration in risk management, especially considering changes in trading volume as an early indicator of increasing volatility in the Bitcoin market.

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