

Understanding the Volatility of Bitcoin Returns: Dynamic Estimation and Predictive Analysis Based on Specific GARCH Approaches

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Abstract. *In the financial sphere, volatility is a key factor. This study aims to analyse and predict the volatility associated with Bitcoin's daily returns between January 2019 and August 2025. Using the GARCH (1,1) autoregressive model sequentially with normal, Student's t and generalised error (GE) distributions in sequence demonstrates an understanding of the volatility transmission mechanism of this innovative financial asset within the context of the complex investment process. The empirical evidence obtained indicates a tendency for negative daily Bitcoin returns, reflecting persistent and high volatility during the analysed period. Furthermore, predictive analysis suggests that this high volatility is due to economic and financial uncertainty caused by the pandemic, high inflation rates, and the war between Russia and Ukraine. Conversely, predictive analysis shows that Bitcoin is becoming a risk diversification option and is currently playing the role of a risk diversifier, targeting long-term reverse volatility of approximately 4.89%. Finally, the study emphasises that investors are paying much closer attention to, and are much more concerned about, changes in the cryptocurrency market.*

Keywords: Bitcoin, digital finance, daily returns, clustering-volatility, GARCH models, forecast analysis, financial instability.

Introduction

Digital finance has recently emerged as a significant and relevant discipline, becoming an integral part of the financial sector. Notable developments in this area include the adoption and circulation of digital and virtual currencies, which are now widely recognised as a viable alternative to traditional currencies.

A growing number of specialised studies are focusing on how cryptocurrency markets function. These studies analyse the characteristics of these currencies and examine how the global financial system reacts to and responds to them, all the while ensuring and protecting financial stability. From this perspective, a growing body of research is attempting to answer questions about the future of digital currency markets.

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These studies address financial regulatory issues and examine the relationships between economic, financial, social and political factors, as well as the evolving nature of digital currency prices. Most analyses provide recommendations and strategies to help financial decision-makers ensure the sustainability of the financial ecosystem at individual and aggregate, or macroeconomic, levels (Feng & Gu, 2014; Mnohoghitnei et al., 2022; Pratas et al., 2023; Nedelcu and Busu, 2016).

Conversely, analysing the volatility of virtual currencies and identifying the factors influencing volatility dynamics over time are topical issues that are becoming increasingly prevalent in modern finance literature. This line of research employs autoregressive models such as GARCH, multifactorial regressions and more complex machine learning methodologies with the overarching aim of measuring and predicting cryptocurrency price volatility over different time intervals.

For instance, Yu (2019) examined the impact of leverage and uncertainty on Bitcoin volatility by analysing high-frequency data. Meanwhile, Fang et al. (2020) assessed the effectiveness of five cryptocurrencies as hedging instruments using the GARCH-MIDAS autoregressive model, which incorporates the implied volatility index (VIX). Their study concluded that uncertainty derived from investor perception, sentiment and aversion was a much more significant predictor of the volatility of these digital currencies than economic uncertainty.

Bergsli et al. (2022) demonstrate that asymmetric autoregressive models (such as EGARCH and APARCH) offer reliable long-term forecasts of Bitcoin price volatility, while heterogeneous autoregressive models (such as HAR) offer reliable short-term forecasts. Other empirical studies (Xia et al., 2022; Raza et al., 2023; Yildirim & Bekun, 2023; Busu and Busu, 2019) have shown that financial regulatory uncertainty has a significant negative impact on the volatility of digital currencies when the GARCH-MIDAS autoregressive model is used.

Considering this, the present study aims to analyse the estimation and prediction of daily volatility in Bitcoin's returns between January 2019 and August 2025. This study is motivated by the fact that volatility is a key factor influencing investment, protection, and risk management decisions in the medium and long term. At an aggregate level, it also affects trends, developments and operating mechanisms in digital currency markets.

The study's contributions are as follows:

(1) measuring and estimating the conditional volatility of Bitcoin's daily returns during the specified timeframe (January 2019–August 2025) using a GARCH autoregressive model under various conditions and distribution forms (normal, Student's, and generalised error).

(2) conducting stability and robustness tests to select the most accurate predictive model.

(3) conducting and evaluating a volatility prediction analysis for the entire timeframe (January 2019–August 2025) and modified periods: January 2019–December 2022 and January 2023–August 2025.

(4) providing recommendations and policy proposals relating to volatility dynamics, market making, risk management, and portfolio selection and optimisation. Finally, the analysis aims to provide recommendations relating to volatility dynamics, market making, risk management, portfolio selection and optimisation.

The study is organised into the following sections: Section 2 provides a literature review on the volatility of digital currencies. Section 3 contains methodological information on the data sources, models, and methods employed. Section 4 presents the results and discusses the study's main practical implications. Section 5 presents the study's conclusions.

Literature review

The measurement and prediction of risk for financial and non-financial assets is a widely discussed topic among financial analysts. Specifically, there is a growing interest in analysing the volatility of virtual currencies, also known as cryptocurrencies. Financial analyses often focus on Bitcoin; a virtual currency created in 2008 by Satoshi Nakamoto. Bitcoin emerged alongside the acceleration of technology and digitisation.

Consequently, measuring its volatility and investigating its possible connections with, and causal and interdependent relationships with, other factors remain a topical issue in finance and risk management. This is the focus of the study by López-Cabarcos et al. (2021). They found that Bitcoin is highly volatile, particularly during periods of political and economic instability and in speculative situations. Nevertheless, it remains one of the most widely traded digital currencies. The same study (Busu et al., 2025; López-Cabarcos et al., 2021) also found that Bitcoin volatility is influenced by various factors, such as investor sentiment, S&P 500 returns and VIX returns. These findings were validated by applying GARCH and EGARCH autoregressive models. Other studies have investigated the role of these virtual and digital currencies in the functioning of financial markets.

For example, Baur et al. (2018) and Bartos (2015) identified two key characteristics of Bitcoin. Firstly, it is a currency used for commercial transactions. Secondly, it is an asset that investors can hold in their portfolios. These characteristics fulfil the efficient market hypothesis and serve as a hedging instrument.

Bakas et al. (2022) analysed the main factors influencing volatility in the virtual currency market using the dynamic Bayesian model. Focusing on the Bitcoin market, they found that risk was directly associated with investor aversion, confidence, and sentiment towards the currency, as well as with market information generated by Google Trends, and with the dynamics of the S&P 500 composite index and Bitcoin circulation volume.

Meanwhile, Bariviera and Merediz-Solà (2021) conducted a multidisciplinary analysis to systematically evaluate the economic and financial implications of adopting digital currency markets. Their analysis revealed that virtual currencies are riskier than other financial and non-financial assets, such as gold, oil and exchange rates. They also emphasised the importance of measuring virtual currency volatility, considering parameters such as macroeconomic conditions, the functioning of financial markets, market sentiment, the adoption of macroprudential policies, and the management and control of uncertainty.

Conversely, an increasing number of researchers are investigating the potential links between how the Bitcoin market functions and economic situations that cause uncertainty and panic. Consequently, several analyses have examined Bitcoin's volatility during the Coronavirus pandemic. In this regard, Wan et al. (2023) provide robust empirical evidence of the Bitcoin market's functioning capacity during the pandemic. Their study employs a sophisticated methodology incorporating Granger causality tests, multifactorial regressions, and VAR and VEC autoregressive model implementation. The main results clearly demonstrate the significant impact of the pandemic on the Bitcoin futures market. As investors became increasingly concerned about the health crisis, Bitcoin returns fell significantly, leading to heightened volatility in the immediate aftermath of the pandemic.

At the same time, the effects of the pandemic have been far-reaching. Investors are now much more interested in trading virtual and digital currencies than traditional ones. This shift in focus could intensify volatility (David & Leustean, 2009; Stancioiu & Ionescu, 2011; Wang et al., 2021; Smales, 2022; Vozlyublennaya, 2014).

During the pandemic, a growing number of investors chose to invest in digital currencies. Bitcoin emerged as an important asset and defence mechanism against uncertainties in regulated financial systems, such as the devaluation of traditional currencies, fiscal pressure and political instability. This has facilitated the transition to digital finance (Sarkodie et al., 2022; Khaki et al., 2023; Raza et al., 2022).

Brini and Lenz (2024) present a comprehensive framework for analysing and predicting volatility, incorporating over 80 cryptocurrencies. This study makes an innovative contribution to our understanding of the risk transmission mechanism at both individual and aggregate (macroeconomic) levels. The main finding was an inverted asymmetry, with the daily leverage effect tending to remain negative for most of the analysed cryptocurrencies. The use of high-frequency data also enabled the study to achieve more significant results in terms of dynamically assessing the volatility of these strategic assets.

However, the volatility dynamics of digital currencies are also influenced by the volume of global information and news. For example, Blasco et al. (2025) analyse how global information (e.g. news about the Coronavirus health crisis, the conflict between Russia and Ukraine, and inflation trends) directly impacts Bitcoin price dynamics and evolution between 2018 and 2023. They found that investors react promptly to news about the evolution of the pandemic or war, which enables them to predict how Bitcoin prices may fluctuate. Lastly, following their analysis, the authors of this study (Blasco et al., 2025) note the increasing integration between traditional financial markets and digital currency/cryptocurrency markets.

A notable contribution to the field of study is the scientific paper by Alsulami and Raza (2025), which investigated the short- and long-term symmetric and asymmetric relationships between currency exchange rates, stock market indices and cryptocurrency price volatility between 2020 and 2024. Their findings show that, while it is becoming increasingly challenging to observe how investors react to changes in cryptocurrency prices, it is also becoming increasingly interesting. As virtual currencies are riskier than stock indices and exchange rates, particularly in the short to medium term, the authors recommend that financial policymakers oversee global regulatory standards more effectively.

Another important study investigating the benefits of including Bitcoin in investment portfolios is that of Marinescu et al. (2025). Using an innovative two-stage methodological framework, the researchers identified the asymmetric impact of this digital currency and emphasised its role as a diversifier during periods of high economic uncertainty. Furthermore, the empirical evidence obtained demonstrated that Bitcoin only stimulates risk-adjusted returns during such periods.

Methodology

This study aims to analyse and predict the volatility of Bitcoin returns as a virtual currency between January 2019 and August 2025. This will improve our understanding of volatility and its impact on financial risk management, financial stability, the sustainability of digital currencies and financial products, and the optimisation of investment portfolios. Furthermore, it will demonstrate how Bitcoin can be used to diversify risk during periods of high uncertainty.

To estimate the volatility associated with the daily returns of the Bitcoin digital currency, historical data covering the period between January 3, 2019, and August 25, 2025, was used. For the predictive analysis, the data was divided into two periods. The first period spanned from January 3, 2019, to December 30, 2022. The second period spanned from January 3, 2023, to

August 25, 2025. This division of the data allowed us to adequately understand the level of volatility associated with Bitcoin digital currency.

Data

This study focuses on Bitcoin as the primary digital and virtual currency due to its widespread global trading and status as one of the most popular cryptocurrencies since its introduction in 2008. Another advantage of using this currency is that historical data is available showing strong correlations with other digital currencies.

The data used in this study was collected and downloaded from the Yahoo Finance platform on August 28, 2025. The data was used responsibly and appropriately. Based on this data, a correct and transparent analysis of the estimation and prediction of volatility associated with Bitcoin's daily returns was possible. The datasets used and analyzed in this study are available from the corresponding author upon reasonable request. Figure 1 illustrates the evolution and change of these prices over time.

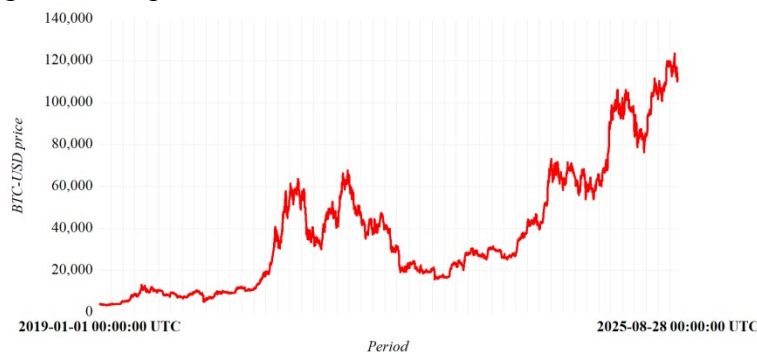


Figure 1. Evolution of the Bitcoin daily price (January 2019- August 2025)

Source: Authors' own research.

Interestingly, during the analysed period (2019–2025), there were several significant and unexpected changes in the price of Bitcoin, which are often referred to in financial practice as 'price jumps'.

Several key moments that contributed to these sudden and consistent price changes can be identified:

(1) the period from 2019 to 2020, characterised by the unpredictability and high volatility of digital currencies.

(2) the period from 2020 to 2022, which saw the emergence of the decentralised financial system (DeFi) and the adoption of institutional services offering cryptocurrency trading.

(3) the period from 2023 to 2025, which saw the introduction of new financial innovations in the form of memecoins and hybrid trading platforms.

Lastly, the unpredictability and financial and economic uncertainty caused by the Coronavirus pandemic, which began in December 2019, and the outbreak of war between Russia and Ukraine on 24 February 2022 can be attributed to Bitcoin's price fluctuations. These global events have therefore negatively impacted the functioning of the crypto market, generating high volatility in these traded digital currencies and altering investor perceptions. Studies have shown that investors are paying closer attention to news and developments regarding the pandemic and the war. These prices made it possible to calculate the daily return for Bitcoin, as shown in Equation 1.

$$\text{Bitcoin daily return} = \frac{P_t - P_{t-1}}{P_{t-1}} \times 100 \quad \text{Eq. (1)}$$

where: P_t and P_{t-1} are the adjusted closing price at the time t and $t-1$.

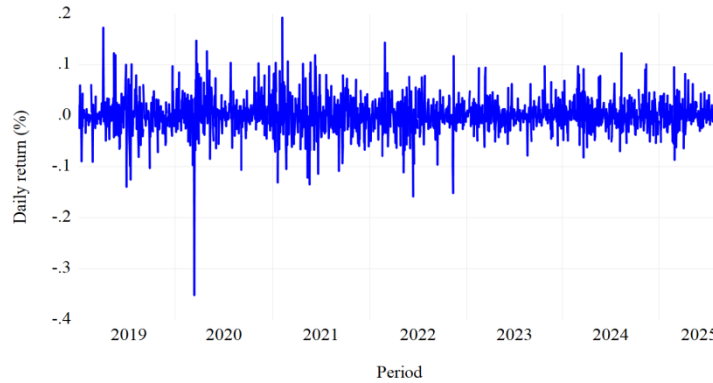


Figure 2. Daily returns of Bitcoin (January 2019- August 2025)

Source: Authors' own research.

Figure 2 shows how daily returns have changed over time between 2019 and 2025. Table 1 provides a statistical overview of the daily returns achieved during this period.

Table 1. Descriptive statistics and histogram of the daily return of Bitcoin (January 2019-August 2025)

Statistical indicator	Value
Mean	0.1169%
Median	0,0206%
Maximum	19,247%
Minimum	−35,1903%
Standard Deviation	3.4938%
Skewness	−0.4137
Kurtosis	11.9861
Jarque-Bera	5639.30 (0.0000)
Observations	1662

Note: The Jarque-Bera test probability value (p-value) is included in brackets.

Source: Authors' own calculation.

The analysis yielded 1,662 observations. From a statistical perspective, the daily returns of Bitcoin follow a leptokurtic distribution with left asymmetry, i.e. negative returns are more likely than positive ones. This is confirmed by the skewness and kurtosis coefficients.

The average daily return is around 0.12%, ranging from a maximum of 19.25% to a minimum of -35%. Returns deviate from the average by around 3.5%. The series of daily returns indicates non-normality, as confirmed by the Jarque–Bera test's extremely high, statistically significant value. From a descriptive statistical point of view, two features typically observed in financial analysis are evident: fat tails (i.e. significant price fluctuations in Bitcoin) and volatility clustering (i.e. periods of high volatility during which prices fluctuate considerably).

The Model

This study employed autoregressive models from the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) class. Although these models were developed by Bollerslev in 1986, they remain highly effective for analysing volatility and can be applied to most financial and non-financial assets, as well as assets of different maturities (Muşetescu et al., 2022; Kumar et al., 2024; Fiszeder et al., 2024; Sözen, 2025). Equations (2)– (4) demonstrate the general form of the GARCH (1, 1) model and its stability conditions.

$$\text{GARCH (p,q)} \rightarrow \sigma_t^2 = \alpha + \sum_{k=1}^p \theta_k \times \sigma_{t-k}^2 + \sum_{i=1}^q b_i \times \varepsilon_{t-i}^2 \quad \text{Eq. (2)}$$

where: σ_t^2 = the conditional variance depends both on the past values of the shocks captured by the lagged squared error term and the past values of itself; ε_{t-i}^2 = the lagged squared error term; σ_{t-k}^2 = past values of itself; p = lagged terms of squared residual error term; q = lagged conditional variances; θ_k = GARCH coefficient; b_i = ARCH coefficient; α = constant term (intercept); θ_k and $b_i > 0$; $\theta_k + b_i < 1$

Specifically, by adapting the formula of the conditional variance of the GARCH (1,1) it is obtained this:

$$\text{GARCH (1,1)} \rightarrow \sigma_t^2 = \alpha + \theta_1 \times \sigma_{t-1}^2 + b_1 \times \varepsilon_{t-1}^2 \quad \text{Eq. (3)}$$

$$\text{Long-run variance} = \frac{\alpha}{1 - \theta_1 - b_1} \quad \text{Eq. (4)}$$

Another key advantage of GARCH models is that they present volatility as a stationary, noise-free process that incorporates an AR (1) component. Lastly, GARCH models can estimate two equations: (a) the average return equation and (b) the conditional variance estimation equation. Consequently, GARCH models are an effective means of modelling variance dynamics based on past error terms and previous variance values (Sözen, 2025; Peatas et al., 2023). Specifically, when analysing and predicting Bitcoin's conditional volatility, the GARCH (1,1) model was applied alongside normal, Student's t, and generalised error distributions.

Methodological procedure

The analysis involved several sequential steps. Firstly, examining the price and daily returns of Bitcoin enabled us to identify and emphasise the events and situations that had the greatest impact on volatility between 2019 and 2025. Secondly, we statistically described the daily return series for Bitcoin to validate aspects commonly encountered in financial practice, such as fat tails, volatility clustering, and normality of the data. Thirdly, ADF and PP stationarity tests were performed, as well as testing for seasonal effects and the LM test, to verify the presence of ARCH effects in the daily Bitcoin return series.

Equation (5) illustrates the condition for the stationarity hypothesis, while Equations (6) and (7) show how to verify the presence of ARCH effects and carry out the necessary tests on the analysed daily return series.

$$y_t = \alpha y_{t-1} + \beta x_e + \varepsilon \quad \text{Eq. (5)}$$

where: y_t = the value of the time series at time t ; x_e = an exogenous variable (a separate explanatory variable, which is also a time series); ε = error term.

$$\varepsilon_t^2 = \alpha_0 + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + u_t \quad \text{Eq. (6)}$$

where: ε_t^2 = squared error term; α_i = influence of past squared errors on the current error term; q = number of lagged terms; u_t = white noise error term or random variation.

$$\text{ARCH LM test} = nR^2 \quad \text{Eq. (7)}$$

where: R^2 = R-squared coefficient; n = number of the observation.

Following these preliminary analyses, the next step was to estimate conditional volatility and measure it by applying the GARCH (1,1) model to the three error distributions.

A series of comparative tests were then conducted to evaluate the accuracy and suitability of conditional heteroscedastic autoregressive models. The objective was to select the most suitable model for predicting volatility. The statistical significance of the estimated coefficients, the highest adjusted R^2 , the highest log-likelihood ratio, the lowest SIC and the fact that the models are homoscedastic and do not exhibit error autocorrelation were all considered. Equation (8) shows the formula for the Bayesian information criterion, while equation (9) shows the statistical condition for autocorrelations.

$$\text{SIC} = -2 \ln(L) + k \ln(N) \quad \text{Eq. (8)}$$

where: SIC = Bayesian or Schwarz Information Criterion; L = maximum likelihood estimate; k = number of parameters; N = total number of observations

$$\text{DW test} = \frac{\sum_{t=2}^n (\varepsilon_t - \varepsilon_{t-1})^2}{\sum_{t=1}^n \varepsilon_t^2} \quad \text{Eq. (9)}$$

where: DW = Durbin-Watson; ε_t is the error terms.

Finally, the study conducted a predictive and evaluative analysis of Bitcoin's conditional volatility. This considered the in-sample period (2019–2025) alongside two out-of-sample periods: January 2019–December 2022 and January 2023–August 2025. The prediction evaluation (see Equations 8–13) was based on loss function indicators: Root mean square deviation (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and Theil's inequality coefficient.

$$\text{RMSE} = \sqrt{\sum_{i=1}^N \frac{(\hat{\sigma}_t^2 - \sigma_t^2)^2}{n}} \quad \text{Eq. (10)}$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |(\hat{\sigma}_t^2 - \sigma_t^2)| \quad \text{Eq. (11)}$$

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \frac{|(\hat{\sigma}_t^2 - \sigma_t^2)|}{\sigma_t^2} \quad \text{Eq. (12)}$$

$$\text{Theil's Inequality coefficient} = \sqrt{\frac{\sum_{i=1}^n \left[\frac{\hat{\sigma}_t^2 - \sigma_t^2}{\sigma_{t-1}^2} \right]^2}{\sum_{i=1}^n \left[\frac{\sigma_t^2 - \sigma_{t-1}^2}{\sigma_{t-1}^2} \right]^2}} \quad \text{Eq. (13)}$$

where: RMSE = Root Mean Square Error; MAE = Mean Absolute Error; MAPE = Mean Absolute Percentage Error; $\hat{\sigma}_t^2$ is predicted value of conditional variance of Bitcoin; σ_t^2 is the observed values of conditional variance of Bitcoin; n is the number of observations; and t is the period.

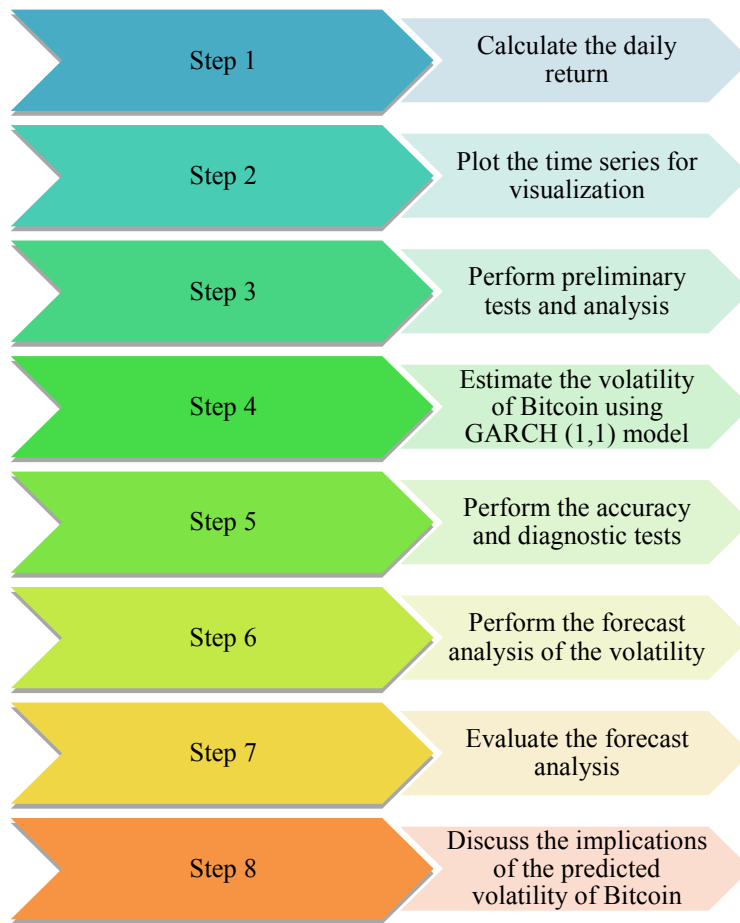


Figure 3. Flow chart of the analysis performed in this study.

Source: Authors' own creation.

The analysis was performed using EViews 12 and Python. Figure 3 shows the steps taken to carry out the analysis.

Results and discussions

This section presents and discusses the key findings of the volatility analysis of Bitcoin returns, as determined by the proposed autoregressive methodology.

From this perspective, the section is organised into three subsections, which concern the following:

- (i) a preliminary analysis of testing and evaluating hypotheses regarding stationarity, the ARCH effect, and the seasonal effect of the data series.
- (ii) an analysis of estimating and evaluating conditional volatility using the GARCH (1,1) model with different distribution specifications (normal, Student's t-distribution and generalised error).

- (iii) an analysis of making predictions and evaluating performance in terms of volatility over three periods: in-sample (2019–2025), out-of-sample (January 2019 -December 2022 and January 2023–August 2025).

Preliminary analysis

Before estimating and predicting volatility using heteroscedastic autoregressive GARCH-type models, a preliminary analysis of the daily Bitcoin return series must be conducted.

The first step is to test for stationarity using ADF and PP tests. As can be seen in Table 2, the results confirm that the daily Bitcoin return series is stationary and does not exhibit a unit root at an extremely significant 1% relevance threshold.

Table 2. Results of the unit root tests

Augmented Dickey-Fuller (ADF) test		
<i>Specification</i>	<i>t-statistic</i>	<i>Prob.</i>
Level: Intercept	−42.89	0.0000*
Level: Trend and Intercept	−42.87	0.0000*
Level: None	−42.80	0.0001*
Phillips-Perron (PP) test		
<i>Specification</i>	<i>t-statistic</i>	<i>Prob.</i>
Level: Intercept	−42.89	0.0000*
Level: Trend and Intercept	−42.87	0.0000*
Level: None	−42.79	0.0001*

Note:*indicate significance level at 1% p-value.

Source: Authors' own calculation.

Before applying GARCH models, it is necessary to verify another condition: testing for ARCH effects. In other words, it is necessary to check whether the error terms exhibit constant variance over time. The ARCH-LM test detects conditional heteroskedasticity, or changing variance, in a time series, which is a key aspect of modelling financial volatility. The null hypothesis of this test assumes that there are no ARCH effects, i.e. that the error terms exhibit constant variance. In contrast, the alternative hypothesis indicates the presence of ARCH effects, i.e. time-dependent variance.

Table 3. Results of ARCH and seasonality effects

Heteroskedasticity test: ARCH	
Obs*R-squared	6.7383
Prob.	0.0094*
Serial Correlation LM test	
Obs*R-squared	2.6969
Prob.	0.2729
Durbin-Watson statistic	2.0045

Note:*indicate statistical significance at 1% level.

Source: Authors' own calculation.

The results of the ARC-LM test, presented in Table 3, lead to the following conclusion: since the p-value is significantly lower than the 1% significance level, the null hypothesis is rejected. This indicates that Bitcoin's daily returns exhibit time-varying volatility and should be modelled using GARCH-type approaches.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.001	0.001	0.0037	0.952
		2	0.030	0.030	2.2112	0.331
		3	0.000	-0.000	2.2112	0.530
		4	0.036	0.036	5.4451	0.245
		5	0.009	0.009	5.6627	0.340
		6	-0.003	-0.005	5.6873	0.459
		7	-0.008	-0.008	5.8363	0.559
		8	-0.032	-0.033	8.2959	0.405
		9	0.022	0.022	9.4850	0.394
		10	0.019	0.021	10.386	0.407
		11	-0.003	-0.004	10.413	0.494
		12	0.002	0.004	10.426	0.579
		13	0.043	0.042	14.962	0.310
		14	0.004	0.002	15.005	0.378
		15	0.020	0.017	15.973	0.384
		16	-0.006	-0.007	16.072	0.448
		17	0.025	0.022	17.558	0.417
		18	-0.020	-0.020	18.569	0.419
		19	-0.010	-0.014	18.823	0.468
		20	-0.012	-0.010	19.163	0.511
		21	-0.031	-0.029	21.575	0.424
		22	-0.029	-0.029	23.571	0.370
		23	-0.023	-0.020	24.843	0.358
		24	0.040	0.043	28.869	0.225
		25	0.019	0.023	29.750	0.234
		26	0.027	0.023	31.482	0.211
		27	0.017	0.016	32.172	0.226
		28	0.040	0.036	36.193	0.138
		29	-0.025	-0.030	37.739	0.128
		30	0.013	0.006	38.129	0.146
		31	0.035	0.039	41.198	0.104
		32	-0.016	-0.015	41.860	0.114
		33	0.045	0.047	46.807	0.056
		34	0.003	0.006	46.830	0.070
		35	-0.001	-0.003	46.833	0.087
		36	-0.033	-0.031	49.580	0.065

Figure 4. Results of the serial correlation test

Source: Authors' own calculation.

Finally, examining the correlogram (Figure 4) revealed that the daily return series for Bitcoin does not exhibit autocorrelation or serial correlation, with values falling within the 5% significance limits. The correlogram is also an effective tool for identifying seasonal effects in analysed data.

Estimation analysis

This subsection presents and discusses the key findings from the estimation of Bitcoin return volatility between January 2019 and August 2025. To this end, the widely recognised GARCH (1,1) autoregressive model — one of the most popular econometric methods in the literature (Sözen, 2025; Bergsli et al., 2022; Yildirim & Bekun, 2023) — was employed.

In this analysis, the GARCH (1,1) model was incrementally applied, considering various distribution-related specifications. Table 4 therefore presents the estimated coefficients for the GARCH (1,1) model with three types of distribution: normal, Student's t and generalised error.

Firstly, it can be confirmed that all estimated coefficients are statistically significant at the 1% level of relevance. In all three cases, the free parameter reflecting the level of underlying volatility is also very low. Meanwhile, the ARCH and GARCH parameters indicate high and persistent volatility in Bitcoin returns during the analysed period.

This can be explained by the uncertainty and insecurity caused by the health crisis and the outbreak of war between Russia and Ukraine. These events have led to sudden changes and fluctuations in the price of Bitcoin. Another notable point is the way in which cryptocurrency

markets react to changes in the economic, political or social situation, becoming increasingly sensitive to them.

Therefore, Bitcoin volatility can be viewed as a spiral: the occurrence of uncertain events automatically triggers a market reaction, resulting in dramatic and increasingly sudden price fluctuations in the medium and long term.

The estimated values for the GARCH parameters vary between 0.81 and 0.92 across the three distribution specifications. This suggests that, although volatility remains high and persistent over time, it can adapt to market price asymmetry; therefore, volatility is dynamic.

Table 4. Estimated coefficients from GARCH(1,1) model with different specifications

(I) Method: ML ARCH – Normal Distribution				
Variable	Coefficient	Standard error	z-statistic	Prob.
α	0.0000106*	0.00000138	7.6675	0.0000
θ_1 (GARCH parameter)	0.8102*	0.0214	37.7680	0.0000
b_1 (ARCH parameter)	0.1091*	0.0132	8.2675	0.0000
Conditional Variance equation	$\sigma_t^2=0.000106+0.8101\sigma_{t-1}^2+0.1091u_{t-1}^2$			
(II) Method: ML ARCH - Student's t Distribution				
Variable	Coefficient	Standard error	z-statistic	Prob.
α	0.00000311**	0.00000136	2.2766	0.0228
θ_1 (GARCH parameter)	0.9171*	0.0179	51.0058	0.0000
b_1 (ARCH parameter)	0.0816*	0.02135	3.8221	0.0001
Conditional Variance equation	$\sigma_t^2=0.00000311+0.9171\sigma_{t-1}^2+0.0816u_{t-1}^2$			
(III) Method: ML ARCH – Generalized Error Distribution (GED)				
Variable	Coefficient	Standard error	z-statistic	Prob.
α	0.00000471*	0.00000169	2.7761	0.0055
θ_1 (GARCH parameter)	0.8867*	0.02742	32.3310	0.0000
b_1 (ARCH parameter)	0.0754*	0.01819	4.1461	0.0000
Conditional Variance equation	$\sigma_t^2=0.00000471+0.8867\sigma_{t-1}^2+0.0754u_{t-1}^2$			

Note: * indicate statistical significance at 1% level; ** indicate statistical significance at 5% level.

Source: Authors' own calculation.

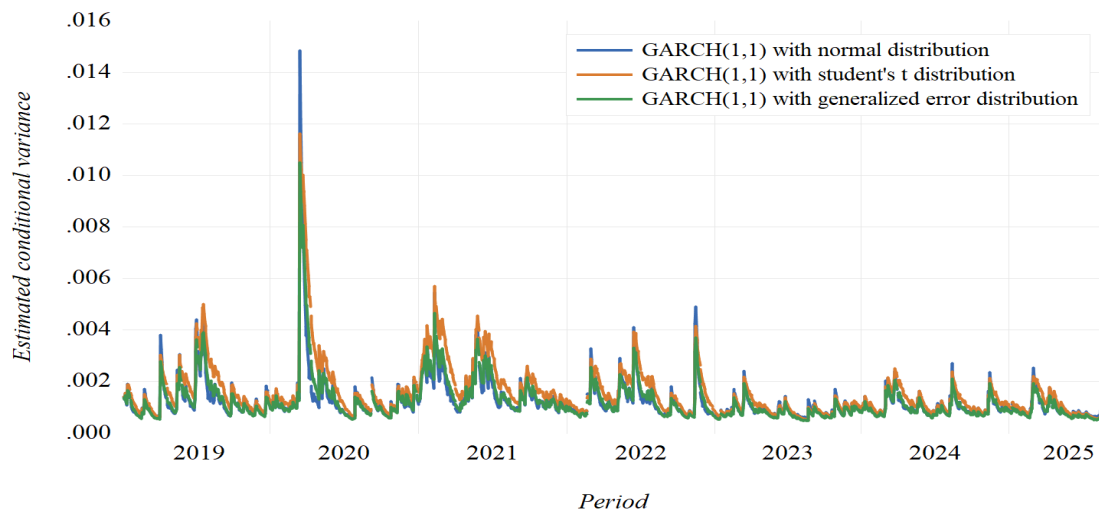


Figure 5. Estimated conditional variance of Bitcoin in the entire sample (January 2019- August 2025)

Source: Authors' own creation.

The results of the present study on the persistence of Bitcoin volatility are robust and validated and are consistent with the findings of previous studies (Sözen, 2025; Sapuric et al., 2022; Ardia et al., 2019). At the same time, the GARCH (1,1) model with a student's t-distribution indicates the highest volatility value for the period from 2019 to 2025 (the sum of the ARCH and GARCH coefficients is approximately 0.9987).

The obtained ARCH and GARCH coefficients were stable and positive, and their sum consistently remained below 1. This successfully validated the stationarity hypothesis regarding the daily Bitcoin return series. Lastly, Table 4 shows that the GARCH model adequately estimates the conditional volatility equation with three distribution specifications. Figure 5 illustrates how these models capture volatility over time during the analysed period.

Moving forward, it is important to investigate which model best captures the volatility associated with Bitcoin returns. To this end, a series of accuracy and diagnostic tests were performed to select the best-performing model. The results of these tests are shown in Table 5.

Table 5. Robustness and diagnostic test results of the GARCH (1,1) models

Method: GARCH (1,1)	Normal distribution specification	Student's t distribution specification	Generalized error distribution specification
Adjusted R ²	0.0014	0.0012	-0.00056
Log Likelihood	3286.265	3457.475	3456.34
Schwarz Information Criterion (SIC)	-3.9346	-4.1363	-4.1349
ARCH-LM test	0.0032 (0.9542)	0.3737 (0.5410)	0.1564 (0.6924)
Autocorrelation (via correlogram)	>0.05	>0.05	>0.05
Durbin-Watson test	2.044	1.9843	1.9556

Note: The probability of the ARCH-LM test is included in brackets.

Source: Authors' own calculation.

Firstly, as previously mentioned, the statistical significance of all the coefficients used to estimate and measure conditional volatility was an important factor in ensuring the robustness of the models (see Table 4).

Another important aspect is that the models provide the highest possible coefficient of determination. This is confirmed by the GARCH (1, 1) model with a normal distribution. The results also showed that the three applied GARCH models are homoscedastic, meaning that the errors have constant variance over time. This is confirmed by the results of the ARCH-LM test, with p-values greater than the 5% level of significance.

Furthermore, the long-term conditional volatility associated with the daily returns of the Bitcoin digital currency is estimated at about 4.89%. This estimate was calculated using the GARCH (1,1) model with a Student's t-distribution. This model provided the most appropriate and relevant results. Based on the parameters obtained from this model, the following calculation algorithm was derived:

- $\alpha = 0.00000311$
- θ_1 (GARCH parameter) = 0.9171
- b_1 (ARCH parameter) = 0.0816
- The long-term conditional volatility =
$$\sqrt{\frac{\alpha}{1-\theta_1-b_1}} \times 100 = \sqrt{\frac{0.00000311}{1-0.9171-0.0816}} \times 100 =$$
$$\sqrt{\frac{0.00000311}{0.0013}} \times 100 = 4.89\%$$

The models are free from autocorrelation, as can be seen from the correlogram (see Appendix 1) and the Durbin–Watson test values, which are very close to 2.00. At the same time, the best-performing model must be stable and provide the most accurate results possible. In this sense, models in the GARCH family should have the highest log likelihood function values and the lowest Bayesian Information Criterion performance indicator values. The GARCH (1,1) model with a Student's t distribution meets these criteria and is therefore the best-performing model. This model will be used for the volatility prediction analysis associated with the daily returns of the Bitcoin digital currency.

Forecast analysis

This study aims to provide a comparative analysis of Bitcoin yield volatility predictions over different time horizons. Specifically, it compares in-sample predictions for the entire analysed period (January 2019 to August 2025) with out-of-sample predictions for modified periods (January 2019 to December 2022, and January 2023 to August 2025). Figure 6-8 illustrates the results of the prediction analysis, while Table 6 shows the analysis evaluation.

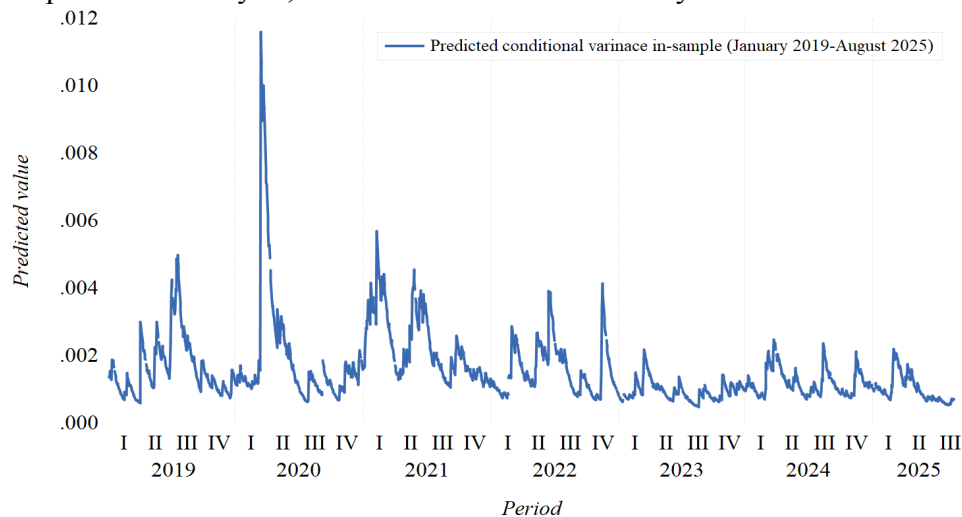


Figure 6. Predicted conditional volatility of Bitcoin (January 2019-August 2025)

Source: Authors' own creation.

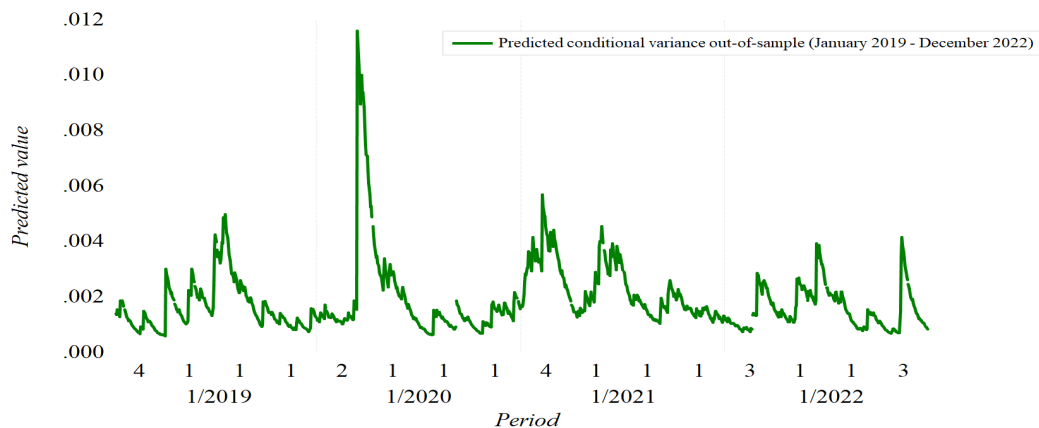


Figure 7. Predicted conditional volatility of Bitcoin (January 2019-December 2022)

Source: Authors' own creation.

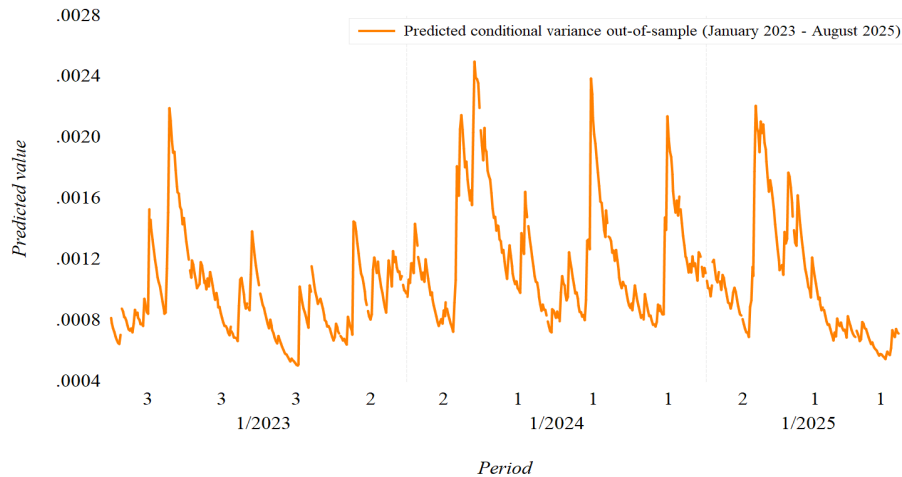


Figure 8. Predicted conditional volatility of Bitcoin (January 2023-August 2025)

Source: Authors' own creation.

Firstly, it should be noted that predicted volatility remains high and persistent for both the in-sample and out-of-sample periods. During the period from January 2019 to December 2022, volatility reached levels ranging from 9.50% to 11%, as observed in Sözen's (2025) study. Predictive analysis revealed that volatility was higher during this period, primarily due to the turmoil and negative consequences for the global financial system caused by the SARS-CoV-2 pandemic and the subsequent Russia–Ukraine war, which began in February 2022.

Conversely, it is anticipated that volatility will decrease between 2023 and 2025, with values expected to reach around 5%. This suggests that investors may consider Bitcoin as a hedging instrument and a means of diversifying risk. (Bergsli et al., 2022; Kumar et al., 2024; Marinescu et al., 2025).

Table 6. Forecast evaluation results

Loss function indicators	In-sample (January 2019-August 2025)	Out-of-sample (January 2019-December 2022)	Out-of-sample (January 2023-August 2025)
RMSE	0.03490	0.0393	0.02670
MAE	0.0236	0.0266	0.0189
MAPE	137.57	144.75	126.66
Theil Inequality Coefficient	0.9510	0.9423	0.9370
Bias proportion	0.0007	0.0001	0.0040

Source: Authors' own calculation.

Lastly, evaluating the predictive analysis using loss function indicators produces consistent, robust and unbiased results. Analysis performance exceeds 90% in all three investigated periods. However, the results suggest that the optimal values for predicting Bitcoin return volatility in the out-of-sample period (January 2023–August 2025) are those with the lowest RMSE, MAE and MAPE.

The practical implications of the study emphasise the importance of risk estimation and forecasting for optimising the investment process, ensuring the efficient functioning of the financial market, and informing investor attitudes and sentiment towards the risks associated with digital currencies. The study's results demonstrate that volatility is highly persistent and that market shocks have long-lasting effects. Forecasts obtained using GARCH-family models suggest that volatility exhibits long memory, meaning that uncertainties in financial markets have

a prolonged effect on cryptocurrencies (Leirvik, 2022; Anand & Sharan, 2025). Finally, any movement or fluctuation in the price of Bitcoin is associated with market turbulence and dysfunction triggered by crises, wars, conflicts and pandemics. All these events have occurred within the last six years.

Conclusion

The aim of this study was to analyse and predict volatility in the daily returns' series for the Bitcoin digital currency. The analysed period ran from January 2019 to August 2025. During this time, empirical evidence of volatility was identified following the application of GARCH autoregressive models. Specifically, GARCH (1, 1) models with normal, Student's t and generalised error distributions were used.

The main practical implication of the results was an improved understanding of the volatility associated with this digital currency about investment decisions, portfolio construction and diversification.

Following an analysis of volatility estimation and measurement, it was demonstrated that digital currencies, and Bitcoin in particular, are still risky and volatile financial assets. This indicates their persistent nature, which changes in response to disruption or shocks in the global cryptocurrency market.

Another finding showed that the applied GARCH models are robust and accurate, as they are unaffected by autocorrelation or heteroscedasticity. The models generate statistically significant coefficients and satisfy the conditions of stationarity and stability. Furthermore, the GARCH(1,1) model with a Student's t distribution was found to provide the most accurate estimate for measuring and predicting Bitcoin volatility.

Conversely, the forecast analysis revealed the impact of recent events on the functioning of the crypto market. Consequently, investors have become more cautious when selecting assets for their portfolios, and their attitude towards Bitcoin has changed.

For instance, while investing in Bitcoin was riskier between 2019 and 2022 due to frequent price fluctuations, investors now view virtual currencies as viable instruments for hedging and diversifying investments. Moreover, the study emphasises the importance of financial policymakers being aware of fluctuations and developments in cryptocurrency prices when designing and implementing policies.

Thus, a growing concern within the academic community is the analysis of regulatory issues and how these markets can achieve financial stability in future. Studies have shown that cryptocurrency markets operate independently of the traditional financial system. In conclusion, volatility is a key topic in the financial sphere. However, when it comes to analysing digital currencies, volatility remains an interesting and challenging topic. This study will examine how volatility and volatility dynamics are influenced by other explanatory factors, providing a clearer picture of interdependent and causal relationships.

Another area for future study could be a comparative analysis of the volatility of other digital currencies versus financial and non-financial assets held by investors. It would also be interesting to investigate how the volatility of a portfolio including such digital currencies changes over time. Further research could address the limitations of GARCH models, as well as the fact that this study only examined the volatility of one digital currency, Bitcoin. Therefore, alternative methods and models for predicting and measuring volatility should be applied, such as multivariate regression, panel analysis and machine learning.

Since this study used GARCH autoregressive models to estimate and predict Bitcoin's conditional volatility, the main limitation can be viewed as an opportunity to expand and propose new research directions for the study by integrating and using other types of models, such as machine learning and automatic learning models, to determine and predict Bitcoin's daily return volatility. For example:

- First, integrating and using other types of models, such as machine learning and automatic learning models (e.g., hybrid ML, long- and short-term memory, and artificial neural network models), to determine and predict the volatility of Bitcoin's daily returns.
- Second, it could provide a comparative analysis of the performance of traditional autoregressive models, such as ARCH, GARCH, or ARIMA, and new, innovative models for predicting the volatility associated with this digital currency.
- Third, extend this study by integrating and including other digital currencies and analyzing risk prediction from two perspectives: individual (for each digital currency) and aggregate (when building an investment portfolio based on these digital currencies).
- Another possible extension of the study would be to apply multivariate models based on multifactorial regressions to explain and predict Bitcoin volatility based on other economic, political, or social factors.

Acknowledgments

“First, the article was conceived and written in Romanian, then translated into English, with all these steps carried out by the authors of the article. To ensure better coherence in English, we used DeepL Translate; the text was not produced or generated by AI.”

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Appendix 1

The autocorrelation results of the GARCH(1,1) are presented in Appendix 1. These results are shown via correlograms.

Date: 09/05/25 Time: 16:35

Sample (adjusted): 1/04/2019 8/25/2025

Q-statistic probabilities adjusted for 1 dynamic regressor

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Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob*	
		1	0.012	0.012	0.2420	0.623
		2	0.010	0.010	0.4105	0.814
		3	-0.023	-0.023	1.2831	0.733
		4	-0.015	-0.014	1.6491	0.800
		5	-0.006	-0.005	1.7039	0.888
		6	-0.009	-0.009	1.8441	0.933
		7	0.049	0.049	5.8319	0.560
		8	-0.022	-0.023	6.6193	0.578
		9	0.053	0.052	11.241	0.260
		10	-0.014	-0.013	11.552	0.316
		11	0.042	0.042	14.529	0.205
		12	-0.018	-0.017	15.095	0.236
		13	-0.005	-0.004	15.145	0.298
		14	-0.023	-0.024	16.034	0.311
		15	-0.015	-0.011	16.426	0.354
		16	0.005	0.000	16.477	0.420
		17	-0.009	-0.006	16.618	0.481
		18	0.036	0.028	18.857	0.401
		19	0.033	0.037	20.669	0.355
		20	0.003	-0.004	20.686	0.416
		21	-0.001	0.004	20.690	0.478
		22	0.042	0.043	23.652	0.366
		23	-0.010	-0.007	23.821	0.414
		24	-0.005	-0.002	23.856	0.470
		25	0.001	0.001	23.859	0.528
		26	0.034	0.034	25.784	0.475
		27	-0.002	-0.007	25.794	0.530
		28	0.007	0.005	25.879	0.580
		29	-0.003	-0.009	25.896	0.631
		30	-0.012	-0.010	26.127	0.669
		31	0.001	-0.001	26.131	0.715
		32	0.007	0.011	26.224	0.754
		33	-0.054	-0.060	31.196	0.557
		34	-0.013	-0.007	31.476	0.592
		35	0.007	0.005	31.556	0.635
		36	0.016	0.018	32.015	0.659

*Probabilities may not be valid for this equation specification.

Figure A1. Autocorrelation results according to GARCH (1,1) with a normal distribution.

Source: Authors' own creation.

Date: 09/05/25 Time: 16:38
Sample (adjusted): 1/04/2019 8/25/2025
Q-statistic probabilities adjusted for 1 dynamic regressor

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.039	0.039	2.5539	0.110
		2	0.012	0.011	2.7990	0.247
		3	-0.027	-0.028	3.9865	0.263
		4	-0.017	-0.015	4.4580	0.348
		5	-0.004	-0.002	4.4882	0.481
		6	-0.008	-0.009	4.6075	0.595
		7	0.045	0.045	8.0572	0.328
		8	-0.017	-0.021	8.5352	0.383
		9	0.052	0.052	12.990	0.163
		10	-0.009	-0.010	13.118	0.217
		11	0.042	0.043	16.141	0.136
		12	-0.011	-0.012	16.342	0.176
		13	0.002	0.004	16.350	0.231
		14	-0.026	-0.026	17.450	0.233
		15	-0.011	-0.005	17.641	0.282
		16	0.013	0.009	17.930	0.328
		17	-0.008	-0.006	18.031	0.387
		18	0.035	0.027	20.106	0.327
		19	0.028	0.029	21.397	0.315
		20	0.002	-0.007	21.402	0.374
		21	0.003	0.009	21.421	0.433
		22	0.038	0.037	23.799	0.358
		23	-0.014	-0.015	24.140	0.396
		24	0.003	0.006	24.161	0.452
		25	-0.000	-0.000	24.161	0.510
		26	0.028	0.029	25.521	0.490
		27	-0.008	-0.013	25.618	0.540
		28	0.008	0.007	25.733	0.588
		29	-0.003	-0.008	25.751	0.639
		30	-0.015	-0.013	26.145	0.668
		31	0.005	0.002	26.186	0.712
		32	0.012	0.016	26.437	0.744
		33	-0.048	-0.056	30.369	0.599
		34	-0.012	-0.004	30.597	0.635
		35	0.006	0.004	30.668	0.677
		36	0.018	0.020	31.239	0.694

*Probabilities may not be valid for this equation specification.

Figure A2. Autocorrelation results according to GARCH (1,1) with student's t distribution.

Source: Authors' own creation.

Date: 09/05/25 Time: 16:39
Sample (adjusted): 1/04/2019 8/25/2025
Q-statistic probabilities adjusted for 1 dynamic regressor

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob*	
		1	0.048	0.048	3.8110	0.051
		2	0.010	0.008	3.9943	0.136
		3	-0.026	-0.027	5.1468	0.161
		4	-0.016	-0.014	5.5873	0.232
		5	-0.006	-0.004	5.6564	0.341
		6	-0.008	-0.008	5.7631	0.450
		7	0.046	0.046	9.3310	0.230
		8	-0.017	-0.021	9.7928	0.280
		9	0.051	0.052	14.151	0.117
		10	-0.009	-0.012	14.297	0.160
		11	0.042	0.043	17.263	0.100
		12	-0.014	-0.016	17.585	0.129
		13	-0.002	0.001	17.590	0.174
		14	-0.025	-0.025	18.634	0.179
		15	-0.013	-0.007	18.915	0.218
		16	0.009	0.005	19.051	0.266
		17	-0.007	-0.005	19.142	0.320
		18	0.036	0.029	21.350	0.262
		19	0.031	0.032	22.928	0.241
		20	0.003	-0.006	22.947	0.291
		21	0.002	0.008	22.956	0.346
		22	0.039	0.040	25.567	0.271
		23	-0.012	-0.012	25.809	0.310
		24	-0.000	0.003	25.809	0.363
		25	0.001	0.002	25.813	0.418
		26	0.031	0.031	27.408	0.388
		27	-0.005	-0.011	27.445	0.440
		28	0.008	0.006	27.541	0.489
		29	-0.004	-0.009	27.566	0.541
		30	-0.013	-0.011	27.869	0.577
		31	0.003	0.001	27.888	0.627
		32	0.010	0.014	28.061	0.666
		33	-0.051	-0.058	32.516	0.491
		34	-0.014	-0.004	32.825	0.525
		35	0.006	0.004	32.894	0.570
		36	0.018	0.020	33.476	0.589

*Probabilities may not be valid for this equation specification.

Figure A3. Autocorrelation results according to GARCH (1,1) with generalized error distribution.

Source: Authors' own creation.