E3S Web of Conferences **687**, 01015 (2026) https://doi.org/10.1051/e3sconf/202668701015
InCASST 2025

Modelling Bitcoin Price Volatility and The Bitcoin Mining Dilemma on Global Health

Maria Andriani Uge[1] and *Ignatius Aris* Dwiatmoko[1*]

[1] Department of Mathematics, Sanata Dharma University, Yogyakarta, Indonesia

Abstract. In the digital age, Bitcoin remains the first and most notable cryptocurrency. Over the years, its value has increased, making it a desirable digital asset with millions of enthusiasts who trade and invest daily. Bitcoin is highly volatile in comparison with traditional assets and in absolute terms. Understanding its volatility history helps investors decide whether to buy, sell, or hold. A mathematical model that accounts for volatility is essential for these decisions. Unfortunately, Bitcoin's vast profit potential for investors comes with the dilemma of its negative impact on global environmental health, which needs serious attention. This study aims to model Bitcoin's return volatility that can support investment decisions and, on the other hand, the negative impact of Bitcoin mining and outline the actions necessary to mitigate it.

1 Introduction

Bitcoin, as one of the earliest and most influential digital currencies, has attracted considerable global attention as both an investment vehicle and a medium of exchange. Operating on a decentralized network and secured through cryptographic protocol, Bitcoin records all transactions via blockchain technology, a distributed digital ledger.

A defining characteristic of Bitcoin is its pronounced price volatility. These shifts are shaped by factors such as market supply and demand, regulatory interventions, technological developments, and global economic sentiment. While volatility offers opportunities for speculative profit, it also entails significant financial risk, necessitating effective risk management strategies. Understanding and modelling these fluctuations is therefore essential for informed decision-making. Among the available economic approaches, the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model offers a robust framework for analysing and forecasting such volatility. Beyond financial considerations, Bitcoin's growth raises critical environmental concerns. The mining process, integral to transaction validation and coin generation, consumes vast amounts of energy, much of it derived from fossil fuels, resulting in notable ecological impacts. This dual reality presents ethical and economic dilemmas for participants in the Bitcoin ecosystem.

* Corresponding author: aris.dwiatmoko@usd.ac.id

This study aims to model Bitcoin price volatility using the GRACH framework while examining the associated environmental challenges. By integrating these perspectives, the research seeks to provide a holistic understanding of opportunities and constraints for Bitcoin's future.

2 Method

This section presents the methodological background for estimating a time series model of bitcoin volatility changes.

2.1 Bitcoin Price data

This research uses historical data of Bitcoin closing price from Yahoo Finance, a popular website and media property within the Yahoo network that provides financial news, data, and tools for investors interested in the stock market. It offers a wide range of resources, including real-time stock quotes, market analysis, portfolio tracking, and educational content.

Historical Bitcoin closing price data was collected from January 1, 2023, to March 31, 2025, with daily frequency. This period was selected based on preliminary studies showing that from 2023 to 2024, Bitcoin's price movement began to show signs of stability compared to previous years. To model Bitcoin price volatility, two models will be applied: ARIMA and GARCH. The ARIMA model is applied first because it is a classic model for time series data and is a competitor to the GARCH model when several statistical assumptions are met. For this purpose, the data is divided into two parts: training data used to build the model and test data used to test the model's ability to describe actual Bitcoin volatility and price. The training data set spans from January 1, 2023, to December 31, 2024, a period regarded as stable. In contrast, the test data set covers the time frame from January 1, 2025, to March 31, 2025.

Next, the ecological impacts of the Bitcoin industry are described through a literature review, and the steps needed to minimize these impacts are summarized.

2.2 Volatility

Volatility in time series refers to the degree of variability or fluctuation in data over time. In a financial context, it measures the magnitude of price changes for an asset within a given period. High volatility indicates sharp price movements, increasing investment risk, whereas low volatility reflects more stable prices. In unregulated financial markets, unlike traditional markets, accurately estimating volatility is particularly important for assessing potential risk exposure. Employing an appropriate volatility model can improve investment decisions and strengthen risk management strategies. As a key element of financial forecasting, volatility can be explored visually through graphs, which help reveal its underlying structure for model development [1].

2.3 ARIMA Modeling

ARIMA (*Autoregressive Integrated Moving Average*) modelling is a widely used technique for time series analysis. It combines autoregressive, integrated, and moving average components to model and predict future values based on past observations.

A time series, y_t, is called homogeneous nonstationary if it is nonstationary, but becomes stationary after taking its differences, $w_t = (1 - B)^d y_t$, where d is the order of differences.

We say that y_t, follows an autoregressive integrated moving average (ARIMA) process of orders p, d, and q, or ARIMA(p, d, q), if its d-th difference, $w_t = (1-B)^d y_t$ is a stationary ARMA(p, q) process. The term integrated refers to the fact that when $d = 1$, y_t can be expressed as the cumulative sum of the w_t process, $y_t = w_t + y_{t-1} = w_t + y_{t-1} + y_{t-2} = w_t + w_{t-1} + \cdots . + w_1 + y_0$.

The non-seasonal autoregressive integrated moving average process is denoted by ARIMA$(\boldsymbol{p}, \boldsymbol{d}, \boldsymbol{q})$ and be defined as

$$\boldsymbol{\Phi}(\boldsymbol{B})(\mathbf{1}-\boldsymbol{B})^{\boldsymbol{d}} \boldsymbol{x}_{\boldsymbol{t}} = \boldsymbol{\delta} + \boldsymbol{\Theta}(\boldsymbol{B}) \boldsymbol{\epsilon}_{\boldsymbol{t}} \tag{1}$$

where $\boldsymbol{\epsilon}_{\boldsymbol{t}}$ = white noise, $\boldsymbol{\Phi}(\boldsymbol{B}) = \mathbf{1} - \boldsymbol{\phi}_{\mathbf{1}}\boldsymbol{B} - \boldsymbol{\phi}_{\mathbf{2}}\boldsymbol{B}^{\mathbf{2}} - \cdots - \boldsymbol{\phi}_{\boldsymbol{p}}\boldsymbol{B}^{\boldsymbol{p}}$ is AR non-seasonal component and $\boldsymbol{\Theta}(\boldsymbol{B}) = \mathbf{1} - \boldsymbol{\theta}_{\mathbf{1}}\boldsymbol{B} - \boldsymbol{\theta}_{\mathbf{2}}\boldsymbol{B}^{\mathbf{2}} - \cdots - \boldsymbol{\theta}_{\boldsymbol{q}}\boldsymbol{B}^{\boldsymbol{q}}$ is MA non-seasonal component.

The Box-Jenkins method is a powerful approach for modelling and forecasting time series data using ARIMA processes. It involves identifying an appropriate ARIMA model, fitting it to the data, and using it for forecasting.

The selection of the appropriate ARIMA model for time series forecasting involves various criteria. Romanuke [2] proposed a method that minimizes both root-mean-square-error (RMSE) and maximum absolute error (MaxAE) to determine the optimal model. Information criteria like the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are widely used methods for model selection. Furthermore, diagnostic checks, including tests for independence, normality, and homoscedasticity of residuals, are essential in the model-building process [5]. Some normality tests may be used, such as Shapiro-Wilk, Anderson-Darling, and Lilliefors. The power of these tests varies with sample size and the underlying distribution, emphasizing the importance of choosing an appropriate test based on the specific characteristics of the data.

2.4 ARCH and GARCH Model

The ARCH (Auto Regressive Conditional Heteroskedastic) and GARCH (Generalized ARCH) models are widely used in financial forecasting and volatility modeling. These models capture volatility clustering and asymmetry in asset returns. GARCH variants such as sGARCH, eGARCH, gjrGARCH, and FIGARCH are employed to analyze different assets, with each model showing strengths for specific markets [4].

Essentially, the ARCH model explains that the error variance is not constant over time but depends on information from previous periods. Therefore, the ARCH model explains that changes in value at one point in time are not directly related sequentially to changes at previous points in time.

ARCH(m) model is defined as

$$x_t = \sigma_t \epsilon_t \tag{2}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 x_{t-1}^2 + \alpha_2 x_{t-2}^2 + \cdots + \alpha_m x_{t-m}^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i x_{t-i}^2 \tag{3}$$

where $\epsilon_t \sim WN(0,1)$, $\alpha_0 > 0$, $0 < \alpha_i < 1$, and m is the number of error variance lag. This model is very useful for capturing volatility patterns in data that cannot be explained by ARIMA models, thus providing a solid foundation for the development of GARCH models and their derivatives. The GARCH model is an extension of the ARCH model, introduced to provide flexibility in analyzing and predicting volatility in time series data. In the GARCH model, current volatility is influenced by two main components: the error from the previous period and the conditional volatility from the past. This combination represents the AR component of the conditional variance and the MA component of the error. This approach allows the GARCH model to capture more complex volatility patterns than the ARCH model, making it a more effective choice for financial data that often exhibits periods of high volatility followed by stable periods.

GARCH(m, n) model is defined by

$$x_t = \sigma_t \epsilon_t \tag{4}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i x_{t-i}^2 + \sum_{j=1}^{n} \beta_j \sigma_{t-j}^2 \tag{5}$$

where $\alpha_0 > 0, \alpha_i > 0, \beta_j > 0, \sum_{i=1}^{m} \alpha_i + \sum_{j=1}^{n} \beta_j < 1$, m is the number of error variance lag, n is the number of conditional variance lag, and ϵ_t is standard normal *White Noise*.

GARCH model defined by

$$x_t = \sigma_t \epsilon_t \tag{6}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \beta_i \sigma_{t-i}^2 + \sum_{j=1}^{n} (1 - \beta_j) x_{t-j}^2 \tag{7}$$

is called *Integrated* GARCH (iGARCH). It is a special case of Eq.(5) when $\sum_{i=1}^{m} \alpha_i + \sum_{j=1}^{n} \beta_j = 1$.

GARCH model defined by

$$x_t = \sigma_t \epsilon_t \tag{8}$$

$$\log(\sigma_t^2) = \alpha_0 + \alpha_1 g\left(\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right) + \beta_1 \log(\sigma_{t-1}^2) \tag{9}$$

which

$$g\left(\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right) = \theta_1 \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \left(\left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right| - E\left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right|\right) \tag{10}$$

is called *Exponential* GARCH (eGARCH). It is used to capture the asymmetric effect in volatility. Function $g\left(\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right)$ is an asymmetric component that allows volatility to respond differently to positive and negative fluctuations. The coefficient θ_1 captures the asymmetric directional effect, while $\left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right| - E\left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right|$ describes the model sensitivity to the magnitude of fluctuations.

Volatility asymmetry describes a condition in which volatility reacts more strongly to declines in value or price than to equivalent increases. In models such as EGARCH, this feature is crucial for accurately representing volatility behaviour, particularly in datasets that are highly sensitive to value or price fluctuations.

The parameter estimation process for the GARCH(m, n) model is essentially an extension of that used in the ARCH(m) model. In ARCH(m), the conditional variance is determined solely by past errors from the previous period up to the m-th lag. In contrast, GARCH(m, n) also incorporates the influence of past conditional variance up to the n-th lag. Similar to ARCH, the parameters of the GARCH(m, n) model are typically estimated using the Maximum Likelihood Estimation (MLE) method. In this study, the GARCH(m, n) modeling steps using the Box-Jenkins method. To determine the most suitable ARCH model from several candidates, four key criteria must be met: significant parameter estimates, the lowest AIC and BIC values, residuals that are white noise and normally distributed, and the model's ability to capture both the ARCH effect and volatility asymmetry.

In many cases, model residuals are not normally distributed, indicating irregularities in the data such as excess kurtosis or heavy tails. To handle this, heteroskedastic models can be combined with alternative distributions, including the Student-*t*, Generalized Error Distribution (GED), Skewed Student-*t*, or Skewed GED. Such adaptations allow the model to better capture and predict data characterized by large fluctuations.

R. Cerqueti et al. highlight that GARCH-based methods for modeling cryptocurrency volatility can relax the error normality assumption [6]. By incorporating non-normal distributions, GARCH models offer greater flexibility in capturing heavy tails, leading to improved performance. Their analysis indicates that the skewed GED model is the most suitable choice for modelling and forecasting volatility in cryptocurrency markets.

3 Result and Discussion

Based on Bitcoin price fluctuation extracted using R software from the Bitbo Bitcoin Calendar, Bitcoin has experienced substantial volatility since 2015, driven by regulatory actions, institutional participation, and global economic events. Major downturns occurred in 2018 and 2022, while recoveries in 2020 and 2021 highlighted its appeal as both a speculative and institutional asset. From these facts, it is evident that Bitcoin prices are susceptible to regulatory development, which contributes to substantial volatility. However, from 2023 to early 2025, Bitcoin's price movements have shown a more structured response to market forces and global policy shifts. This trend reflects growing acceptance of Bitcoin not only among institutional and retail investors but also within government circles worldwide. Expanding support for the crypto ecosystem, coupled with more open policy measures, has reinforced the perception that Bitcoin is evolving from a purely speculative asset into a credible long-term investment vehicle. This shift has contributed to a tendency toward more stable volatility in Bitcoin during this period, an important signal for enhancing risk prediction models and fostering more rational investment decisions in the crypto market.

In this study, the historical Bitcoin closing price data spans January 1, 2023, to March 31, 2025, with daily frequency. The dataset is split into two segments: training data, covering January 1, 2023, to December 31, 2024 – identified as a relatively stable period – and test data, covering January 1, 2025, to March 31, 2025, used to evaluate the model's ability to capture Bitcoin's volatility and price behaviour.

3.1 Bitcoin's Price Volatility Modelling

3.1.1 ARIMA Modelling

During the model identification stage, the ADF test at $\boldsymbol{\alpha = 0.05}$ significance level indicated that Bitcoin's closing price data was non-stationary, with a *p*-value of 0.5835 > a. To address this, and in line with S. A. Gyamerah (2019), financial analysis often transforms the data by computing the log return of original prices [7]. If $\boldsymbol{x_t}$ and $\boldsymbol{x_{t-1}}$ denote the Bitcoin prices on the current and previous day, respectively, the log return can be illustrated as shown in Figure 1, and it is calculated as:

$$r_t = \log(x_t) - \log(x_{t-1}) \tag{11}$$

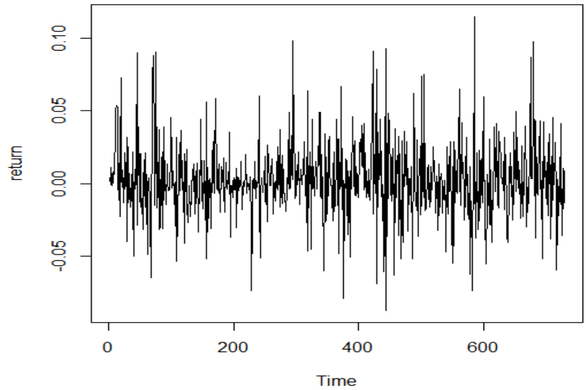

Fig. 1. Log return Bitcoin price fluctuation of training data

Repeated ADF stationary test gives p-value = 0.01< a, the Bitcoin closing price return is stationary. At the ARIMA model estimation stage, an ARIMA(0,0,0) model with a non-zero mean was produced as the best model, m=0.0024, and $AIC = -3289.75$ with the equation $x_t = 0.0024 + \epsilon_t$. However, at the model diagnostic examination stage, the model meets the white noise error assumption (*p-value*=0.3768 > *a*), but fails to meet the normality assumption ($p - value = 1.133 \times 10^{-13} < \alpha$). This non-normality may indicate the presence of fat tails or volatility patterns that cannot be captured by ARIMA(0,0,0) model. Therefore, a GARCH model is needed that can accommodate heteroscedasticity and capture volatility patterns common in financial asset returns.

3.1.2 GARCH Modeling

The GARCH model identification process begins by testing for the presence of an ARCH effect using the residuals from the preceding ARIMA(0,0,0) model. The formal LM test produces a p-value of 0.01558, which is less than α = 0.05, indicating a significant ARCH effect. This result confirms the presence of heteroscedasticity, making the application of the GARCH model appropriate. During the log-return model estimation phase, several GARCH variants are evaluated, including the standard GARCH model with specific orders, the iGARCH, and eGARCH models. Below are the parameter estimation results for sGARCH(1,1), iGARCH(1,1), and eGARCH(1,1) models, each estimated under the assumption of a non-normal error distribution. The estimation process was done using the R software.

By comparing the models utilizing Student-t, skewed Student-t, GED and skewed GED, it indicates that skewed GED is the most suitable distribution for capturing the characteristics of the historical data analyzed. Furthermore, a more in-depth analysis of skewed GED in indicates that all parameters are significant only in the eGARCH(1,1) model. Therefore, a diagnostic check is conducted on this model to verify whether it can be considered the optimal choice.

Based on the results of Table 1, it can be confirmed that the eGARCH(1,1) model with Skewed GED is the best model that describes the historical Bitcoin closing price data for the period January 1, 2023, to December 31, 2024.

 https://doi.org/10.1051/e3sconf/202668701015

Table 1. Diagnostic check results of eGARCH (1, 1) model with *Skewed* GED

White Noise		**The existence of the ARCH effect**		**The existence of the Asymmetrical effect**	
p-value	Yes/No	p-value	Yes/No	p-value	Yes/No
0.5955	Y	0.7158	T	0.4241	T

3.1.3 Bitcoin Price volatility Prediction with the Best Model

After applying the eGARCH(1,1) model with a skewed GED distribution to historical Bitcoin data, the next step is to use it for forecasting conditional volatility, providing essential insights into market uncertainty. This information is critical for guiding investment decisions, enabling investors to better manage risk and develop strategies that respond effectively to anticipated price fluctuations. Figure 2 compares historical volatility data with predicted values, extracted from numerical calculations in the period from January to March, 2025. The Bitcoin volatility plot shows a downward trend, suggesting lower risk for market participants during this period. Using the GARCH(1,1) model, the predictions closely track actual volatility movements, with an RSME of 0.00142 and an MAE of 0.00081, both relatively small error values. This indicates the model's high accuracy in capturing the key characteristics of Bitcoin log return volatility, including the nonlinear and asymmetric pattern common in crypto markets.

The eGARCH model's strong performance highlights its advantage over simple historical methods, offering smoother estimates while remaining responsive to market shocks. This makes it a valuable tool for volatility forecasting, risk management, and Bitcoin investment planning.

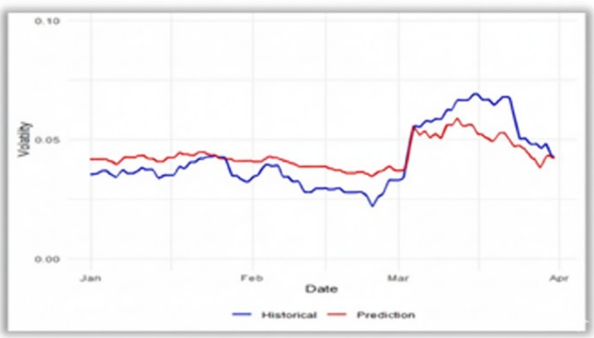

Fig. 2. Plot of historical and prediction volatility

3.1.4 Bitcoin Business Dilemma

Known as one of the cryptocurrencies, Bitcoin is often described as a digital or virtual form of money. Operating independently of centralized legal authorities, they exist outside traditional regulatory frameworks, making direct control challenging. Owing to their substantial market capitalization and high transaction volumes, cryptocurrencies have become a significant phenomenon in the global economy.

Acquisition is not limited to trading on Bitcoin exchanges; individuals can also obtain them through the process of mining, whereby new coins are generated. The rapid expansion of Bitcoin markets in recent years has drawn considerable public and institutional interest.

Beyond their roles as investment vehicles and payment methods, the potential to generate income through mining has played a pivotal role in driving broader adoption of these digital assets. The primary motivation for high financial returns is the reason for the emergence of the problem of high energy consumption. This drives the massive use of high-powered machines. The three countries with the highest Bitcoin mining volume are the US (38%), China (21%), and Kazakhstan (12%), all of which are heavily dependent on fossil fuels [8].

Based on recent peer-reviewed studies, Bitcoin poses multiple environmental challenges with far-reaching implications. First, the environmental impact of Bitcoin mining has become a serious issue due to its enormous energy use and resulting pollution. Between mid-2022 and mid-2023, the 34 largest Bitcoin facilities in the U.S used 32.3 terrawatt-hours of electricity, with 85% coming from fossil fuels. This led to 1.9 million Americans being exposed to extra PM 2.5 air pollution [9]. On a global scale, Bitcoin mining consumed 173.42 TWh of electricity in 2020-2021, releasing more than 85.89 Mt of CO2eq - the same as burning 84 billion pounds of coal. In addition to carbon emissions, Bitcoin mining also places heavy demands on natural resources, consuming 1.65 km^3 of water worldwide in 2020-2021 and requiring over 1,870 square kilometers of land [10], Magdalena, R., et al [5] examined the environmental impact of Bitcoin (BTC) mining, focusing on water and carbon footprints, and the role of energy transition in top BTC-emitting countries. The result showed Bitcoin mining was found to harm the environment, with water usage having a limiting impact. Moreover, according to the Cambridge Centre for Alternative Finance (CCAF), a research center at the Cambridge Judge Business School, University of Cambridge, Bitcoin consumes more energy than all other cryptocurrencies combined, representing 60-70% of global crypto electricity use, with 62% of its power coming from fossil fuels and only 26% from renewables. Beyond emissions, mining generates substantial heat and short-lived hardware waste, around 30.7 kilotons annually, similar to all IT waste from the Netherlands, posing a risk of toxic pollution. If the trend continues, Bitcoin e-waste could exceed 64.4 kilotons annually, worsening the global e-waste problem.

Second, its climate-related damages are substantial, with estimates indicating that each dollar of bitcoin market value generates approximately $0.35 in global climate harm, and in some periods, these damages have exceeded the cryptocurrency's own market price [11]. Bitcoin uses a "proof-of-work" (PoW) algorithm to validate its transactions. This Algorithm requires intensive computation that grows progressively more complex over time, resulting in a substantial increase in the computer power needed [12]. A wide range of studies have investigated the impact of cryptocurrency mining on global health. The studies examine the environmental and health risks of PoW cryptocurrency mining, especially Bitcoin, due to its high energy consumption and carbon emissions. PoW mining requires vast computational power, leading to significant pollution and health issues, such as respiratory and cardiovascular diseases from harmful emissions. The studies stress the urgent need for a shift to renewable energy sources and a more sustainable consensus mechanism like Proof-of-Stake (PoS), which is less energy-intensive. Third, rapid hardware obsolescence contributes to electronic waste generation, with specialized mining devices averaging only 1.3 years of use and producing around 30,7000 tons of e-waste each year. Fourth**,** mining operations place a heavy burden on water and land resources, using an estimated 1.65 km^3 of water and occupying 1,870 km^2 of land during 2020-2021, which can strain ecosystems and local communities [13].

3.1.5 The relationship between Bitcoin price volatility and environmental costs

From the above discussion of Bitcoin price volatility, it can be concluded that the eGARCH(1,1) model is the best one. This model will then be described to get a better roadmap in relation to the environmental parameters (e.g., CO2, e-waste). The primary conclusion obtained from this model is that it yields valuable insights toward Bitcoin price stability, which can be utilized to guide investors in making decisions toward transactions (purchase, sale, or holding) with reduced economic risk. Price stability enhances investors' confidence in Bitcoin transactions. A second-order question arises: how much does the decreased volatility indicated by the model (Figure 2) relate to patterns of mining efficiency or energy consumption? As indicated in the previous subsection, Bitcoin mining has a direct effect on energy consumption and environmental degradation. The correlation between the elasticity of volatility and energy consumption in Bitcoin can be grasped by analyzing significant concepts in economics and network characteristics of Bitcoin. Volatility in Bitcoin refers to the extreme price volatility, and the elasticity of volatility is the way the price movement reacts to such circumstances as investor sentiment, market depth, or mining cost. The energy use of Bitcoin, fueled by its Proof-of-Work (PoW) consensus mechanism, has created environmental issues over the last few years: a). Volatility and Market Behavior. Price volatility of Bitcoin, driven by speculation and market sentiment, will draw investors into the market, b). Elasticity and Energy Consumption. Volatility elasticity measures how responsive Bitcoin is to changes in events such as network size, mining reward, or advancements in technology.

Some important findings regarding the relationship between Bitcoin price volatility and environmental health issues can be summarized as follows.

3.1.5.1 Bidirectional causality between volatility and electricity consumption

A recent study [14], which uses daily data from March 2019 to March 2023, finds that there is bidirectional causality between Bitcoin's electricity consumption and crypto market volatility. The study concludes that volatility (or market risk, crypto volatility index, etc.) appears to be associated with electricity consumption, although the relationship is more complex/non-linear. Bitcoin price causes electricity consumption, but consumption does not cause price.

3.1.5.2 Price correlates with energy consumption

Multiple studies show that Bitcoin's price rises, mining becomes more profitable, which tends to lead to higher energy consumption (more miners operating, possibly older/less efficient hardware being used, more hash rate) because the incentives increase.

The "Bitcoin-energy markets interrelationships" paper finds positive correlation and growing interaction between Bitcoin price volatility and utility/energy markets (for example, in the U.S.), especially during price surges like late-2017/early-2018.

Another study, ”Impact of Bitcoin mining and crypto market determinants and Bitcoin-based energy consumption”, shows that the crypto market index and Ethereum price (with lags) influence Bitcoin's electricity consumption and carbon emissions.

3.1.5.3 Mining continues even in loss, if price expectations are positive

One unexpected finding is that some miners continue operating even when operating at a loss, if they believe the price will go up–consistent with value-investing behaviour [14].

The causal relationship between Bitcoin price volatility and environmental costs that can be represented by the eGARCH(1,1) model suggests some recommendations. The significant environmental consequences of Bitcoin mining pose major challenges to its otherwise profitable industry. It is essential to implement measures that can prevent, or at least lessen, these effects to protect the sustainability of our planet. Based on recent scholarly research, several strategies have been proposed to mitigate the environmental impact of Bitcoin mining. First**,** integrating renewable energy sources, such as a photovoltaic system combined with grid connections and an energy-swapping mechanism, can substantially lower carbon emissions, with studies recommending policy mandates to ensure renewable adoption in large-scale mining facilities [15]. Second, enhancing hardware efficiency through the use of high-performance ASIC miners, optimized operating conditions (e.g., overclocking and undervolting), and extending device lifespans can reduce electricity consumption per unit of computation. Third, a transition to a low-energy consensus mechanism, particularly Proof-of-Stake, offers the potential to reduce energy demand by orders of magnitude compared to Proof-of-Work, as demonstrated by Ethereum's network shift [15]. Fourth**,** mining operations powered by renewables can serve as a flexible load resource, absorbing surplus energy during periods of low demand, which helps stabilize the grid and encourages further expansion of renewable capacity. Finally, policy and governance intervention, including regulations that mandate renewable use, incentivize decentralization, promote carbon offset tracking, and support the adoption of energy-efficient protocols, is necessary for ensuring the sector's long-term environmental sustainability.

4 Conclusion

Bitcoin was able to create an international community and start an entirely new industry from scratch in the form of a business centered around investment trading by using Bitcoin. For Bitcoin market players, mathematical models capable of forecasting investment risks are of great importance. This study suggests that the GARCH model, specifically eGARCH (1,1) with skewed GED, is the most suitable and can support investment decisions and risk management in the Bitcoin market.

An increase in Bitcoin's price enhances mining profitability, which encourages more miners to participate or results in activation of less efficient, more energy-intensive operations. Consequently, this leads to an increase energy consumption. When volatility rises, the eGARCH model provides a warning, particularly with significant price fluctuations or expectations of future price growth. Miners may expand their operations or continue mining during downturns in anticipation of a rebound. Thus, volatility can indirectly drive higher energy consumption by influencing price dynamics or market expectations.

Bitcoin mining poses numerous environmental challenges that have wide-ranging consequences, namely: high energy use, carbon emissions, e-waste, and heavy water and land demands, which endanger ecosystems and public health. Its reliance on fossil fuels and Proof-of-Work worsens climate damage, making sustainability unattainable without change. Key solutions include renewable energy adoption, efficient hardware, low-energy consensus mechanisms, and strong regulatory measures, though significant implementation barriers remain.

The limitation of this study is that the data used does not allow for an integrated analysis of the direct impact of price volatility on environmental cost. Price fluctuation directly influences mining profitability, which in turn drives changes in energy consumption, carbon emissions, and resource use. Future research should develop integrated models that link price volatility with environmental forecasting, develop econometric or machine learning models that jointly forecast Bitcoin price volatility and environmental impacts, providing policymakers and stakeholders with more accurate tools to assess both financial risk and sustainability challenges.

The authors would like to express their sincere gratitude to the Head of the Mathematics Study Program, Sanata Dharma University, for the generous financial support provided, which enabled the presentation of this work at the International Conference on Applied Sciences and Smart Technologies 2025. This support has been invaluable in facilitating the dissemination of our research to the international academic community. Authors' contributions and responsibilities: M.A.U. explore the main idea, data gathering, formal statistical analysis and modelling; I.A.D.: propose the main idea, validating the statistical analysis, writing the initial draft; All authors reviewed the final manuscript.

References

1. A.J. Lawrance, Exploratory Graphics for Financial Time Series Volatility, J. R. Stat. Soc. Ser. C: Appl. Stat. **62**(5), 669–686 (2013). https://doi.org/10.1111/rssc.12016
2. I. Romanuke, ARIMA Model Optimal Selection for Time Series Forecasting, Marit. Technol. J. **224**(1), 28–40 (2022). https://doi.org/10.2478/sjpna-2022-0003
3. J. Bai, S. Ng, Tests for Skewness, Kurtosis, and Normality for Time Series Data, J. Bus. Econ. Stat. **23**(1), 49–60 (2005). https://www.jstor.org/stable/27638793
4. A. Ampountolas, Enhancing Forecasting Accuracy in Commodity and Financial Markets: Insight from GARCH and SVR Models. Int. J. Financial Stud. **12**(3), 59 (2024). https://doi.org/10.3390/ijfs12030059
5. R. Magdalena, et al. Evaluating the environmental effects of bitcoin mining on energy and water use in the context of the energy transition. Sci Rep 15, 8230 (2025). https://doi.org/10.1038/s41598-025-92314-z
6. R. Cerqueti, et al., Skewed non-Gaussian GARCH Models for Cryptocurrencies Volatility Modelling. arXiv:2004.11674 (2004). https://arxiv.org/abs/2004.11674
7. S. A. Gyamerah, Modelling the Volatility of Bitcoin Returns using GARCH Models. Quantitative Finance and Economics **3**(4), 739-753 (2019). doi: 10.3934/QFE.2019.4.739
8. F. Ulaşan, The Environmental Effect of Cryptocurrency Mining in the World, J. Sustain. Econ. Manag. Stud. **3**(1), 1–20 (2022). https://dergipark.org.tr/en/download/article-file/3464588
9. G. Guidi, et al., The Environmental Burden of the United States 'Bitcoin Mining Boom, Research Square **1** (2024). https://doi.org/10.21203/rs.3.rs-5306015/v1
10. U. Draz, et al., Decentralized Energy Swapping for Sustainable Wireless Sensor Networks Using Blockchain Technology. Mathematics, **13**(395), (2025). https://doi.org/10.3390/math13030395
11. B.A. Jones, A.L. Goodkind, R.P. Berrens, Economic Estimation of Bitcoin Mining's Climate Damages, Sci. Rep. **12**(14512), (2022). https://doi.org/10.1038/s41598-022-18686-8
12. M.D. Willis, et al., Potential Health Hazards of Cryptocurrency Mining: Protecting Health in a "Digital Oil Boom", JAMA **332**(16), 1329–1330 (2024). https://doi.org/10.1001/jama.2024.15917
13. S. Chamanara, et al., The Environmental Footprint of Bitcoin Mining Across the Globe: Call for Urgent Action. Earth's Future, **11**(10), (2023). https://doi.org/10.1029/2023EF003871

14. N. Sapra, et al., Uncovering Bitcoin's electricity consumption relationships with volatility and price: Environmental Repercussions. Journal of Environmental Management (2024). https://doi.org/10.1016/j.jenvman.2024.120528
15. A.Hakimi, M.Pazuki, M.Salimi, M.Amidpour, Renewable Energy and Cryptocurrency: A Dual Approach to Economic Viability and Environmental Sustainability, Heliyon. **10**(22), e39765 (2024). https://doi.org/10.1016/j.heliyon.2024.e39765