Yıldırım and Bekun *Future Business Journal* (2023) 9:75
https://doi.org/10.1186/s43093-023-00255-8

Future Business Journal

RESEARCH

Open Access

Predicting volatility of bitcoin returns with ARCH, GARCH and EGARCH models

Hakan Yıldırım[1] and Festus Victor Bekun[1*]

Abstract

The ınvestment decisions of institutional and individual investors in financial markets are largely influenced by market uncertainty and volatility of the investment instruments. Thus, the prediction of the uncertainty and volatilities of the prices and returns of the investment instruments becomes imperative for successful investment. In this study we seek to identify the best fit model that can predict the volatility of return of Bitcoin, which is in high demand as an investment tool in recent times. Using the opening data of weekly Bitcoin prices for the period of 11.24.2013–03.22.2020, their logarithmic returns were calculated. The stationarity properties of the Bitcoin return series was tested by applying the ADF unit root test and the series were found to be stationary. After reaching the average equation model as ARMA (2.2), it was tested whether there was an ARCH effect in the ARMA (2,2) model. As a result of the applied ARCH-LM test, it is reached that the residuals of the average equation model selected have ARCH effect. Volatility of Bitcoin return series after detection of ARCH effect has been tried to predict with conditional variance models such as ARCH (1), ARCH (2), ARCH (3), GARCH (1,1), GARCH (1,2), GARCH (1,3), GARCH (2,1), GARCH (2,2), EGARCH (1,1) and EGARCH (1,2). While the obtained findings indicate that the best model is in the direction of GARCH (1,1) according to Akaike info criterion, it was found that GARCH (1,1) model does not have ARCH effect as a result of the applied ARCH-LM test. Thus, our empirical findings highlight an ample guide on appropriate modeling of price information in the Bitcoin market.

Keywords Bitcoin volume, Volatility returns, ARMA, ARCH, GARCH

JEL classifications C22, C32, G15

Introduction

Investment decisions of institutional and individual investors in financial markets are important both in terms of pricing of financial markets and returns of investors. Investment decisions are related to volatility, which is representative of the concept of uncertainty. Volatility is a concept that explains the frequency and magnitude of changes in the prices of financial assets [5, 6, 8, 16, 25, 29]. Generally, financial instruments and their returns are characterized by measures of uncertainty with bubbles and bursts. This is because they mirror firm's financial status and prospects as highlighted by Balcilar et al. [6]. As a result of the uncertainty brought about by volatility, investors' investment habits may change and this situation may negatively affect both investors and financial markets. This indicates how important the volatility concept is for investors and markets. As a result of being affected by globalization in financial markets and economies, all financial markets act as if there is only one financial market. The biggest example of this is VIX index. The VIX index, known as the fear index worldwide, has become an important indicator of volatility in global markets and plays an important role in investors' decisions. Increases in the level of volatility in commodities, stocks, foreign currency and similar investment

*Correspondence:
Festus Victor Bekun
fbekun@gelisim.edu.tr
[1] Department of Logistic Management, Faculty of Economic, Administrative and Social Sciences, Istanbul Gelisim University, Istanbul, Turkey

instruments may cause uncertainty over prices, which may cause investors to face greater risks.

Although investors behave in different investment decisions, they are more likely to suffer huge loss when the volatility the investment instrument is high.. In this case, it is beneficial for investors to minimize uncertainty and thus decrease in risk level. It is an important issue in terms of finance literature with which models of volatility exposed to different investment instruments in different financial markets can be estimated.

In other words, volatility forecasting models are needed to develop issues such as portfolio optimization, more effective implementation of hedging methods and pricing in derivative instruments [7, 28].

When the literature is examined, the volatility model first appeared in the study of Engle [14] as the autoregressive conditional heteroskedasticity (ARCH) model. In the study of Bollerslev [10], generalized autoregressive conditional heteroscedasticity (GARCH) model was introduced, such that the trajectory of volatility models started to diversify. While the diversity in volatility models causes the financial environment to focus on which model can give better results, changing data and time series prevent a common idea about which model can perform better. This makes a great contribution to the emergence of new models, as well as to try out existing models.

Therefore, this study estimated the volatility of Bitcoin return with various models and evaluated and compared the forecasting performances of the models. Hence, the contribution of this study hinges on the determination of the most suitable model of estimating volatility in Bitcoin returns. Volatility models such as ARCH, GARCH and EGARCH were applied in the study and it was found that the most suitable volatility model according to Akaike info criterion (AIC) was GARCH (1,1).

The remainder of this study follows with a stylized review of related literature is presented in "Literature review" section. Subsequently, "Data and methodology" section focuses on data and econometrics procedures. "Empirical findings and discussions" section provides empirical results discussion. Finally, concluding remarks are rendered in "Conclusion" section with study based implications.

Literature review

When the literature is analyzed, all of the existing volatility models have been tried on different financial instruments and new opinions are raised which one gives better results. For this reason, instead of the volatility models tested only on Bitcoin prices, the studies on volatility models tested on different investment instruments in financial markets will also be mentioned. The motivation of the previous studies varies but centred on the modelling of the volatility characteristics and predictability of several investment instruments and prices.

The first volatility modeling related to exchange rates was introduced in Bollerslev [11]. In the study of Bollerslev [11], it was investigated which model works better in order to estimate the volatility in Dollar/Mark and Dollar/Pound exchange rates. As a result of the applied ARCH and GARCH models, it was found that the GARCH (1,1) model predicted the daily exchange rate changes most effectively.

In the study of West and Cho [33], the short- and long-term prediction of dollar rate volatility was tested. The findings are that the GARCH model gives better results in the short run in the dollar rate volatility, while it is not sufficient in the long-term forecasts. Fong [15] attempted to estimate Japanese securities return volatility using ARCH and SWARCH methods. As a result of a comparison of the applied methods, it has been reached that the SWARCH model explains the data better.

Murari's (2015) study, the volatility of the Indian Rubi against the Euro, the US Dollar, the Yen and the Pound was modeled. As a result of the GARCH method applied for the period 2000–2013, it has been reached that the GARCH (2,1) model is a suitable model for finding symmetrical effects. In the study of Kumar [20], which is a similar study, the model with which the volatility of the Euro exchange rate in the spot market can be analyzed most effectively was tested. In the study in which ARCH group models were used, it was found that GARCH (1,1) model was the most suitable model in forecasting estimation.

In Birau et al. [9], the most appropriate model was tried to be determined in the estimation of the volatility structure for the Indian Bombay exchange bank index. As a result of the obtained findings, the most effective model in the Indian Bombay exchange bank index volatility prediction was determined as the GARCH (1,1) model.

Yildirim [34] study, in which the volatility estimation in crude oil prices is tested, which model is best tested, ARCH and GARCH models were applied and the findings obtained were found to be able to test the volatility in crude oil prices with the most effective GARCH (1,1) model.

In a recent study of Katsiampa [19], it was investigated which model could best be applied in estimating the volatility in Bitcoin prices. The findings obtained in the study where models such as GARCH, EGARCH, TGARCH, AP GARCH, C-GARCH and asymmetric component GARCH are applied are the CGARCH model that is the most successful model that measures the volatility in Bitcoin prices. In a similar study, Şahin and Özkan [31] investigated which model is best for estimating volatility for Bitcoin prices. The findings obtained as a result of the applied ARCH, GARCH, ARCHM, EGARCH and TARCH models have been reached to be the TARCH model of the best volatility forecast model in Bitcoin prices.

In the study of Amjad and Sahah [3], it was investigated which model would be more accurate to use in terms of estimating past prices and future prices of Bitcoin. As a result of the obtained results, it has been reached that the ARIMA method will give more accurate results.

In the study of Jang and Lee [18], the Bitcoin price of Bayesian neural network technique is modeling and prediction has been found to give better results than other linear and nonlinear models.

Sutiksno et al. [30], the model with which the Bitcoin prices can be estimated has been investigated and as a result of the methods such as ARIMA, NNAR models and the α-Sutte indicator method, it has been reached that the Bitcoin prices can be estimated more effectively with the α-Sutte indicator method. In McNally [23] study, it is tried to be guessed in which trend the Bitcoin price will be priced. As a result of comparing the predictive findings of ARIMA and deep learning methods, it was found that deep learning method gave better results. Furthermore, Lahmiri and Bekiros [21], the most effective model for predicting the most traded crypto money prices findings have been reached that it is a deep learning technique.

This study is different from the previous literature. The current study applied return volatility prediction models instead of the volatility prediction model in price movements which were commonly used in the literature. Also, while the ARCH and GARCH models, which are common in the selection of the suitable volatility model in the literature, are preferred for the Bitcoin returns, the EGARCH model was applied in addition to the ARCH and GARCH models.

Data and methodology

In this section, the econometric structure of the data set and models used in the research will be discussed. In this study, it is aimed to obtain the most suitable model in order to predict the variability in Bitcoin prices. A series of analyses were applied to weekly data from 11.24.2013 to 03.22.2020 from the investing.com website. The applied analyses were carried out using the EViews 9 program.

Before testing volatility prediction models, the logarithmic return of weekly Bitcoin prices was calculated and volatility prediction models were tested in the light of the series obtained. While calculating the logarithmic return of weekly Bitcoin prices, the following formula was used [32]:

$$r = \log\left(\frac{x_t}{x_{t-1}}\right) \tag{1}$$

Volatility models such as ARCH, GARCH and EGARCH were applied to the weekly logarithmic data obtained and the best model was chosen as a result of the findings obtained. Explanation of the econometric infrastructure of the three mentioned models is important for the effectiveness of the study.

In the modeling of financial time series with variable volatility, variance ARCH model, which is one of the first models, accepting that it is not fixed, is one of the most common models in the literature.

In the study of Engle [14], the error terms in the period t of u_t it has been suggested that the variance is consecutively dependent on the variance of u_t in the previous periods and the ARCH model has been developed [27: 341].

Under conditions of $\omega > 0; \alpha_i \geq 0; \sum_{i=1}^{q} \alpha_i < 1$, the general ARCH ($q$) process is shown in Eq. (2) format:

$$\begin{aligned} h_t &= Var\left(u_{tq}\right) = \sigma_t^2 \\ &= \omega + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 \\ &\quad + \alpha_q u_{t-q}^2 = \omega + \sum\nolimits_{i=1}^{q} \alpha_i u_{t-i}^2 \end{aligned} \tag{2}$$

The ARCH model developed in the Engle [14] study could contain parameter estimates with negative variance. In order to prevent this limitation, Bollerslev [10] study generalized autoregressive conditional heteroscedasticity (GARCH) model was developed. The GARCH model allows both autoregressive and moving average terms to be used in conditional variance modeling [4: 53].

Under $\omega > 0; \alpha_i \geq 0; \beta_j \geq 0; \sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{P} \beta_j < 1$ conditions, the GARCH (p, q) model process is expressed in Eq. (3):

$$h_t = \omega + \sum\nolimits_{j=1}^{P} \beta_j h_{t-j} + \sum\nolimits_{i=1}^{q} \alpha_i u_{t-i}^2 \tag{3}$$

GARCH model against positive and negative shocks assumes volatility reacts symmetrically and leverage may be inadequate in modeling the effect. In order to eliminate these deficiencies, the EGARCH model was developed in the study of Nelson [26].

In the EGARCH model, the natural logarithm of conditional variance has its own delay values are $\frac{|u_{t-i}|}{\sqrt{h_{t-i}}}$ conditional to the standardized error term rather than the interpolated error term frame[12, 27: 344]. The developed EGARCH model is expressed in Eq. (4) [26]:

$$\log(h_t) = \omega + \sum_{j=1}^{p} \beta_j \log(h_{t-j}) + \sum_{i=1}^{q} \alpha_i \frac{|u_{t-i}|}{\sqrt{h_{t-i}}} + \sum_{i=1}^{q} \gamma_i \frac{|u_{t-i}|}{\sqrt{h_{t-i}}} \quad (4)$$

These models are applied because they are identified to be the most commonly and best performing volatility models [1, 2].

We started the estimation procedure with unit root test to establish stationarity characteristics of the series. This is important because the basic assumption of the ARCH and GARCH models is that the series are stationary. This is also the reason for the use of the return series. After the stationarity test, we proceed to the ARCH test, using ARCH-LM test to examine the volatility of the series. Then, we applied the ARCH, GARCH, and the EGARCH models to estimate and forecast the volitility of the series.

Empirical findings and discussions

In this section, various tests were conducted for the model selection of weekly Bitcoin return volatility for the period of 11.24.2013–03.22.2020, the findings of the applied tests. ARCH, GARCH and EGARCH results were included in order to select the most suitable model and the findings were interpreted.

Firstly, when the time series related to logarithmic returns is examined as reported in Table 1, the median return is 0.004408, the minimum return is -0.536040 and the maximum return is 0.533432. On the other hand, the height of the kurtosis 5.913069 indicates that the series is pointed, while the skewness is 0.026048 indicates that the series is symmetrical. The fact that the series mean value is very close to 0 indicates that the series may be stationary.

Table 2 Unit root test at *I* (0) level of logarithmic returns of bitcoin price movements

	None	Constant	Constant and trend
ADF test statistic	− 19.01228***	− 19.04361***	− 19.02500***
1% critical value	− 2.572031	− 3.450099	− 3.986284
5% critical value	− 1.941793	− 2.870137	− 3.423585
10% critical value	− 1.616052	− 2.571420	− 3.134762

According to MacKinnon (1996) one side *p* values *,** and*** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Maximum lags is (32)

Stationarity of the logarithmic return series was tested as presented in Table 2 after obtaining and interpreting descriptive statistical values. The periodic presence of volatility on the chart was tested before applying the augmented Dickey–Fuller [13] test, which tests whether the series contains unit roots.

Figure 1 clearly shows the volatility cluster in the Bitcoin logarithmic return series. Large changes in logarithmic returns follow large movements and small changes follow small movements. This situation clearly reveals the clustering of volatility and volatility of Bitcoin prices.

Since the time series is used in the study, the stationarity of the Bitcoin return series should be tested before volatility models are tested. In order to test the stationarity, augmented Dickey and Fuller [13] test was applied and it was tested whether the series contained unit root. If the series contains unit root as a result of the unit root test, this means that the series is not stationary. Since non-stationary time series give inaccurate results, series should be made stationary when they are not stationary. Unit root results for the Bitcoin return series are given in Table 2.

When the results of the Bitcoin return series are analyzed, it is found that the ADF test statistics are higher than the critical values of Mac-Kinnon (1996) as absolute values such as none, constant, constant and trending. On the

Table 1 Descriptive statistics. Source: Authors computation

Mean	0.007901
Median	0.004408
Maximum	0.533432
Minimum	−0.536040
Std. Dev.	0.114597
Skewness	0.026048
Kurtosis	5.913069
Jarque–Bera	116.3657
Probability	0.000000
Sum	2.599342
Sum Sq. Dev.	4.307446
Observations	329

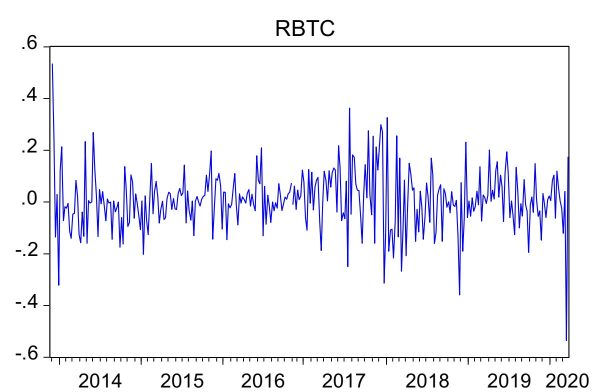

Fig. 1 Logarithmic returns of bitcoin price movements

other hand, the results obtained were found to be significant at the level of 1%, 5% and 10% significance. This indicates that there is no unit root in the Bitcoin return series and the series is stationary. Thus, the ARCH effect for the Bitcoin return series was tested after it was reached that the series were stationary at their own levels. While testing the ARCH effect, ARCH-LM (ARCH–Lagrange multiple) test was applied.

In order to determine the presence of the ARCH effect in the return series, the appropriate conditional equation needs to be established using the Least Squares (OLS) method and whether autocorrelation should be tested. As a result of the least squares (OLS) method applied, it was found that the most suitable model for the conditional average equation is ARMA (2,2). As a result of the Least Squares (OLS) method applied, the conditional average equation is given below.

$$\begin{aligned}\mathrm{RBTC} =& 0.007768 - 1.060144\mathrm{AR}(1) - 0.999224\mathrm{AR}(2) + 1.051866\mathrm{MA}(1)\\ &+ 0.999869\mathrm{MA}(2)\end{aligned}$$

As a result of the applied model, AR (1) + AR (2) < 1 and MA (1) + MA (2) < 1 condition has been reached. On the other hand, the parameters AR (1), AR (2), MA (1) and MA (2) < 0.05 have been reached. This indicates that the parameters are statistically significant.

ARCH-LM test was applied to the conditional average equation and the results are shown in Table 3.

As a result of the applied ARCH-LM test, probability values were found to be significant at 1% level. This indicates that H0: $\beta 1 = \beta 2 = \ldots = \beta n = 0$ null hypothesis is rejected. This indicates that the H_0 hypothesis, which indicates equal variance, will be rejected and the existence of the ARCH effect will be accepted [14].

Table 3 ARCH-LM test

F-statistic	9.021.390	Prob. *F*(1,326)	0.0029***
Obs**R*-squared	8.832.319	Prob. Chi-square(1)	0.0030***

*, ** and *** indicate statistical significance at the 10%, 5% and 1%

After the acceptance of the presence of ARCH effect on the return series, ARCH and GARCH models were tested for the selection of the suitable ARCH type model, and EGARCH model, which is an effective model in determining the asymmetric effect of the shocks on volatility, was also applied.

The coefficients of the applied volatility models and Akaike info criterion, Schwarz criterion and Hannan–Quinn criterion values are given in Table 4.

The coefficients of the applied ARCH, GARCH and EGARCH models yielded statistically significant results at the level of 1%, 5% and 10%. On the other hand, as a result of applied ARCH, GARCH and EGARCH models, it has been reached that there is no autocorrelation at 5% error level. The most suitable model for Bitcoin returns is selected according to Akaike Information Criterion (AIC) values. According to Akaike ınformation criterion (AIC), the lowest value was observed to be −1.724.458. In this case, GARCH (1,1) has been found to be the best model that can predict Bitcoin returns volatility.

For the GARCH (1,1) model, which can best predict the volatility of the Bitcoin return series, the existence of the ARCH effect has been tested and the results are shown in Table 5.

As a result of the applied ARCH-LM test, it was reached that both probability values were greater than 5% and in this case, it was found that there was no ARCH effect between the error terms of the GARCH (1,1) model.

Table 4 ARCH, GARCH and EGARCH models forecast results

	ARCH (1)	ARCH (2)	ARCH (3)	GARCH (1,1)	GARCH (1,2)
C	0.005720	0.007297	0.007210	0.005828	0.005848
Θ1	0.932688	1.080.169	1.089.076	0.610510	0.610576
Θ2	−0.515757	−0.652587	−0.647935	−0.925314	−0.926474
*φ*1	−0.973332	−1.103.220	−1.119.591	−0.612437	−0.611955
*φ*2	0.598896	0.722064	0.720196	0.947975	0.948839
ω	0.009080	0.155794	0.006141	0.001147	0.001100
α	0.253701	0.183899	0.166212	0.196003	0.181672
β		0.432484	0.318186	0.716033	0.903755
γ			0.053515		−0.169018
Akaike info criterion	−1.596.814	−1.596.814	−1.646.406	−1.724.458	−1.719.377
Schwarz criterion	−1.515.684	−1.515.684	−1.542.095	−1.631.738	−1.615.066
Hannan–Quinn criter.	−1.564.442	−1.564.442	−1.604.784	−1.687.461	−1.677.756
Durbin–Watson stat.	2.031.371	2.031.371	2.048.640	2.107.864	2.108.853
	GARCH (1,3)	**GARCH (2,1)**	**GARCH (2,2)**	**EGARCH (1,1)**	**EGARCH (1,2)**
C	0.005706	0.007297	0.007266	0.008382	0.009037
Θ1	0.610257	1.080.169	1.085.014	1.065.849	0.261344
Θ2	−0.953563	−0.652587	−0.677699	−0.646230	−0.892373
*φ*1	−0.616998	−1.103.220	−1.114.328	−1.084.083	−0.268463
*φ*2	0.976040	0.722064	0.750366	0.712109	0.979715
ω	0.202820	0.003077	0.162719	−0.866121	−1.047.696
α	1.057.449	0.155794	0.265304	0.343801	0.447054
β	−0.779683	0.183899	0.100971	0.016852	−0.013109
γ	0.448112	0.432484	0.210256	0.866892	0.947965
Akaike info criterion	−1.720.201	−1.650.739	−1.647.606	−1.708.610	−1.684.218
Schwarz criterion	−1.604.300	−1.546.428	−1.531.705	−1.604.299	−1.568.317
Hannan–Quinn criter.	−1.673.955	−1.609.118	−1.601.360	−1.666.988	−1.637.972
Durbin–Watson stat.	2.090.906	2.063.984	2.052.077	2.073.688	2.076.747

Table 5 ARCH-LM test

F-statistic	0.115988	Prob. *F*(1,326)	0.7336
Obs*R-squared	0.116662	Prob. Chi-square(1)	0.7327

Conclusion

Corporate and financial investors desire to earn income from their investments while some of the investors try to avoid the risk of volatility, volatility is perceived as an opportunity for others. Therefore, although investors' perspectives are different, the concept of volatility is the same for all types of investors. Investment decisions, which have a significant impact especially on the direction of the markets, are made taking into account volatility.

For this reason, the importance of volatility models is increasing in the financial literature. Besides researching which volatility model is more suitable for which investment tool and time series, it is important for markets and investors to participate in the literature in their new models.

The fact that ARCH and GARCH models are insufficient to predict the volatility of financial assets that give asymmetrical reactions caused the emergence of models such as EGARCH and TGARCH. It is known that EGARCH and TGARCH models are effective in measuring the effect of negative and positive shocks on volatility. On the other hand, there is a difference between GARCH and GARCH models. While the lever effect is exponential in the EGARCH model, the lever effect is quadratic in the TGARCH model [22, 27].

Therefore, in addition to ARCH and GARCH models, EGARCH model was also applied for Bitcoin returns in the study. The choice of the most suitable model among the volatility models has been determined according to Akaike info criterion and it has been reached that the most common model for Bitcoin returns is the GARCH

(1,1) model. GARCH (1,1) is followed by GARCH (1,3) and EGARCH (1,1), respectively.

The γ parameter in the EGARCH (1,1) model is statistically significant at the level of 5%, which indicates that the shocks formed have an asymmetrical effect on return volatility. In cases where GARCH (1,1) and GARCH (1,3) models are insufficient, EGARCH (1,1) volatility model can be suggested. This finding supports the submissions of Alhassan and Kilishi [2] and Alao et al. [1] that the asymmetric GARCH models outperform the symmetric models. Thus, this study contributes to the volatility forecasting models debate which is need in times of proliferation in the extant literature to methodological advancement to amerloirte issues such as portfolio optimization, more effective implementation of hedging methods and pricing in derivative instruments.

The findings are similar to some of the studies in the literature and support the findings of studies such as West and Cho [33], Kumar [20], Birau et al. [9], Yıldırım [34]. Using only Bitcoin returns as crypto money in the study can be considered as the most important constraint of the study. Thus, our empirical findings highlights an ample guide on appropriate modelling of price information in the Bitcoin market.

The limited of this study is that it considered only Bitcoint among several other cryptocurrencies. Hence, further study to examine the volatility modelling of other cryptocurrencies such as Ethereum, Riple, Tether, Litecoin, Eos and Tezos, which are not included in the analysis, will make a great contribution to the literature.

Abbreviations

ARCH	Autoregressive conditional heteroskedasticity
GARCH	Generalized autoregressive conditional heteroskedasticity
ADF	Augmented dicky fully test
EGARCH	Exponential general autoregressive conditional heteroskedastic
ARMA	Autoregressive moving average
ARCH-LM	Autoregressive conditional heteroskedasticity-Lagrange multiplier

Acknowledgements

Author gratitude is extended to the prospective editor(s) and reviewers that will/have spared time to guide toward a successful publication.
The Authors of this article also assures that they follow the springer publishing procedures and agree to publish it as any form of access article confirming to subscribe access standards and licensing.

Author contributions

All authors carefully read and approved the final version.

Funding

I hereby declare that there is no form of funding received for this study.

Availability of data and materials

The data for this present study are sourced from world development indicators (WDI) available at www.data.worldbank.org

Declarations

Ethics approval and consent to participate

Authors mentioned in the manuscript have agreed for authorship read and approved the manuscript, and given consent for submission and subsequent publication of the manuscript.

Consent for publication

Applicable.

Competing interests

I wish to disclose here that there are no potential conflicts of interest at any level of this study.

Received: 19 December 2022 Accepted: 6 September 2023
Published online: 15 September 2023

References

1. Alao RO, Alhassan A, Alao S, Olanipekun IO, Olasehinde-Williams GO, Usman O (2023) Symmetric and asymmetric GARCH estimations of the impact of oil price uncertainty on output growth: evidence from the G7. Lett Spat Resour Sci 16(1):5
2. Alhassan A, Kilishi AA (2016) Analysing oil price-macroeconomic volatility in Nigeria. CBN J Appl Stat (JAS) 7(1):1
3. Amjad M, Shah D (2017) Trading bitcoin and online time series prediction. In: Proceedings of the NIPS 2016 time series workshop, pp 1–15
4. Atakan T (2009) İstanbul Menkul Kıymetler Borsası'nda değişkenliğin (volatilitenin) ARCHGARCH yöntemleri ile modellenmesi. Yönetim Dergisi 62:48–61
5. Balcilar M, Gupta R, Kyei C (2018) Predicting stock returns and volatility with investor sentiment indices: a reconsideration using a nonparametric causality-in-quantiles test. Bull Econ Res 70(1):74–87
6. Balcilar M, Gupta R, Kim WJ, Kyei C (2019) The role of economic policy uncertainties in predicting stock returns and their volatility for Hong Kong, Malaysia and South Korea. Int Rev Econ Financ 59:150–163
7. Balcilar M, Bouri E, Gupta R, Kyei CK (2021) High-frequency predictability of housing market movements of the United States: the role of economic sentiment. J Behav Financ 22(4):490–498
8. Ben Sita B (2019) Crude oil and gasoline volatility risk into a realized-EGARCH model. Rev Quant Financ Account 53(3):701–720
9. Birau R, Trivedi J, Antonescu M (2015) Modeling S&P Bombay stock exchange BANKEX ındex volatility patterns using GARCH model. Procedia Econ Financ 32(1):520–525
10. Bollerslev T (1986) Generalized autoregressive conditional heteroscedasticity. J Econom 31:307–327
11. Bollerslev T (1987) A conditionally heteroskedastic time series model for speculative prices and rates of return. Rev Econ Stat 69(3):542–547
12. Demirel B, Bozdağ EG, İnci AG (2008) Döviz Kurundaki Dalgalanmaların Gelen Turist Sayısına Etkisi: Türkiye Örneği. DEU Ulusal İktisat Kongresi, Izmir
13. Dickey DA, Fuller WA (1979) Autoregressive time series with a unit root. J Am Stat Assoc 74:427–431
14. Engle RF (1982) Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. Econometrica 50(4):987–1008
15. Fong WM (1997) Volatility persistence and switching ARCH in Japanese markets. Financ Eng Jpn Mark 4:37–57
16. Güneş, H, Saltoğlu B (1998) İMKB Getiri Volatilitesinin Makroekonomik Konjonktür Bağlamında İrdelenmesi, İMKB Yayınları.
17. https://tr.investing.com/crypto/bitcoin/btc-usd-historical-data
18. Jang H, Lee J (2017) An empirical study on modeling and prediction of bitcoin prices with Bayesian neural networks based on Blockchain information. Access 6:5427–5437
19. Katsiampa P (2017) Volatility estimation for bitcoin: a comparison of GARCH models. Econ Lett 158:3–6
20. Kumar H (2015) Impact of currency futures on volatility in exchange rate: a study of indian currency market. Paradigm 19(1):95–108

21. Lahmiri S, Bekiros S (2019) Cryptocurrency forecasting with deep learning chaotic neural networks. Chaos Solitons Fractals 118:35–40. https://doi.org/10.1016/j.chaos.2018.11.014
22. Mapa DS (2004) A forecast comparison of financial volatility models.
23. McNally S, Roche J, Caton S (2018) Predicting the price of bitcoin using machine learning. In: Proceedings of the 2018 26th euromicro ınternational conference on parallel, distributed and network-based processing (PDP), IEEE, pp 339–343
24. Murarı K (2015) Exchange rate volatility estimation using GARCH models, with special reference to Indian rupee against world currencies. IUP J Appl Finan 21(1):22–37
25. Nasr AB, Lux T, Ajmi AN, Gupta R (2016) Forecasting the volatility of the Dow Jones Islamic stock market index: long memory vs. regime switching. Int Rev Econ Financ 45:559–571
26. Nelson D (1991) Conditional heteroskedasticity in asset returns: a new approach. Econometrica 59(2):347–370
27. Özden ÜH (2008) İMKB bileşik 100 endeksi getiri volatilitesinin analizi. İstanbul Ticaret Üniversitesi Sosyal Bilimler Dergisi 13:339–350
28. Sadorsky P (2012) Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. Energy Econ 34(1):248–255
29. Syed QR, Bouri E (2021) Spillovers from global economic policy uncertainty and oil price volatility to the volatility of stock markets of oil importers and exporters. Environ Sci Pollut Res 29:1–11
30. Sutiksno DU, Ahmar AS, Kurniasih N, Susanto E, Leiwakabessy A (2018) Forecasting historical data of bitcoin using ARIMA and α-sutte indicator. Proc J Phys Conf Ser 1028(1):012194
31. Şahin E, Özkan O (2018) Asimetrik Volatilitenin Tahmini: Kripto Para Bitcoin Uygulaması. Bilecik Şeyh Edebali Üniversitesi Sosyal Bilimler Enstitüsü Dergisi 3(2):240–247. https://doi.org/10.33905/bseusbed.450018
32. Uğurlu E (2019) Research data analysis using EViews: an empirical example of modeling volatility. In: Bhardwaj RK, Banks P (eds) Research data access and management in modern libraries. IGI, USA, pp 292–324
33. West KD, Cho D (1995) The predictive ability of several models of exchange rate volatility. J Econom 69:367–391
34. Yıldırım H (2017) ARCH–GARCH model on volatility of crude oil. Int J Discip Econ Adm Sci Stud 3(1):17–22. https://doi.org/10.26728/ideas.11

Publisher's Note