ANALYSIS OF CRYPTOCURRENCY PRICE PREDICTIONS AND VOLATILITY AMID GLOBAL GEOPOLITICAL UNCERTAINTY

Ilyasin Aditya Rahman[1]*, Sri Suharsih[2], Hariestya Zaki Akmal Aulia[3]
[1] Independent Researcher (Indonesia)
[2,3]UPN Veteran Yogyakarta (Indonesia)
**) email: ilyasinaditya537@gmail.com*

Abstract

Digital currency, especially cryptocurrencies, is experiencing rapid growth and is noted for its high price volatility, driven by factors such as global geopolitical instability. Major events like the Russia-Ukraine war, recent conflicts between Israel and Iran, and the United States military operation targeting Venezuela's president on January 3, 2026, have all stirred sharp price fluctuations. This demonstrates that analysing how geopolitical situations influence cryptocurrency volatility is essential. This research aims to provide timely analysis and price predictions, serving as a vital resource for investors seeking to make informed decisions amid current global tensions approaching the brink of World War III. This study only uses Bitcoin and Ethereum as samples for analysis because Bitcoin has the largest valuation at present, while Ethereum ranks second with the largest market capitalization. Bitcoin is also widely used worldwide, and its price dynamics remain somewhat controversial (Abid et al., 2023). Therefore, it is very important to understand the volatility of these two coins and make short-term predictions, considering the recent escalation in geopolitical conditions. This research uses secondary data for the period from February 24, 2022, which marks the beginning of Russia's invasion of Ukraine, until January 18, 2026, on a daily basis with quantitative descriptive analysis. The data were obtained from investing.com and coinmarketcap.com. The benefits of this study include understanding future trends related to Bitcoin and Ethereum prices in the short term. This makes investors have a reference in making investment decisions, and furthermore, this research also provides an important contribution to understanding the volatility dynamics of Bitcoin and Ethereum prices. The results of this study show that GARCH (Generalized Autoregressive Conditional Heteroskedasticity) is the best model.

Keywords: Cryptocurrency, Bitcoin, Ethereum, Volatility.

1. INTRODUCTION

The use of technology in the era of the digital revolution has made technology a primary necessity, and with current developments, technology can be utilized in all fields. In the economic sector, payments are no longer limited to conventional physical payments, but can also be made through digital transactions without the need for physical money. One digital transaction that is currently rapidly developing is encrypted digital currency, commonly known as cryptocurrency (Faturahman et al., 2021). In a short period, the existence of cryptocurrency continues to grow by integrating a number of innovative technologies, such as blockchain, cryptography, and smart contracts. This currency has a high level of volatility, which can create both risks and opportunities (García-Corral et al., 2022).

The first digital currency to gain popularity was Bitcoin, which was founded in 2008 by Satoshi Nakamoto. Although there were earlier digital currencies, such as E-gold in 1996 or Liberty Reserve in 2006, Bitcoin was the first to become widely recognized by the public (Garcia et al., 2014). However, in some previous studies, there is still debate about whether Bitcoin has certain hedging characteristics during economic uncertainty (Dutta, 2025; Wang et al., 2023). Therefore, this study aims to determine the specific volatility level of Bitcoin and examine the trends that occur during economic uncertainty.

In addition, there is Ethereum, which is the second-largest cryptocurrency after Bitcoin. Ethereum is a second-generation blockchain system designed to store various types of information besides transactions. Moreover, Ethereum's smart contracts, which are functions to carry out transactions under certain conditions, increase Ethereum's value (Kim et al., 2021). This makes the Ethereum blockchain superior to Bitcoin, as Ethereum is more than just a peer-to-peer transaction network. Currently, many other cryptocurrencies use the Ethereum blockchain (Urquhart, 2022). Furthermore, Ethereum is the blockchain for Non-Fungible Tokens (NFTs), which continue to grow rapidly in size and popularity, even influencing the development of studies on this cryptocurrency (Alvarez-Ramirez & Rodriguez, 2021; Kim et al., 2021).

Table 1. Coin Market (USD)

No	Name	Price	Market Cap	Volume
1.	Bitcoin	93.089,99	1.857,81B	37,84B
2.	Ethereum	3.228,37	389,24B	28,19B
3.	Tether	0,9993	186,89B	96,17B
4.	BNB	926,54	126,34B	2,92B

Source: (CoinMarketCap, 2026)

Bitcoin and Ethereum are the most representative cryptocurrencies, having recorded the highest trading volumes and market values. Based on Table 1, as of January 2026, Bitcoin recorded a trading volume of USD 37.84 billion with a market value of USD 1,857 billion, while Ethereum reached a trading volume of USD 28.19 billion with a market value of USD 389.24 billion. The strength of these two cryptocurrencies in the global market reinforces the rationale for choosing Bitcoin and Ethereum as the subjects of study, particularly to analyze their volatility and trends amid economic uncertainty. This study aims to delve deeper into the impact of the volatility of these two digital currencies due to the unpredictable global economy and digital investment.

Although cryptocurrency has tremendous potential, the high volatility risk cannot be ignored. Additionally, uncertainties such as global escalation can further increase the volatility risk in financial markets (Kumar et al., 2023). Research conducted by Boubaker et al. (2022) shows that the impact of the Russia-Ukraine war has resulted in negative cumulative abnormal returns. This can occur considering that the sanctions imposed on Russia affect the economy, not only in terms of oil, given Russia's abundant reserves for export, but also in relation to countries partnering with Russia

(Bali & Rapelanoro, 2021). These sanctions have led SWIFT to freeze Russia in international transactions.

In theory, the volatility of financial asset prices reflects the level of uncertainty and risk faced by market participants. In the context of the cryptocurrency market, the Efficient Market Hypothesis (EMH) posits that asset prices reflect all available information, so price changes occur in response to new information (Fama, 1970). In cryptocurrency markets, the characteristics of decentralization and limited regulation cause external information, including geopolitical sentiment, to potentially trigger price volatility that is more extreme compared to conventional assets. Thus, this theory implies that an investor will not be able to outperform the market in the long term, except through luck or taking on higher risk.

Furthermore, behavioural finance theory explains that investor behaviour is not always rational, as assumed in classical financial theory. Investors are often influenced by psychological factors, emotions, and cognitive biases, such as overreaction, loss aversion, and herding behaviour, which can lead to price deviations from fundamental values (Barberis et al., 1998; Shiller, 2003). In markets with high levels of uncertainty, emotional responses to negative information tend to amplify the volatility of financial asset prices. In social sciences, humans think and act in situations of uncertainty, known as Uncertainty Theory. The phenomenon of globalization since 2000 has led to increased interconnectivity between trade and finance in a country, including market conditions resulting from uncertainty in the economy and politics (Yang et al., 2024). As a result, market behaviour driven by stocks and other commodities has led to investor uncertainty or doubt, prompting them to flock to safe-haven assets to protect their investments during price volatility, particularly in cryptocurrency (Wulan et al., 2024).

Based on the theoretical review, several empirical studies have examined the price behaviour and volatility of Bitcoin and Ethereum under conditions of economic and geopolitical uncertainty. Federle et al. (2022) confirmed that countries located near conflict zones have implications for returns. Other studies indicate that global escalation will lead to increased cryptocurrency volatility (Będowska-Sójka et al., 2024; Bouri et al., 2021).

Although the growth of studies on the crypto market is progressing rapidly, there is still no consensus regarding the function of cryptocurrency as a hedge or a safe haven in situations of economic and geopolitical uncertainty. Most of the existing literature emphasizes long-term correlations with traditional assets or general price behaviour, yet little attention is given to the volatility of Bitcoin and Ethereum in the specific context of the Russia-Ukraine war and sanctions disrupting international markets. Furthermore, empirical research using econometric models such as ARCH and GARCH tests to capture and predict volatility in such abnormal conditions remains limited. This gap underscores the importance of analysing the behaviour of Bitcoin and Ethereum during the ongoing global crisis to understand their future trajectory.

The aim of this study is to analyse the price dynamics of Bitcoin and Ethereum amid global uncertainty triggered by the Russia-Ukraine war, with a particular focus on identifying levels of volatility and potential future trajectories. Specifically, this research aims to examine how negative market sentiment has shaped Bitcoin price trends, measure volatility levels using ARCH and GARCH testing methods, and provide projections of potential price movements. Thus, this study seeks to contribute to a deeper understanding of the behaviour of Bitcoin and Ethereum under extraordinary geopolitical and financial disruptions, offering insights that may be valuable to academics and market participants.

In this study concerning cryptocurrency volatility, which focuses on Bitcoin and Ethereum, the research problems are as follows: how the price trends of Bitcoin and Ethereum behave after being influenced by negative sentiment due to uncertain global conditions; then, how the price volatility of Bitcoin and Ethereum occurs during disruptions caused by uncertain global conditions resulting from the war between Russia and Ukraine; and finally, the prediction of the prices of both coins after the war between Russia and Ukraine.

This study reviews the literature on the impact of global uncertainty caused by the war between Russia and Ukraine, which has triggered shocks in cryptocurrencies, particularly Bitcoin and Ethereum.

2. METHODOLOGY

This study uses secondary data with a descriptive quantitative research design and employs time series data. The data consist of daily Bitcoin price records obtained from www.investing.com. The study period spans February 24, 2022, to January 18, 2026, resulting in a time series with 1,425 observations. Sampling was done purposively, focusing on periods relevant to global uncertainty conditions. The ARCH and GARCH models are used to calculate cryptocurrency volatility. These models are applied when there is high or low data volatility. Such volatility causes heteroskedasticity because errors depend on the variance, which changes in patterns or errors from previous periods.

This study proposes a dynamic autoregressive conditional heteroscedasticity (ARCH) network model suitable for high-dimensional cases where multivariate models are typically no longer applicable (Mattera & Otto, 2024). The ARCH model, which takes into account a simple linear regression equation, is carried out as follows:

$$\gamma_t | \, I_{t-1} = \sigma + \beta X_t + e_t$$

Description:

y = Dependent variable

I_{t-1} = Information available up to the present moment (t-1)

X = Independent variable

e_t = Error term

To account for the ARCH effect, the equation becomes:

$$\sigma_t^2 = \gamma_0 + \gamma_1 e_{t-1}^2$$

Model ARCH (p):

$$\sigma_t^2 = \gamma_0 + \gamma_1 e_{t-1}^2 + \gamma_2 e_{t-2}^2 + \cdots + \gamma_p e_{t-p}^2$$

If ARCH is indicated, proceed with statistical F testing with the following hypothesis:

$$\mathrm{H}_0 : \gamma_1 = \gamma_2 = \cdots = \gamma_\mathrm{p} = 0$$

This ACRH model can be used as an alternative to predict time-related data (Mutiara et al., 2023).

Next, an alternative specification of the Generalized Autoregressive Conditionally Heteroscedastic (GARCH) type is used to model the volatility that varies over time in cryptocurrency return series, as well as to provide an overview of the innovation distribution. Secondly, the selection criteria that will be used to determine the most appropriate GARCH type specification are also explained.

The GARCH model used to model conditional volatility is specified as follows:

$$\sigma_t^2 = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

Where ω > 0, α ≥ 0, and β ≥ 0 are unknown parameters. The constraints on the parameters ensure that the conditional variance is always positive. The necessary and sufficient condition for 2 to be uniquely stationary is α + β < 1, and the unconditional variance is given by ω / (1− (α + β)), thereby ensuring the existence of higher-order moments. If the GARCH model is correctly specified, the model will converge to this long-term variance as the forecasting horizon increases (Hegde, 2025; Ngunyi et al., 2019).

3. FINDINGS AND DISCUSSION

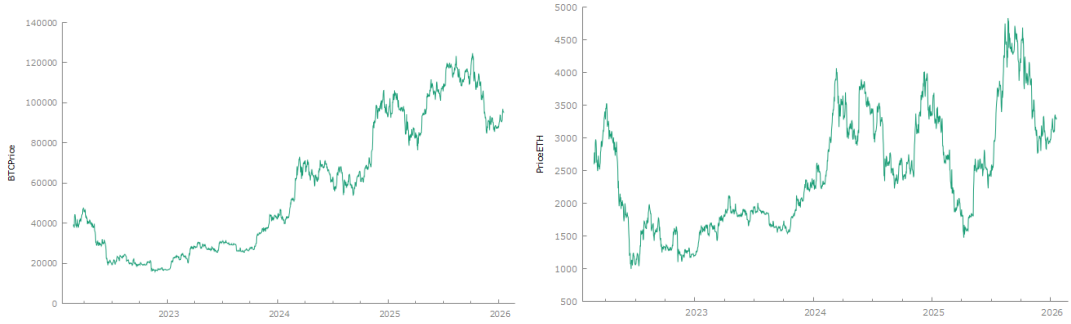
From the processed data and analysis obtained using time series data of 1,425 daily records from February 24, 2022, to January 18, 2026, we determined the best model for prediction.

3.1 Volatility Analysis

In volatility testing, it is very important to first understand the fluctuations of the sample to be tested. The pattern is as follows:

3.1.1 Pattern Analysis

Picture 1. Trend BTC and ETH



Sumber: Data Processed, 2026

In the results obtained, the image on the left shows the trend of Bitcoin (BTC), which indicates price fluctuations, and the image on the right shows the trend of Ethereum (ETH), which displays a fluctuation pattern almost similar to Bitcoin.

3.1.2 Min Model Analysis

This analysis is crucial for understanding the level of fluctuations before further processing is carried out. The following is an analysis of the Bitcoin OLS model.

Table 2. Model 1: OLS, using observations 2022-02-24:2026-01-18 (T = 1425) Dependent variable: Bitcoin Price

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	57200.2	870.279	65.73	<0.0001	***

Mean dependent var	57200.21	S.D. dependent var	32852.32
Sum squared resid	1.54e+12	S.E. of regression	32852.32
R-squared	0.000000	Adjusted R-squared	0.000000
Log-likelihood	−16841.17	Akaike criterion	33684.34
Schwarz criterion	33689.60	Hannan-Quinn	33686.31
rho	0.999251	Durbin-Watson	0.002203

Source: Data Processed, 2026

The daily Bitcoin data shows that the average price during this period was $57,200.21. This figure is statistically significant, but the standard deviation of $32,852.32 proves that Bitcoin prices have an extremely high level of fluctuation or volatility. In addition, the very low Durbin-Watson value of 0.0022 and Rho, which is almost 1 (0.999), indicate a very strong relationship between today's price and the previous one, or autocorrelation, so this data needs to be further processed to determine a more accurate prediction.

Table 3. Model 2: OLS, using observations 2022-02-24:2026-01-18 (T = 1425) Dependent variable: Ethereum Price

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	2463.27	23.2345	106.0	<0.0001	***

Mean dependent var	2463.274	S.D. dependent var	877.0835
Sum squared resid	1.10e+09	S.E. of regression	877.0835
R-squared	0.000000	Adjusted R-squared	0.000000
Log-likelihood	−11678.15	Akaike criterion	23358.29
Schwarz criterion	23363.55	Hannan-Quinn	23360.26
rho	0.994813	Durbin-Watson	0.010964

Source: Data Processed, 2026

The daily Ethereum data shows that the average price during this period was $2,463.27. This constant value is statistically significant because it has a p-value of less than 0.0001, even though Ethereum recorded a fairly large standard deviation of $877.08. This model also shows indications of very strong positive autocorrelation in the daily price data, as seen from the rho value of 0.994 and the very low Durbin

Watson value of 0.0109. Overall, the R-squared value is 0.000, meaning that the model only represents historical average values, and further testing is needed.

3.1.3 Unit Root Test

This analysis is to ensure that the data has a stable mean and variance over time.

Table 4. Unit Root Test Bitcoin and Ethereum

Coin	Stasioner Test	
	Level	First Diference
Bitcoin (BTC)	0,8679	3,44E-13
Ethereum (ETH)	0,347	4,07E-16

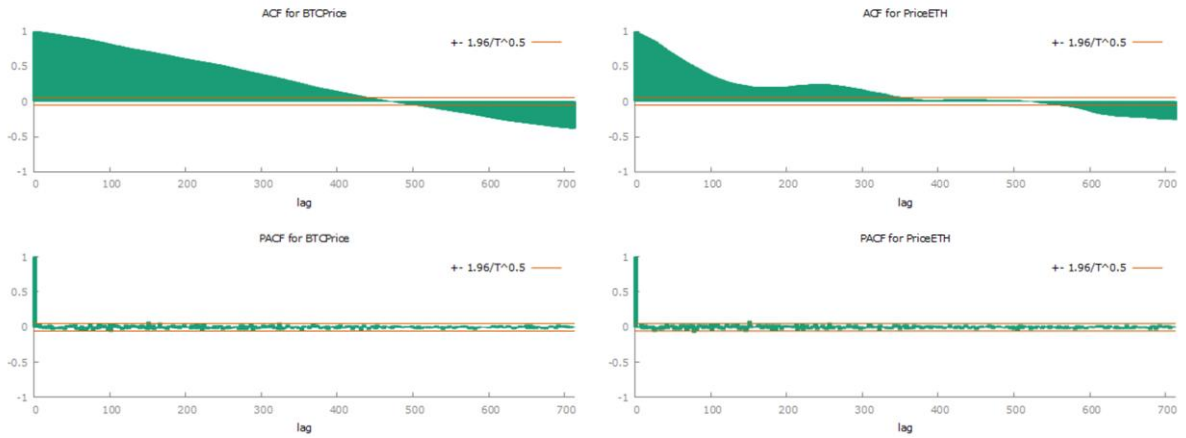
Source: Data Processed, 2026

The test results showed that at the Level, both coins were not stationary because they had probability values of 0.8679 for Bitcoin and 0.347 for Ethereum. However, both coins showed significant figures at the First Difference stage with probability values well below 0.05. This proves that the Bitcoin and Ethereum data became stationary after undergoing the First Difference process, making the data suitable for further time series analysis.

3.1.4 Correlogram ACF and PACF

This analysis, the ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) correlogram, is very important in time series data, serving as a compass in determining the type of model to be used after proving stationarity at the First Difference stage.

Picture 2. Autocorrelation Function and Partial Autocorrelation Function on BTC and ETH Coin



Source: Data Processed, 2026

For the ACF and PACF values in the image above, there is an intersection at Lag 1. Therefore, the following conclusion can be drawn:

- p = Leg (ACF) = 1
- d = (Level = 0, First Difference = 1, Second Difference = 2), stationary at the First difference level 3.44E-13< 0.005 on Bitcoin and 4.07E-16< 0.005 on Ethereum, therefore Lag 1

- q = Leg (PACF) =1

So that the next step can be taken, an ARCH test can be performed.

3.1.4 ARCH Test

The ARCH test is very important in identifying the phenomenon of volatility clustering, which is a condition where periods of high price fluctuations tend to be followed by other high fluctuations, which is very common in crypto assets.

Tabel 4. ARCH Test Bitcoin and Ethereum

Coin	ARCH Test
Bitcoin (BTC)	2,10462e-21
Ethereum (ETH)	6,53805e-14

Source: Data Processed, 2026

In the ARCH Test, it was shown that the p-value for Bitcoin and Ethereum was much smaller than the standard 5% or 0.05. Therefore, since the significance value is below the 5% threshold, it can be concluded that the Bitcoin and Ethereum data contain an ARCH Effect.

3.1.5. GARCH Test

The presence of an ARCH effect through previous diagnostic tests makes it very important to refine volatility analysis on Bitcoin and Ethereum. The urgency of this model lies in its ability to consider past market shocks while also simultaneously considering the variance or risk from previous periods.

Tabel 4. GARCH Test Bitcoin and Ethereum

Coin	GARCH Test			
	alpha (1)	beta (1)	p-value	Likelihood Ratio Test
Bitcoin (BTC)	0,0862	0,9137	1.50e-06 dan 0,000 < 5%	4,15E-135
Ethereum (ETH)	0,0409	0,9569	4.02e-09 dan 0,00 < 5%	7.35e-078

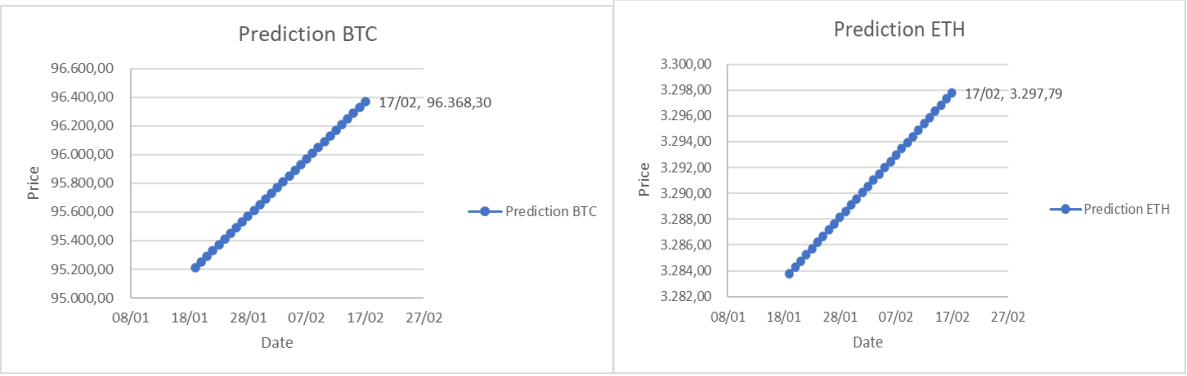
Source: Data Processed, 2026

In the GARCH model, Bitcoin shows that price volatility is greatly influenced by recent market shocks and past volatility conditions. This is evidenced by an alpha (1) value of 0.0862 and a beta (1) value of 0.9137, both of which have highly significant p-values of less than 0.0001. The high beta value, which is close to one, indicates that Bitcoin price fluctuations have a strong or persistent memory effect, meaning that the current highly volatile market conditions are likely to continue for several periods to come. The results of the GARCH model analysis on Ethereum show that price volatility is significantly influenced by past information and previous volatility conditions. This can be seen from the alpha (1) value of 0.0409 and the beta (1) value of 0.9569, both of which have highly significant p-values or are well below 5%. The high beta value, which is close to one, indicates that volatility shocks in the Ethereum market are persistent or long-lasting, so that large price fluctuations at one point in time tend to be followed by large fluctuations in the following period. In addition, the Likelihood ratio test results with a very small p-value of 7.35e-078 confirm that this GARCH model is much more precise and accurate.

3.1.5. Forecasting Bitcoin and Ethereum Price

This forecasting stage is the culmination of a series of data analyses carried out to determine the projected price movements of Bitcoin and Ethereum in the future amidst uncertain geopolitical turmoil.

Picture 3. Forecast BTC and ETH Price



Source: Data Processed, 2026

Overall, the forecasting results for these two cryptocurrencies indicate a correlation of movement in the same direction, where both Bitcoin and Ethereum are predicted to close the 30-day period at higher prices compared to the opening price on January 19, 2026. This suggests that, based on historical data, there is projected stability in short-term price growth. Bitcoin has a higher growth rate of around 1.23% compared to Ethereum's 0.42% during the forecast period. This is consistent with the previous GARCH model results, which showed that Bitcoin has more dynamic volatility persistence.

4. CONCLUSION

Given the uncertain geopolitical conditions, coupled with several conflicts between countries, it makes cryptocurrency, especially Bitcoin and Ethereum, very important to understand in terms of volatility and short-term movements. The findings of this research study show that Bitcoin has an extremely high level of volatility, and the same goes for Ethereum. This is influenced by past historical data and previous volatility, where it is possible that global sentiment regarding uncertain conditions triggers fluctuations in Bitcoin and Ethereum, which are currently the cryptocurrencies with the largest valuation.

In this study, there is no invitation to buy certain coins; rather, the prediction results serve as research findings for reference in decision-making for investors before investing. The prediction results for both Bitcoin and Ethereum show an upward trend in the short term. Although the increase is not very significant, it indicates a positive trend for both within the next 30 days amid the widespread discussion of a potential World War III on social media. Nevertheless, ongoing research on price movements is necessary, considering that Bitcoin and Ethereum have very high volatility.

REFERENCES

Alvarez-Ramirez, J., & Rodriguez, E. (2021). A singular value decomposition approach for testing the efficiency of Bitcoin and Ethereum markets. *Economics Letters*, *206*, 109997. https://doi.org/10.1016/j.econlet.2021.109997

Bali, M., & Rapelanoro, N. (2021). How to simulate international economic sanctions: A multipurpose index modelling illustrated with EU sanctions against Russia. *International Economics*, *168*, 25–39. https://doi.org/10.1016/j.inteco.2021.06.004

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment We are grateful to the NSF for financial support, and to Oliver Blanchard, Alon Brav, John Campbell (a referee), John Cochrane, Edward Glaeser, J.B. Heaton, Danny Kahneman, David Laibson, Owen Lamont, Drazen Prelec, Jay Ritte. *Journal of Financial Economics*, *49*(3), 307–343. https://doi.org/10.1016/S0304-405X(98)00027-0

Będowska-Sójka, B., Górka, J., Hemmings, D., & Zaremba, A. (2024). Uncertainty and cryptocurrency returns: A lesson from turbulent times. *International Review of Financial Analysis*, *94*, 103330. https://doi.org/10.1016/j.irfa.2024.103330

Boubaker, S., Goodell, J. W., Pandey, D. K., & Kumari, V. (2022). Heterogeneous impacts of wars on global equity markets: Evidence from the invasion of Ukraine. *Finance Research Letters*, *48*, 102934. https://doi.org/10.1016/j.frl.2022.102934

Bouri, E., Cepni, O., Gabauer, D., & Gupta, R. (2021). Return connectedness across asset classes around the COVID-19 outbreak. *International Review of Financial Analysis*, *73*, 101646. https://doi.org/10.1016/j.irfa.2020.101646

CoinMarketCap. (2026). *Harga Kripto Hari Ini*. https://coinmarketcap.com/

Dutta, A. (2025). Assessing the Risk of Bitcoin Futures Market: New Evidence. *Annals of Data Science*, *12*(2), 481–497. https://doi.org/10.1007/s40745-024-00517-4

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, *25*(2), 383. https://doi.org/10.2307/2325486

Faturahman, A., Agarwal, V., & Lukita, C. (2021). Blockchain Technology - The Use Of Cryptocurrencies In Digital Revolution. *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, *3*(1), 53–59. https://doi.org/10.34306/itsdi.v3i1.523

Federle, J., Muller, G. J., Meier, A., & Sehn, V. (2022). Proximity to War: The Stock Market Response to the Russian Invasion of Ukraine. *CEPR Discussion Paper No. DP17185*.

García-Corral, F. J., Cordero-García, J. A., de Pablo-Valenciano, J., & Uribe-Toril, J. (2022). A bibliometric review of cryptocurrencies: how have they grown? *Financial Innovation*, *8*(1), 2. https://doi.org/10.1186/s40854-021-00306-5

Garcia, D., Tessone, C. J., Mavrodiev, P., & Perony, N. (2014). The digital traces of bubbles: feedback cycles between socio-economic signals in the Bitcoin economy. *Journal of The Royal Society Interface*, *11*(99), 20140623. https://doi.org/10.1098/rsif.2014.0623

Hegde, P. A. (2025). Assessing the Price Volatility in the Top 50 Blue Chip Companies of Nifty Index - An Analysis using GARCH and ARCH Model. *International Journal for Research in Applied Science and Engineering Technology*, *13*(7), 1481–1490. https://doi.org/10.22214/ijraset.2025.73096

Kim, H.-M., Bock, G.-W., & Lee, G. (2021). Predicting Ethereum prices with machine

learning based on Blockchain information. *Expert Systems with Applications*, *184*, 115480. https://doi.org/10.1016/j.eswa.2021.115480

Kumar, S., Jain, R., Narain, Balli, F., & Billah, M. (2023). Interconnectivity and investment strategies among commodity prices, cryptocurrencies, and G-20 capital markets: A comparative analysis during COVID-19 and Russian-Ukraine war. *International Review of Economics & Finance*, *88*(November 2022), 547–593. https://doi.org/10.1016/j.iref.2023.06.039

Mutiara, A., Fitriyati, N., Studi Matematika, P., Sains dan Teknologi, F., & Islam Negeri Syarif Hidayatullah Jakarta, U. (2023). Analisis Laju Prediksi Inflasi Di Indonesia: Perbandingan Model Garch/Arch Dengan Long Short Term Memory. *Jurnal Ilmiah Pendidikan Matematika, Matematika Dan Statistika*, *4*(1), 94–112.

Ngunyi, A., Mundia, S., & Omari, C. (2019). Modelling Volatility Dynamics of Cryptocurrencies Using GARCH Models. *Journal of Mathematical Finance*, *09*(04), 591–615. https://doi.org/10.4236/jmf.2019.94030

Shiller, R. J. (2003). From Efficient Markets Theory to Behavioral Finance. *Journal of Economic Perspectives*, *17*(1), 83–104. https://doi.org/10.1257/089533003321164967

Urquhart, A. (2022). Under the hood of the Ethereum blockchain. *Finance Research Letters*, *47*, 102628. https://doi.org/10.1016/j.frl.2021.102628

Wang, Q., Huang, Q., Wu, X., Tan, J., & Sun, P. (2023). Categorical uncertainty in policy and bitcoin volatility. *Finance Research Letters*, *58*, 104664. https://doi.org/10.1016/j.frl.2023.104664

Wulan, A., Ma'mun, S. Z., & Maksar, M. S. (2024). Analisis Aset Safe-Haven Untuk Pasar Saham Di Indonesia : Studi Pada Emas Dan Bitcoin. *Jurnal Ilmiah Manajemen, Ekonomi, & Akuntansi (MEA)*, *8*(1), 753–769. https://doi.org/10.31955/mea.v8i1.3737

Yang, C.-W., Hsieh, Y.-S., & Hung, C.-Y. (2024). Economic uncertainty and corporate cash holdings: Evidence from Taiwan. *The North American Journal of Economics and Finance*, *73*(October 2023), 102183. https://doi.org/10.1016/j.najef.2024.102183