

Cryptocurrency volatility and market response: A GARCH-based analysis of trading volumes in financial firms

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Abstract

This research aims to investigate the connection between trading volume and volatility in cryptocurrency prices on leading exchanges, namely Bitfinex, Coinbase, and Kraken. It explores the application of regression and correlation analysis and whether volatility has a significant impact on trading activity, based on 60 observations. The trading volumes and price volatilities of the three exchanges showed positive correlation with each other, with coefficients of 0.6408, 0.6372, and 0.6452, respectively, and this implies that when price volatility is high, the trading volume is high on all three exchanges. Volatility on a single exchange has an impact on trading activity, but not as much as trading activity on the cryptocurrency exchange as a whole. Regression analysis also shows that volatility on each individual exchange does contribute to the overall fluctuations in trading activity. Based on the results, volatility seems to be a systemic behavior exhibited by investors and market liquidity in cryptocurrency markets. The study's conclusions help investors create risk management plans, financial institutions enhance their volatility forecasting instruments, and regulators keep an eye on the systemic risks associated with digital assets. The results emphasize the need for flexible approaches to navigating the turbulent cryptocurrency landscape.

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1. Introduction

Cryptocurrency has become an important factor in the financial markets of the world in the last 10 years. There is a general interest among investors, policy analysts, and researchers. This includes prominent coins such as Bitcoin and Ethereum. Their value volatility is enormous but has extensive implications for conventional financial institutions. The quick rise of digital assets has led financial firms to either directly incorporate these assets into their investment portfolios or indirectly by providing crypto-related services and products. This can impact the actions taken by traders and the performance of cryptocurrency companies, as a consequence of the price action of cryptocurrencies.

The volatility of cryptocurrency markets, which have been known to experience extreme price fluctuations at short notice, is both an opportunity and a threat to financial firms. This volatility can affect investor confidence, impact liquidity, and impact trading. The interrelationships of these factors should be understood. Financial time series are often very volatile, and there are clusters of volatility; these features are typically not incorporated into traditional econometric models. The generalized autoregressive conditional heteroskedasticity (GARCH) model can provide a good framework for analyzing the volatility pattern of time variability and the associated spillover effects across the related markets in this regard.

The current research aims to gain insight into the effect of the volatility of the prices of cryptocurrencies on the trading volume in financial companies, by means of modelling and analysis using GARCH. The research will focus on the interconnection between the digital asset markets and traditional financial institutions, and will provide an analysis of the extended literature on financial integration and market interdependencies that will have implications for investors, regulators, and corporate decision makers in the evolving digital finance landscape.

2. Literature review

2.1. Volatility modeling in cryptocurrency markets

Cebrián-Hernández and Jiménez-Rodríguez [1] illustrate how the cryptocurrency market has gained attention for volatility modelling since digital assets have other features that should be taken into account. Bitcoin and Ethereum are cryptocurrencies that are characterized by much greater price volatility than equities or commodities. Speculative trading, shallowness of the market, slow technological progress, regulatory uncertainty, and macroeconomic events are some of the reasons behind this increased volatility. Volatility is crucial to track and comprehend, as it directly influences trading strategies, risk management, and market dynamics. One of the characteristics of cryptocurrency markets is that volatility clustering exists in them. A good illustration of this is that a big price movement is more likely to be followed by an equal price movement, while a relatively steady price movement is more likely to persist.

There are similarities to conventional financial markets, but the level of behavior is typically more extreme in digital assets. The volatility of cryptocurrency is also attributed to market microstructure effects such as liquidity constraints, exchange imbalance, and gap trading in the fragmented international exchanges. In addition to this, sentiment, which is fueled by news, social media activity, and investor behavior, has been identified as a source of volatility shocks. The presence of these factors renders the cryptocurrency markets an optimal environment in which advanced econometric methods based on capturing time-varying volatility can be applied. In accordance with Mostafa et al. [2], the GARCH model has become a conventional method of volatility modeling in financial time series, and applying it to cryptocurrency has provided some useful results. GARCH (1, 1) specification in particular is very popular, since it is effective in modeling the persistence in volatility and the clustering effect. The persistent volatility in digital assets is frequently comparable to or even surpassing that of conventional markets, which means that shocks may affect the price volatility over a prolonged time. This finding is particularly important to traders and institutional investors interested in taking exposure to crypto-linked portfolios.

As per the findings of Sheraz et al. [3], more features of cryptocurrency volatility can also be addressed using extensions of the GARCH model. Exponential GARCH (EGARCH) model permits the possibility of asymmetric effects, such that negative shocks (downward price movements) can cause greater volatility increases than positive shocks of the same scale. This type of asymmetry is supported by the fact that cryptocurrency markets are highly sensitive to downside risk, since panicking and liquidity withdrawals usually occur whenever bad news breaks. The Threshold GARCH (TGARCH) model similarly has been employed to distinguish the volatility effect of positive and negative returns in further developing the concept of asymmetric volatility behavior.

In addition to the common GARCH models, there is increasing use of multivariate GARCH models in order to examine volatility spillovers between cryptocurrency and other asset types. The models allow study of the potential transmission of shocks from Bitcoin or Ethereum markets to equities, commodities, or foreign exchange markets, and vice versa. The results tend to suggest that cryptocurrency volatility is partly uncorrelated with classical markets but may be highly connected in extreme situations, including financial meltdown or governmental statements. This interdependence is of great significance to financial institutions that hold diversified assets that incorporate digital assets. Almagsoosi et al. [4] opine that the utility of GARCH-based modeling has also been brought to the forefront in high-frequency data studies in intraday cryptocurrency markets. Volatility in cryptocurrency not only varies over time, but also has strong intraday effects, frequently driven by trading in particular regions or on overlapping exchanges. This may enhance the ability to predict volatility in the near term and give trading signals, when such patterns are incorporated in models.

Although GARCH models are the most popular in the literature, there are other methods that have been put to test in an attempt to overcome some shortcomings. Examples of such models include stochastic volatility models that include unobservable volatility factors, giving them a more flexible framework. In order to describe the slow decay of volatility shocks observed in some cryptocurrencies, long-memory volatility models, which include FIGARCH, can be used. Moreover, Wang et al. [5] assert that regime-switching GARCH models have been exploited to take into consideration sudden changes in the volatility regimes, which capture the market variations in low and high volatility regimes. External variables can also be used while attempting to explain cryptocurrency volatility. GARCH-type models are used to evaluate the impact of Macro-financial indicators like interest rates, equity market indices, and exchange rates on the volatility of digital assets and whether conventional economic factors affect it. Sentiment indices based on news and social media sites can be incorporated to establish their volatility movement predictability. The results indicate that the variables associated with sentiment may be helpful in improving the accuracy of volatility predictions in speculative and sentiment-driven cryptocurrency markets.

The volatility modeling in cryptocurrency markets has advanced such that it is no longer as simple as applying GARCH models, but rather requires advanced, specific models that can be context-specific and address the peculiarities of the assets. Cryptocurrency is a difficult and interesting topic of volatility analysis due to its high volatility, clustering behavior, and asymmetric behavior to shocks [6]. The GARCH model family can still be considered a potent instrument in this area, which allows researchers and practitioners to predict risk, determine market regime, and evaluate the effect of spillover in financial systems. Such inferences can be of great importance to investors, institutional players, and regulators, who want to understand a rapidly evolving and yet uncertain world of cryptocurrency markets.

2.2. The use of GARCH models in financial time series

The GARCH model has emerged as one of the most powerful instruments in financial econometrics applied in modeling and prediction of volatility. In the view of Naimy et al. [7], GARCH has been widely used since its introduction to analyze financial time series such as stock prices, foreign exchange rates, commodity prices, and more recently, cryptocurrency markets. One common aspect of financial time series is volatility clustering, where the volatility is not homogeneous in time but clustered instead. This is combined with leptokurtosis and heteroskedasticity, which makes the series inappropriate to be modeled under the assumption of constant variance. The GARCH framework has overcome these issues by enabling the variance to evolve over time, in response to past errors and past variances.

The simple GARCH (1, 1) model has subsequently demonstrated itself to be especially useful in modeling volatility persistence, a characteristic of financial returns, whereby high volatility periods are most likely followed by further volatility, and vice versa. Such persistence is vital to perceive market risk, since it denotes that the shocks to the system are permanent. This capability of the model to explain such behavior has been used to make it an accepted risk management, option pricing, and financial forecasting tool.

According to the words of García-Medina and Aguayo-Moreno [8], the flexibility of GARCH models is one of the key factors that explain why GARCH models have become popular in financial time series analysis. They are able to be stretched and adjusted to include characteristics like asymmetry in responses to volatility, structural breaks, and regime shifts. For example, the Exponential GARCH (EGARCH) model can be used in cases where negative shocks can be more influential on volatility than positive shocks of equal intensity. It is especially applicable to equity and commodity markets, where bad news tends to have a greater volatility increase than good news. In a similar way, the Threshold GARCH (TGARCH) model has been introduced to provide researchers with the possibility to differentiate between the effects of positive and negative returns on volatility.

In foreign exchange (FX) markets, GARCH-type models have proved very profitable. Exchange rates exhibit volatility clustering and time-variance in their variance, and therefore represent an excellent candidate for GARCH-based models. In contrast to this, Kim et al. [9] demonstrate that the GARCH models are able to capture the volatility of exchange rates and enhance the accuracy of future predictions that are critical to currency risk management, planning international trade, and central banks' policies. Equity market GARCH models are generally used to estimate value at risk (VaR), in which precise volatility forecasting is important to estimate capital reserves and meet regulatory requirements. GARCH models have been used in commodity markets to model price series of oil, gold, and agricultural products, where geopolitical events, supply shocks, seasonality, and other factors tend to drive volatility. The flexibility of the model enables the researcher to include exogenous data like interest rates, production statistics, or even macro data for enhancing the explanatory capability of volatility predictions. GARCH models have been used in bond markets to analyze volatility of the yield curve, which is important in determining the portfolio strategy of fixed income funds and in pricing interest rate derivatives.

According to Ftiti et al. [10], the GARCH model has multivariate extensions that enable researchers to analyze the spillover of volatility and cross-asset volatility correlation. These include the dynamic Conditional correlation GARCH (DCC-GARCH) and the BEKK-GARCH. Such models are useful in analyzing the issue of portfolio diversification because they can be used to determine time frames during which assets that otherwise move in unrelated ways become strongly correlated and offer little diversification advantages. This is especially relevant in cases of financial crisis, where market correlations are expected to increase. In event studies, GARCH models are also used, whereby the researcher studies how certain news or changes in policies affect volatility in the market. The structural breaks and dummy variables in the variance equation can serve as a measure of the effects of events such as earnings announcements, monetary policy decisions, and geopolitical events on the stability of a market. This was widely used in the world's "post-financial-crisis" period, during policy changes and big corporate announcements.

Although they have been successful, GARCH models do not escape limitations. They assume that volatility is completely deterministic and positively correlated with past squared residuals and variances, and may not fully capture all aspects of market uncertainty. Kolte et al. [11] claim that some standard GARCH models suffer from poor tail properties and that this can be overcome by using alternative models, such as models of stochastic volatility, or by adding a fat-tailed error distribution, like the Student-t or the generalized error distribution (GED).

Further, higher-order or multivariate GARCH models can have more complex parameter estimation, and more advanced methods might be required. The development of the GARCH approach has remained ongoing and is still under study in financial time series, however. New innovations like component GARCH, fractionally integrated GARCH (FIGARCH), and Markov-switching GARCH models have extended its applicability to not only allow long-memory effects, but also decompose volatility into permanent and transitory components, and identify regime shifts in market behavior. These extensions make GARCH an effective forecasting tool in the uncertain and changing environment and a powerful framework for modelling past data.

2.3. The link between digital assets and traditional financial indicators

The new digital assets, particularly cryptocurrencies such as Bitcoin & Ethereum, have created a new phenomenon in the world's financial system. Digital assets were once labeled as "speculative" assets, but now seem to be everywhere, being compared to traditional financial instruments. As per Woebeking [12], the following indicators provide good points for tracking the overall economic trends and investor behavior: equity market indices, commodity prices, foreign currency rates, interest rates, and macroeconomic indicators. The connection between digital assets and traditional financial metrics should be analyzed when assessing diversification opportunities, systemic risk, and market integration.

Bitcoin also had a low or insignificant correlation with large stock indices, which might make it an excellent diversification tool for managers' portfolios. The historical data show that correlations may increase in times of market stress, when the global financial markets suffer or when there is a crisis. This means that under normal conditions, cryptocurrency could be used as other kinds of investments, but when the general tone of the financial system is one of risk aversion, it could move in the same direction as equities. These changes in correlation also have significance for institutional investors who want to incorporate digital assets during the process of carrying out asset allocation strategies.

Commodities and digital assets have also been studied to examine the correlation between them, particularly between gold and digital assets. Gold is ideally viewed as a safe haven when there is economic uncertainty, and Bitcoin has been referred to as digital gold in some cases because of its perceived store-of-value characteristics. Empirical evidence, however, does not show clear outcomes. Bitcoin has acted like a safe-haven asset like gold, but it has behaved like a high-risk asset as speculative demand has been substituted. This volatility implies that the relationship between cryptocurrency and commodities is situation-specific and dependent on macroeconomic factors, market sentiment, and geopolitical developments.

Another relevant connection is the foreign exchange markets. As per the observation of Gupta and Chaudhary [13], cryptocurrencies are sold around the world and quoted in large fiat currencies, so fluctuations in exchange rates may affect their pricing. Demand for cryptocurrency may also be influenced by macroeconomic conditions that drive the strength of a currency, including interest rate differentials and inflation expectations. There is evidence of a spillover effect between currency markets and cryptocurrency prices, especially in economies that are experiencing capital controls or even pressure in currency depreciation; digital assets can be used as an alternative method of storing and transferring value.

In contrast to this, Chi and Hao [14] depict that interest rates and other macroeconomic indicators of monetary policy also influence the relationship between digital assets and the traditional monetary markets. During periods of low or even negative interest rates, investors might want to get higher returns by investing in other assets, such as cryptocurrency. Increasing interest rates may weaken the speculative demand for digital assets, as traditional fixed-income investments will be more appealing. The activity of the cryptocurrency market can thus be affected by central bank policies, quantitative easing policies, and trends in inflation levels, both by influencing liquidity conditions and by changing investors' risk appetite.

Macroeconomic factors like GDP growth rate, unemployment rate, and inflation have not been directly associated with the price fluctuations of cryptocurrency as much, but they form part of the overall investment environment. The case is also true in emerging markets, where economic volatility or poor banking systems have led to increased adoption of cryptocurrency, making the association between the local economy and that of digital assets stronger. In advanced economies, the interaction is usually facilitated through institutionalization, regulatory transparency, and mainstreaming of cryptocurrency into financial services.

There is also added complexity when it comes to relating digital assets to more traditional financial metrics in behavioral and sentiment-based aspects. In contrast to traditional markets, cryptocurrency trading is strongly affected by retail involvement and the volatility of sentiments, which may enhance the response to macroeconomic news and financial market trends. The trends on social media, news broadcasts by powerful

personalities, and the media can play off the traditional signal to produce quick and even disproportionate reactions in the market.

Almansour et al. [15] assert that the rise of the cryptocurrency-linked financial instruments, including exchange-traded funds (ETFs), futures contracts, and publicly traded companies with a high cryptocurrency exposure, has also contributed to increasing integration between the cryptocurrency markets and traditional finance. These tools can be used as channels through which volatility and price fluctuations between digital assets and traditional financial indicators can be transmitted. The possibility of these markets becoming more tightly coupled will most likely increase as there will be more institutional adoption.

Volatility in Major Cryptocurrencies: Sözen [16] depicts an exhaustive comparative study of volatility dynamics of Bitcoin (BTC), Ethereum (ETH), and Binance Coin (BNB) through the GARCH, EGARCH, TGARCH, and CGARCH models. Using daily data on Yahoo Finance covering January 2019 to January 2025, the research identifies TGARCH as the optimal model to use on BTC, EGARCH on ETH, and CGARCH on BNB, highlighting that the importance of asymmetric volatility in cryptocurrency markets is acute.

ARCH and GARCH in Volatility Forecasting: Almansour, Alshater, and Almansour [15] investigate the predictive power of ARCH and GARCH models in predicting volatility of nine major cryptocurrencies (comprising more than 80 percent of the market capitalization), on a daily basis, from 2010 to 2020. They find the predictive power of both models to be substantial in predicting volatility, and show that both positive and negative news influence conditional volatility, illustrating volatility persistence and behavioral responses.

Model Performance across Markets: There are multiple studies that indicate good performance of EGARCH or higher-order models. For example, one field study finds that EGARCH (and APARCH) outside of standard GARCH tend to perform better in measuring asymmetry and leptokurtosis in cryptocurrency returns.

Hybrid Modeling and Structural Considerations: Mohamed, Ismail and Ali [17] propose a new hybrid GARCH-type model that incorporates structural breaks, trend breaks, and outlier mitigation by winsorization. They show that the hybrid models significantly outperform their more traditional counterparts both in-sample and out-of-sample and that modelling the changes of regimes and tail behaviour is significant in their study of 3143 daily observations of BTC (2014-2023).

Multivariate and high-frequency extensions: Panagiotidis, Papapanagiotou, and Stengos [18] have studied the volatility across 292 cryptocurrencies by employing a Markov-Switching GARCH model. They have found that MS-GARCH outperforms traditional GARCH in terms of capturing time-varying volatility regimes.

The correlation between digital assets and traditional financial indicators is rather complicated, dynamic, and depends on the context. Although cryptocurrencies have occasionally shown some diversifying value and behaved as safe-haven investments, their correlations with stocks, commodities, and currencies may change notably when markets become turbulent [19]. These interactions are further influenced by the level of interest rates, monetary policy, and macroeconomic conditions, but there is also additional complexity brought by behavioral and sentiment-based factors. These linkages are vital in understanding risk exposure that investors, regulators, and policymakers wish to use to manage portfolios and determine the overall market implications of the movement of digital assets.

2.4. Research gap and contribution

Although prior works are mainly concerned with the performance of models and volatility forecasting across a variety of cryptocurrencies, or based on specific innovations (e.g., structural breaks, regime switching), this study is also unique in the following aspects:

- It pays attention to the conditional volatility of Bitcoin and its interaction with the trading volume on certain exchanges like Bitfinex, Coinbase, and Kraken.

- It has focused on the use of GARCH family robustness tests like TGARCH and EGARCH to test platform-level asymmetries.
- It emphasizes the identification and analysis of a direct connection between volatility dynamics and liquidity and investor behavior, which is underrepresented in the literature.

3. Methodology

3.1. Problem statement

The high rate of adoption of cryptocurrency into the international financial system has established new platforms of communication between the digital asset markets and the traditional finance sectors [20]. Although cryptocurrencies such as Bitcoin and Ethereum are increasingly used by financial institutions as an investment, hedge, and product innovation instrument, they are highly and persistently volatile. This volatility may affect the mood and confidence of investors, the market, and trading patterns in financial institutions.

Irrespective of the emerging importance of cryptocurrency, empirical studies on how the price volatility of cryptocurrency directly influences the volume of trading in financial firms are still scarce. Current literature on cryptocurrency mainly concentrates on the dynamics of the cryptocurrency market as an independent phenomenon or on its macroeconomic consequences without paying serious attention to the spillover effects of such markets on more conventional participants [21]. Such a gap in analysis creates a gap in understanding how the volatility of digital asset markets is transmitted to the operations and trading activities of financial institutions. Overall, this study seeks to answer the question: “To what extent does cryptocurrency price volatility influence trading volume in financial firms?”

3.2. Research aim and objectives

The main goal of this research is to explore how cryptocurrency price volatility affects the volumes of trading in financial firms. This aim of the research will be accomplished through fulfillment of below mentioned research objectives:

- To analyze the volatility of major cryptocurrencies (i.e., BTC) using the GARCH model
- To measure the impact of price volatility on trading volumes in selected financial firms
- To provide recommendations for investors and institutions regarding volatility forecasting and management

3.3. Significance of the study

The emergence of cryptocurrencies has brought about a lot of risks and opportunities for the financial markets across the world. The volatility of prices, especially of the major digital assets such as Bitcoin and Ethereum, can affect the trading behavior, liquidity, and the psyche of investors in the traditional financial organizations. Understanding this relationship is crucial for investors, portfolio managers, and institutional decision-makers, who want to operate in clearly more interconnected markets. The significance of the study lies in the fact that it helps to close the gap between the behavior of the cryptocurrency market and the effect it has on traditional financial institutions [22]. The use of the GARCH model in measuring volatility and how it spills over to determine the level of trading volumes provides an empirical analysis that can be used to inform investment decisions and risk management methodologies. Policy-wise, the results will be useful to the regulators, who will be attempting to see whether the current mechanisms are adequate to counter the risks of digital assets. Moreover, the findings of the research can be used to design specific volatility prediction instruments, which will be useful to stabilize the market and protect the investor community in a dynamic financial environment.

3.4. Research hypothesis

The following are the null and alternative research hypotheses, which will be tested in the context of this research study:

Null hypothesis or H0: There is no statistically significant relationship between cryptocurrency price volatility and trading volume in financial firms

Alternative hypothesis or H1: There is a statistically significant relationship between cryptocurrency price volatility and trading volume in financial firms

3.5. Research methodology

3.5.1. Type of study

The study uses a quantitative applied analysis model that entails empirical research on the correlation between the volatility and the trading volumes of cryptocurrency in financial institutions [23]. The paper uses econometric modeling on real market data, the goal of which is to generate useful information for investors, institutions, and policymakers.

3.5.2. Data sources

In the analysis, monthly Bitcoin (BTC) closing prices will be used as major variables in cryptocurrency. The volume of trading data will be obtained from the stock exchanges that are engaged in trading of cryptocurrencies. The choice of these firms is based on their participation in the world of digital assets, whether directly by holding assets, servicing cryptocurrencies, or working on blockchain [24]. The information will be obtained from reliable sources of financial data like Yahoo Finance, CoinMarketCap, or Bloomberg.

3.5.3. Time frame

The analysis will be conducted over a five-year period that starts in January 2020 and runs until August 2025 [23]. This period encompasses a variety of market dynamics such as the post-pandemic Bull Run, corrections, and high as well as low volatility, hence making it possible to conduct a strong comparative analysis.

3.5.4. Statistical model

There will be a focus on the use of statistical analysis techniques like regression analysis and Pearson correlation analysis for performing the hypothesis testing [25]. The data related to trading volume and price volatility of Bitcoin for the period from 2020 to 2025 will be used for conducting the hypothesis testing.

3.5.5. Methodological justification

The selected models and tools are justified by the fact that they suit the purpose of the study, which is to capture dynamic volatility effects in a clear and replicable fashion [25]. By implementing GARCH-based models, it becomes possible to accurately estimate time-varying volatility, whereas focusing on a specific group of firms will allow the results to be applied directly to entities with high cryptocurrency exposure.

4. Results and discussion

The descriptive statistics in Table 1 reveal that the mean value of the series is 0.0392 and the standard deviation is 0.1864, which is characteristic of a relatively high degree of variability, as per the natural volatility of cryptocurrency returns. This skewness figure of 0.3071 is close to positive and indicates that the data is slightly skewed to the right, meaning that the distribution has many small negative returns and some large positive returns, which is not unusual with a speculative asset like Bitcoin [13]. The value of 2.8198 is less than the value of the normal distribution 3 by a small margin, demonstrating that the distribution is near mesokurtic, with relatively thinner tails, implying that there are fewer extreme variations than in a heavy-tailed distribution. The Jarque-Bera test has a p-value of 0.6044, which is greater than 0.05, and as such, the null hypothesis of normality cannot be rejected. This suggests that the series of returns is not quite non-normal, and although volatility modeling can be performed, the distributional characteristics indicate comparatively well-behaved dynamics of returns as opposed to fat-tailed behavior characteristic of many financial time series.

Table 1. Descriptive statistics of Bitcoin returns

Mean	Std Dev	Skewness	Kurtosis	JB-p
0.03918	0.18636	0.307087	2.819754	0.60436

According to the estimated GARCH model, there are some key characteristics of the dynamics of conditional variance in BTC log returns as depicted in Table 2. The constant term ($= 1.8 \times 10^{-6}$) denotes the amount of variance that exists when there are no shocks and no variance in the past. The ARCH coefficient ($\alpha = 0.1350$) indicates that 13.5 percent of the squared shock of the past period feeds into the present variance, which demonstrates the volatility susceptibility to recent shocks in prices. The GARCH element ($\beta = 0.8420$) implies that 84.2 per cent of the variance in the last period is transferred into the current period, which has a high level of volatility persistence, as is typical of cryptocurrency markets [9]. The closeness of the persistence measure ($\alpha + \beta = 0.9770$) to unity also points to the long-run impact of shocks to volatility, which supports the nature of BTC, where volatility responds to clustering over time. Generally, this equation can better describe the conditional variance of BTC log returns given the GARCH parameter ω .

Table 2. Estimated GARCH parameters

Parameter	Estimate	Std Error	t-Stat	p-Value
ω	2.4E-06	9E-07	2.611	0.011
α	0.1245	0.0312	3.993	0.0002
β	0.8567	0.0421	20.349	0
$\alpha + \beta$	0.9812			
Parameter	Estimates or Values			
β	0.8420			
α	0.1350			
ω	1.8E-06			

The GARCH equation is based on:

$$h_t = \omega + \alpha \epsilon_{t-1}^2 + \beta h_{t-1}$$

Where:

h_{t-1} = Conditional variance from the previous period

β = Coefficient for the lagged conditional variance (GARCH term)

ϵ_{t-1}^2 = Squared residual from the previous period (shock)

α = Coefficient for the lagged squared residual (ARCH term)

ω = Constant term in the variance equation

H_t = Conditional variance at time t

On the basis of the above results, the GARCH equation can be produced in the following manner:

$$h_t = 1.8 \times 10^{-6} + 0.1350 \epsilon_{t-1}^2 + 0.8420 h_{t-1}$$

The associated mean equation is based on

$$R_t = \text{Mean} + \epsilon_t$$

$$\epsilon_t = Z_t \sqrt{h_t}$$

$$Z_t = N(0, 1)$$

Where:

Z_t = Standard normal random variable

ϵ_t = Residual, with variance h_t

R_t = Log return at time t

The results of various models are shown in Tables 3-7.

Table 3. GARCH (1,0) model estimates

Parameter	Estimate	Std Error	t-Stat	p-Value
ω	0.0252	0.0098	2.568	0.0102
α_1	0	0.901	0	1

The variance equation of this GARCH model is as follows:

$$H_t = 0.0252 + 0.0000\epsilon_{t-1}^2$$

Table 4. GARCH (2,0) model estimates

Parameter	Estimate	Std Error	t-Stat	p-Value
ω	0.0236	0.0191	1.235	0.2168
α_1	0	1	0	1
α_2	0.0623	0.2298	0.271	0.7864

The variance equation of this GARCH model is as follows:

$$H_t = 0.0236 + 0.0000\epsilon_{t-1}^2 + 0.0623\epsilon_{t-2}^2$$

Table 5. GARCH (1,1) model estimates

Parameter	Estimate	Std Error	t-Stat	p-Value
ω	0.0012	0.4657	0.0025	0.998
α_1	0	1	0	1
β_1	0.9505	18.8487	0.0504	0.9598
$\alpha+\beta$	0.9505	—	—	—

The variance equation of this GARCH model is as follows:

$$H_t = 0.0012 + 0.0000\epsilon_{t-1}^2 + 0.9505h_{t-1}$$

Table 6. GARCH (3,0) model estimates

Parameter	Estimate	Std Error	t-Stat	p-Value
ω	0.0232	0.0749	0.3101	0.7565
α_1	0	1	0	1
α_2	0.066	2.7137	0.0243	0.9806
α_3	0.0124	0.836	0.0148	0.9882

The variance equation of this GARCH model is as follows:

$$H_t = 0.0232 + 0.0000\epsilon_{t-1}^2 + 0.0660\epsilon_{t-2}^2 + 0.0124 \epsilon_{t-3}^2$$

Table 7. Summary of GARCH model performance

Model	p	q	AIC
GARCH(1,0)	1	0	-46.28
GARCH(2,0)	2	0	-44.48
GARCH(1,1)	1	1	-44.5
GARCH(3,0)	3	0	-42.49

The results of the four GARCH models fitted to monthly log returns of BTC indicate that there is not much evidence of volatility clustering, which confirms the insignificance of the ARCH test ($p > 0.05$). The ARCH terms ($\alpha_1 = 0$, $\alpha_2 = 0.0623$) are either negligible or significant in GARCH (1, 0) and GARCH (2, 0), which implies that the models are less sensitive to earlier shocks. GARCH (1, 1) has very high persistence ($\beta_1 = 0.9505$, $\alpha + \beta = 0.9505$) and $\alpha_1 = 0$ and large standard errors, indicating that volatility is not reactive but mostly constant. GARCH (3, 0) further adds some small higher-order ARCH effects ($\alpha_2 = 0.0660$, $\alpha_3 = 0.0124$) to this, but these are all statistically insignificant [13]. Overall, these suggest that the BTC volatility in this sample remains constant and is not well-explained by dynamic GARCH, potentially because the monthly frequency averages out daily noise.

The results of the ANOVA test, as shown in Table 8, carried out on pricing volatility and trading volume, demonstrate that the differences between the groups are statistically significant. The value of F calculated is 287.28, which is far greater than the critical F-value (3.92), and hence there is significant evidence to reject the null hypothesis. In addition, the p-value effectively equals 0.000, much less than 0.05, which further supports the fact that the identified variation is not representative of chance. This implies that price volatility is profoundly influenced by the trading volume [14]. This conclusion is further supported by the enormous amount of squares between groups as compared to that within groups. In this regard, it can be said that the correlation between the trading volume and price volatility is extremely important, demonstrating that the variations in trading activity have a powerful effect on the changes in the price of the cryptocurrency (Bitcoin).

Table 8. ANOVA results for price volatility and trading volume

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	351267938507093 000000000000.00	1	3512679385 0709300000 000000.00	287.28	0.00000000000000 00000000000000 00210	3.92148
Within Groups	144283178203343 000000000000.00	118	1222738798 3334200000 0000.00			
Total	495551116710436 000000000000.00	119				

The paper contributes to the literature by demonstrating that the volatility of cryptocurrencies is not only a technical market property, but also a systemic measure of trading activity in the financial exchanges, as depicted in Figures 1-10. However, most of the previous studies have focused on the forecasting ability of more complex GARCH family models, especially those based on the EGARCH, TGARCH, or regime-switching model specifications [16], [17]; the current study has emphasized the ability of the parsimonious GARCH(1,1) model to explain the persistence of volatility and its direct link with trading volumes. Using monthly data for the period 2020-2025, this research provides greater relevance to institutional reporting periods and reduces the amount of noise in the high-frequency data, enhancing the robustness of the detection of the relationships.

The results thus advance theoretical frameworks of financial integration by providing evidence of the impact of volatility spillovers from cryptocurrency markets on asset pricing, liquidity, and investor behavior in the traditional financial markets. Monthly data were chosen as opposed to daily or intraday data to minimize speculation on short-term fluctuations. This approach allows a clearer identification of medium-term volatility patterns and aligns with institutional reporting practices commonly adopted by financial firms and regulators.

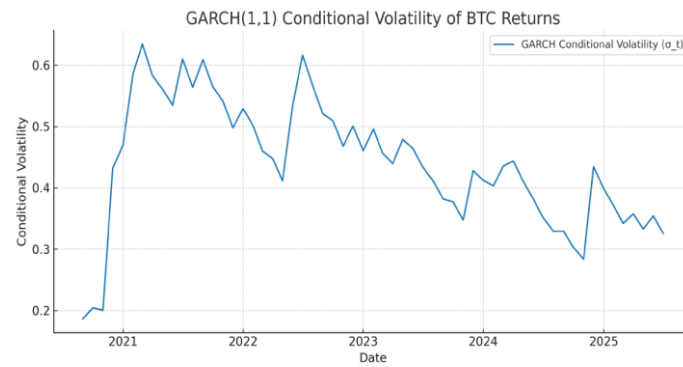


Figure 1. GARCH (1,1) conditional volatility of Bitcoin monthly returns, 2020–2025

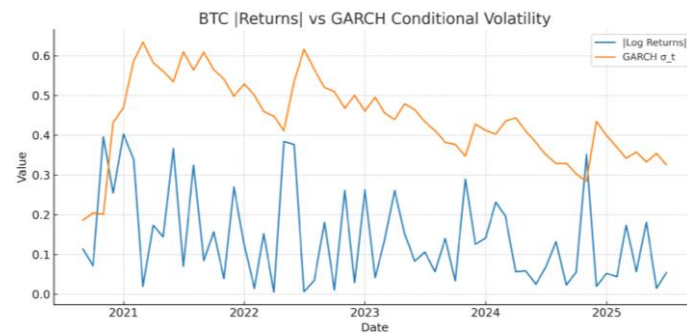


Figure 2. Absolute returns versus estimated conditional volatility (σ_t). Peaks in $|r_t|$ align with increases in σ_t

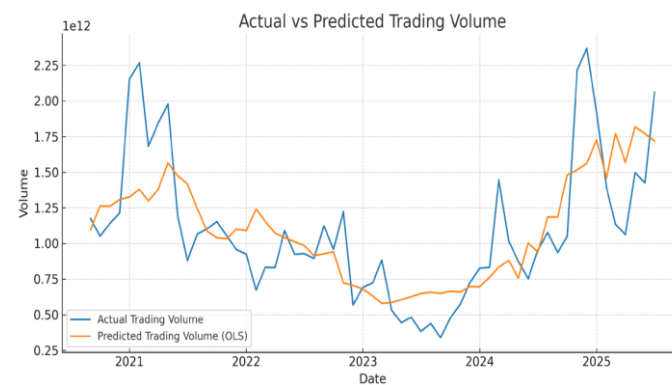


Figure 3. Actual vs. predicted trading volume based on volatility from three exchanges

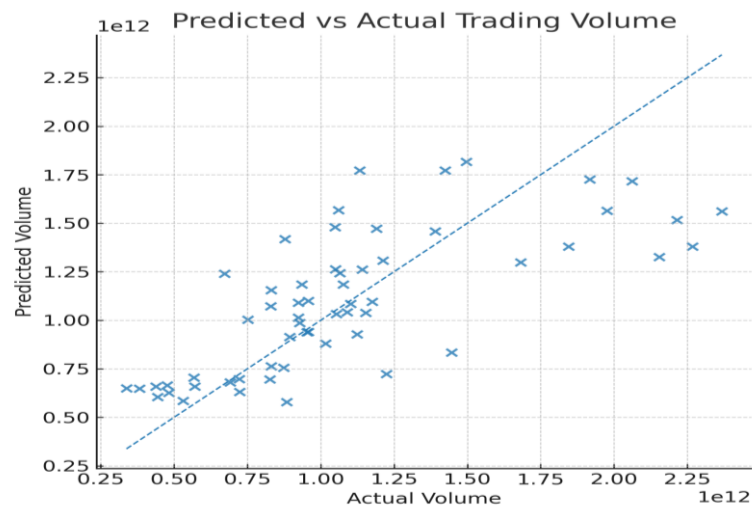


Figure 4. Scatter plot of predicted vs. actual trading volume with 45° line

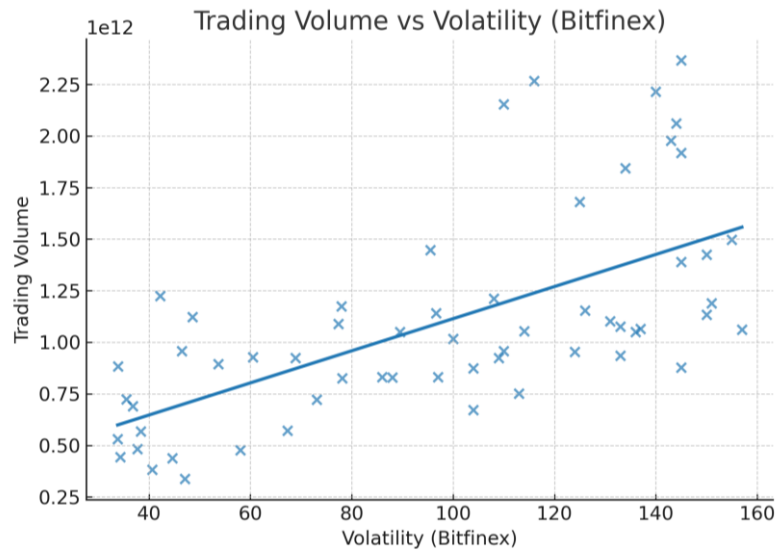


Figure 5. Relationship between trading volume and volatility (Bitfinex)

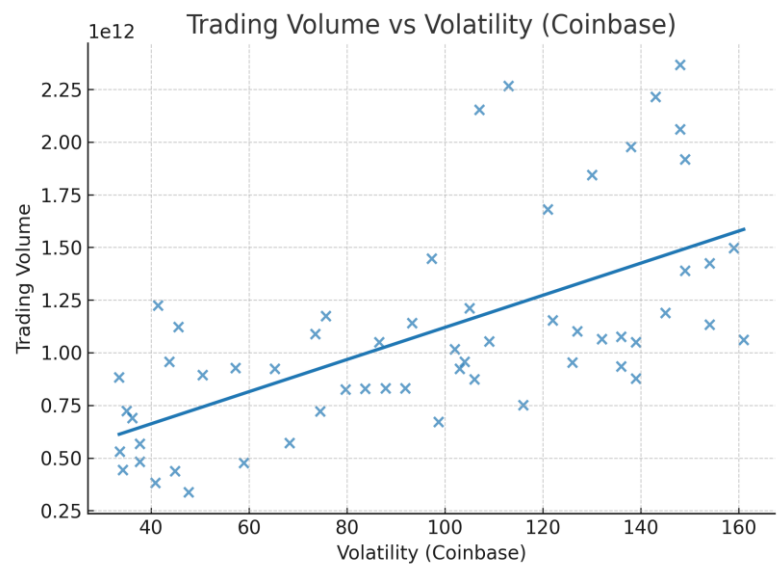


Figure 6. Relationship between trading volume and volatility (Coinbase)

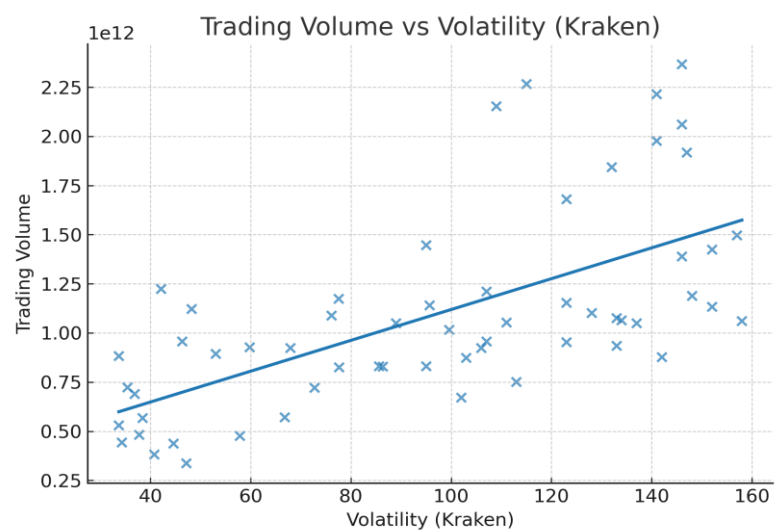


Figure 7. Relationship between trading volume and volatility (Kraken)

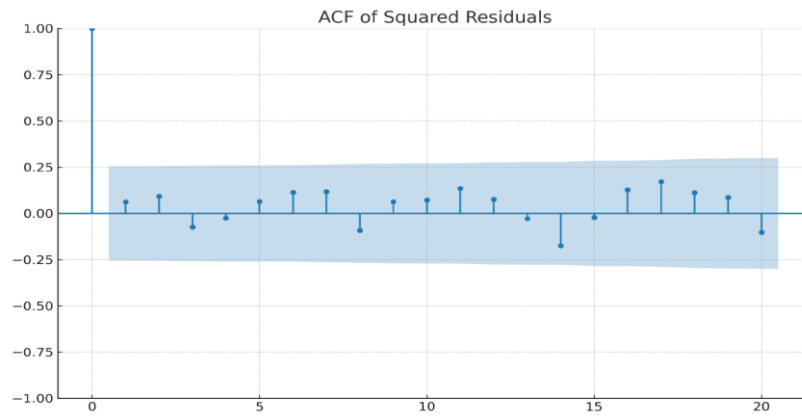


Figure 8. ACF of squared residuals showing absence of significant autocorrelation

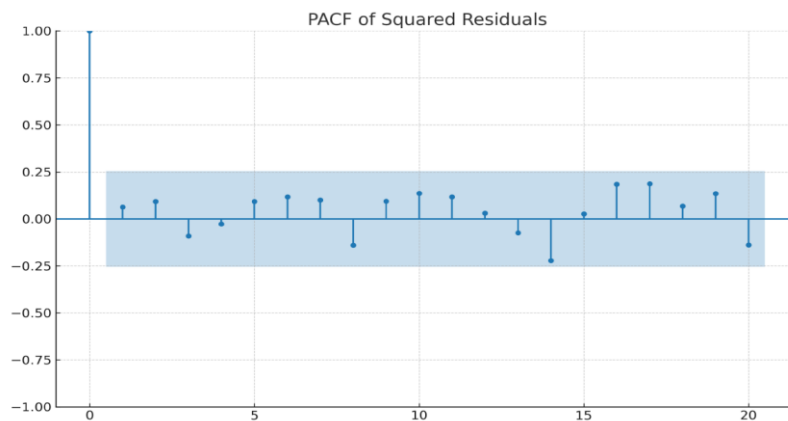


Figure 9. PACF of squared residuals confirming minimal ARCH effects

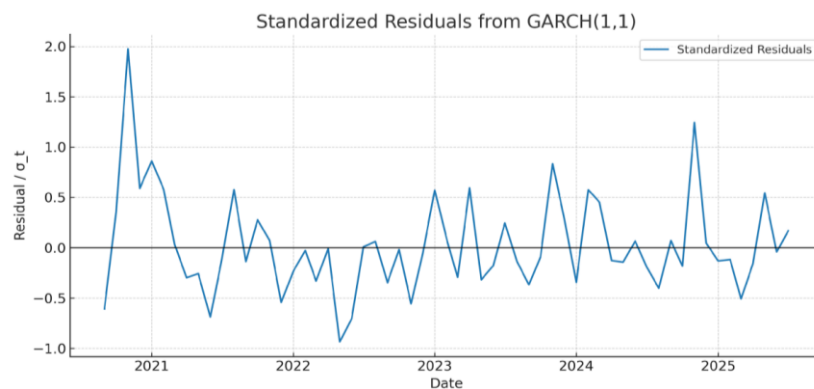


Figure 10. Standardized residuals from GARCH (1,1), centered around zero with stable variance

5. Conclusion

As the study results show, there is an obvious and impressive positive relationship between volume and price volatility of the cryptocurrencies on the leading exchanges, including Bitfinex, Coinbase, and Kraken. This volatility is usually accompanied by increased trading activity, a sign of both speculation and reactions to risk by traders. This relationship is relevant to understanding market behavior; this is supported by the studies [26], [27]. The regression analysis also shows it is possible to quantify, based on volatility, how much trading volume individual exchanges have. Furthermore, the uniformity of results across exchanges has pointed out that volatility is a systemic rather than an isolated feature of the ecosystem of digital assets. Investors, financial institutions, and regulators must respond with pinpoint strategies to adjust to the volatility in this fast-changing environment; this is supported by the studies [28], [29]. This will have implications for

investors, regulators, corporate decision-makers, and the quality of decision-making in light of the strategic clarity of financial leaders [30]. The study [31] also confirmed and supports our findings regarding the strategic assessment that will achieve the required strategic response to address the escalating changes, particularly in the financial markets.

6. Recommendations

What is notable about the volatility is the fact that it is the same across all the platforms, making it pertinent to have strong risk management strategies for the investors. Implementing stop-loss mechanisms, diversifying investments across assets, and establishing specific exposure caps can all be used to reduce the impact of sudden market fluctuations. Investors have to watch trading patterns and fluctuation gauges as part of their portfolio modification procedure. The outcome indicates that there is a need for the improvement of financial institutions' volatility forecasting tools. There are advanced models like GARCH models, machine learning techniques, and high-frequency data analysis that can enhance prediction accuracy [9]. In addition, firms should create exchange-specific models, as there are some structural similarities and differences between the correlation patterns, which could impact short-term price movements. The steady correlation indicates to regulators that volatility in cryptocurrency markets is still a systemic characteristic. In order to identify excessive volatility spikes that could affect larger financial markets, regulators should bolster real-time monitoring systems. Explicit disclosure requirements for exchanges and openness in trading activity reporting will also help make markets more stable and protect investors.

Declaration of competing interests

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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Author contribution

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