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What determines Bitcoin's price over the past decade?

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ABSTRACT

We employ a novel three-stage analysis method of ICEEMDAN-Van der Waerden Test-Elastic Net to analyze Bitcoin's price. Our research aims to explain how Bitcoin's price has been formed at different phases of development over the past decade. We have segmented the daily closing price of Bitcoin from November 1, 2013, to December 31, 2023, into five phases, utilizing the ICEEMDAN method to decompose them into intrinsic mode functions, followed by the reconstruction of high-frequency, low-frequency, and trend curves using the Van der Waerden Test. With Elastic Net, we identify the top ten factors impacting the high-frequency, low-frequency, and trend curves during each phase. Our findings reveal a strong correlation between the high-frequency curve, investor sentiment, and daily transaction frequency in the Bitcoin market. The significant rises and falls in the low-frequency curve correspond to important events in the Bitcoin market or global political and economic occurrences. The trend curve is decisive in determining the long-term trajectory of Bitcoin's price. Over the long term, our analysis indicates that Bitcoin's price is influenced predominantly by macroeconomic fundamentals and market vitality. Bitcoin's price is evolving, shifting from focusing on its internal production factors to relying more on external macroeconomic factors. Of the major asset classes, Bitcoin's correlation with stocks has grown the most significantly. Due to Bitcoin's increasing market vitality and the decrease in Bitcoin's issuance speed changing the supply-demand dynamics, Bitcoin's price is on an upward trajectory in the long term. Furthermore, our findings provide insights into Bitcoin's speculative and safe-haven properties. Our work also facilitates more accurate predictions of Bitcoin's future prices.

1. Introduction

Since Bitcoin first breached $1000 per unit in November 2013, the Bitcoin market has experienced a decade marked by undulations. Over these ten years, Bitcoin's price has rapidly expanded, capturing global attention. Concurrently, the international landscape has been characterized by a series of significant unforeseen events that have intermittently impacted or persistently altered Bitcoin's price trajectory. In light of these considerations, some puzzles arise: What are the determinants of Bitcoin's price in the long term, and what mechanisms underlie the formation of Bitcoin's price?

The resolution of the two puzzles could potentially facilitate a sound understanding of Bitcoin, effectively quieting the long-standing debates about its economic nature. The answers are instrumental in discerning whether Bitcoin possesses the attributes of a safe haven or a hedge (Baur, Dimpfl, & Kuck, 2018; Bouri, Molnár, et al., 2017; Conlon & McGee, 2020; Corbet et al., 2020; Corbet, Meegan, et al., 2018; Dyhrberg, 2016a; Dyhrberg, 2016b). The resolution of the two puzzles also significantly aids in predicting Bitcoin's price. Once we comprehend how Bitcoin's price is established and identify the primary factors influencing Bitcoin's price in the short and long term, we may employ suitable forecasting methods to predict the short-term rises accurately and falls of Bitcoin and its long-term price trends (Akyildirim et al., 2021; Akyildirim et al., 2023; Bergsli et al., 2022; Caliciotti et al., 2024; Chen et al., 2021; Demir et al., 2018; Jana et al., 2021; Khedr et al., 2021; Mtiraoui et al., 2023; Sanli et al., 2023).

In this paper, we endeavor to address the two puzzles. Our method is inspired by the work of some researchers (Zhang et al., 2008; Zhang et al., 2009). We address the two puzzles at different frequencies of Bitcoin's price fluctuations, examining short-term, mid-term, and long-

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term factors during various phases. Our improved methodology allows for a comprehensive understanding of Bitcoin's price formation and fluctuation patterns by analyzing the factors affecting Bitcoin's price fluctuations at different phases of Bitcoin market development. Therefore, we divide the period from November 1, 2013, to December 31, 2023, into five phases. In each phase, we utilize the ICEEMDAN method to decompose the daily closing price of Bitcoin and then apply the Van der Waerden Test to synthesize the IMFs into high-frequency, low-frequency, and trend curves. Subsequently, we employ the Elastic Net regression to identify the top ten factors influencing the high-frequency, low-frequency, and trend curves, respectively, from a list of 47 potential factors impacting Bitcoin's price that we summarized from literature reviews (Aysan et al., 2019; BenSaida, 2023; Bhuiyan et al., 2023; Chen et al., 2021; Ciaian et al., 2016; Corbet, Meegan, et al., 2018; Demir et al., 2018; Khedr et al., 2021; Kristoufek, 2015; Kwon, 2021; Liu et al., 2022; Panagiotidis et al., 2024; Said et al., 2023; Selmi et al., 2018; Shahzad et al., 2019; Shahzad et al., 2020; Su et al., 2022; Urquhart & Zhang, 2019; Wang et al., 2020; Wang & Hausken, 2022; Zhu et al., 2017). We categorize these 47 factors influencing Bitcoin's price into five categories and calculate the overall weights for each category using Elastic Net regression coefficients. This approach provides a more direct means of analyzing how the influence of different factors on Bitcoin's price has evolved over the past decade.

Through analyzing factors influencing the high-frequency, low-frequency, and trend curves of Bitcoin's price across these five phases, we answer the two aforementioned puzzles. The trend curve serves as the long-term determinant of Bitcoin's price, with factors of macroeconomic environment, factors of Bitcoin market conditions, factors of Bitcoin's production and transaction, and factors of Bitcoin's supply-demand dynamics influencing this trend. Bitcoin price formation is a result of short-term (daily) fluctuations driven by investor sentiment and daily trading frequency in the Bitcoin market, medium-term fluctuations triggered by significant events (major Bitcoin market events or global political and economic events), and the long-term price trend of Bitcoin determined by macroeconomic environment and Bitcoin market vitality. Over time, the influence of Bitcoin's production and transaction on Bitcoin's price gradually diminishes, while the impact of macroeconomic factors on Bitcoin's price increases. Bitcoin's interconnectedness to stocks has grown fastest among common financial assets such as stocks, currencies, and commodities.

The contributions of this paper lie in three main aspects. First, we employ a novel three-stage analysis method of ICEEMDAN-Van der Waerden Test-Elastic Net to analyze Bitcoin's price. The Kruskal-Wallis test, a prevalent non-parametric test in single-factor models, operates on data rankings. The Van Der Waerden test combines the precision of standard ANOVA under normality with the robustness of the Kruskal-Wallis test in the absence of normality (Connover, 1999; Kruskal & Wallis, 1952; Van der Waerden, 1952; Van der Waerden, 1953). Second, we analyze the daily closing price of Bitcoin over the past decade, summarizing the significant events that have had a major impact on the Bitcoin market during its evolution. This helps to further understand the mid-term fluctuation patterns of Bitcoin. Third, our answers to the question of how Bitcoin's price is formed could contribute to further discussions on the economic nature of Bitcoin and provide insights into predicting Bitcoin's price. The factors influencing Bitcoin's short-term and mid-term price fluctuations and long-term trend are outlined in our paper, which will assist in predicting Bitcoin's price.

The structure of this paper is as follows. The second section is a literature review of research papers on price discovery of Bitcoin. The third section introduces the Bai-Perron Multiple Breakpoint Test and the ICEEMDAN-Van der Waerden Test-Elastic Net three-stage analysis method. The fourth section elaborates on the data sources used in this paper and provides classifications and explanations for the 47 factors influencing Bitcoin's price. In the fifth section, we analyze the statistical metrics and influencing factors of Bitcoin's price's high-frequency, low-frequency, and trend curves across the five phases. Finally, in the sixth section, we summarize our analysis of Bitcoin's price during these five phases and offer some suggestions for investors in the Bitcoin market.

2. Literature review

Since its inception, the formation of Bitcoin's price, the determination of its fundamental value, and the factors driving its price fluctuations have been persistent questions. Scholars have engaged in extensive debate and offered diverse perspectives on these issues, leading to a lack of consensus. To address this, we present a comprehensive review of the relevant literature spanning the past decade, exploring the insights gleaned from these research endeavors.

The answer to how Bitcoin's price is formed largely depends on the perspective adopted to analyze it. The first study on the formation of Bitcoin's price examined it from an investment perspective, utilizing an augmented version of Barro's model for the gold standard, analyzing the long-term implications of three assumptions regarding the formation of Bitcoin's price: market forces of supply and demand, investment attractiveness, and global macroeconomic and financial developments. Empirical results indicated that market forces of supply and demand significantly influence Bitcoin's price, with demand-driven factors emerging as key drivers of Bitcoin's price in the future (Ciaian et al., 2016). Further analysis of demand-side factors revealed that the value of virtual currencies is influenced by forward-looking investors' purchasing decisions and expectations and the acceptance of virtual currencies for value transactions (Bolt & van Oordt, 2019).

When applying monetary economics theory to explain Bitcoin price formation, some researchers have found that Bitcoin's transactional usage, money supply, and price level play a role in determining its long-term price (Kristoufek, 2015). Others have analyzed Bitcoin's price from the perspective of production, using price data for 66 of the most widely accepted cryptocurrencies. They identified three key drivers of cryptocurrency prices under the Proof-of-Work consensus mechanism, including Bitcoin: the level of competition in cryptocurrency production, unit productivity, and the difficulty of mining cryptocurrencies. This led to the conclusion that Bitcoin's value stems from its production costs (Hayes, 2017). Subsequently, researchers proposed methods to predict price bubbles in Bitcoin based on its production costs (Xiong et al., 2020). Several researchers have recognized that Bitcoin is both a technological innovation and an economic instrument for value transactions. As the Bitcoin market matures and becomes more rational, the influence of mining difficulty on Bitcoin's price diminishes. In the long term, Bitcoin's price aligns with economic fundamentals (Li & Wang, 2017). Analyzing Bitcoin's price from the perspective of asset security and stability reveals that a portion of Bitcoin's price originates from investors' pricing of the risk of systemic attacks. Increased Bitcoin security leads to further appreciation in its price (Pagnotta, 2022).

The debate surrounding Bitcoin's fundamental value has been equally enduring. Early scholars argued that Bitcoin's price contained significant bubbles and its fundamental value was zero (Cheah & Fry, 2015; Fry & Cheah, 2016). Bitcoin is often perceived as a speculative asset (Baur, Hong, & Lee, 2018; Corbet, Lucey, & Yarovaya, 2018). The significant price increases of Bitcoin frequently linked to questionable trading activities (Gandal et al., 2018). Price manipulation exists in the cryptocurrency market, resulting in an average price distortion of 65 % and millions of dollars in suspect transactions (Dhawan & Putnins, 2023). So, how can Bitcoin's fundamental value be defined? Some research defines it as its net trading revenue stream, dependent on its future price. Therefore, variations in Bitcoin's returns partially reflect changes in its fundamental value, while primarily reflecting external fluctuations in its price (Biais et al., 2023). Other studies define Bitcoin's fundamental value as the equilibrium price in a rent-seeking competition between the protocol and miners, where the fundamental value is the marginal cost of mining Bitcoin to its target supply (Podhorsky, 2024).

The aforementioned studies on the formation of Bitcoin's price and fundamental value have unveiled the key factors influencing Bitcoin's price. More specifically, research on Bitcoin's monthly price data has revealed that the US Dollar Index has a far greater impact on Bitcoin's price than gold (Zhu et al., 2017). Studies on the factors influencing Bitcoin's returns have found that among external factors, sentiment and technical factors have the most profound impact on Bitcoin's returns (Panagiotidis et al., 2024). Among intrinsic factors, cryptocurrencies with larger variance tend to have lower subsequent weekly returns (Lee & Wang, 2024). Bitcoin's transaction fees are also often considered a factor influencing Bitcoin's price. The relationship between Bitcoin's transaction fees and its network congestion is highly nonlinear (Huberman et al., 2021). Excessive transaction fees or long waiting times can lead to the departure of potential users, thereby impacting Bitcoin's development as a medium of exchange (Easley et al., 2019).

Decomposing price data to study the price formation of cryptocurrencies is a common research approach. Some scholars have used decomposition methods to separate Bitcoin's price into an efficient component and a noise component, with the noise component often attributed to the high attention from investors in the market (Ibikunle et al., 2020). When analyzing daily price fluctuations in Bitcoin, investors in the Bitcoin market tend to overreact to negative shocks, especially in the 6–24 h following the event (Miralles-Quiros & Miralles-Quiros, 2022). Other researchers have used the Empirical Mode Decomposition (EMD) method to decompose the daily data of the Bitcoin Price Index from December 2010 to June 2015, resulting in 9 IMFs and one residue. These components were then reconstructed into high-frequency, low-frequency, and trend curves using *t*-test. The conclusion drawn was that Bitcoin's price is extremely driven by long-term fundamentals (Bouoiyour et al., 2016).

The method of using Empirical Mode Decomposition (EMD) to study asset prices is also common outside the field of cryptocurrency research. Scholars have applied EMD and *t*-test to investigate the price composition of crude oil over the past decades (Zhang et al., 2008). An event analysis method based on EMD was proposed to analyze the impact of extreme events on the crude oil markets (Zhang et al., 2009). Decomposition and subsequent forecasting of time series using EMD can effectively improve the accuracy and precision of predictions (Liu et al., 2017; Ren et al., 2015; Wang & Yu, 2022).

Inspired by these studies, our research uses the Bai-Perron Multiple Breakpoint Test to divide the ten years of Bitcoin's price data into five phases. Within each phase, we employ the ICEEMDAN method, which is an improved version of EMD, to decompose the Bitcoin's daily closing price over the decade. Subsequently, we utilize the Van der Waerden Test, which makes weaker assumptions about data and is more effective than the *t*-test in nonparametric testing, to reconstruct the obtained IMFs into high-frequency and low-frequency curves, with the residue representing the trend curve. To provide more convincing economic interpretations for the high-frequency, low-frequency, and trend curves, we employ Elastic Net to select from 47 potential factors influencing Bitcoin's price. Therefore, our findings offer a comprehensive and objective explanation of the formation Bitcoin's price across different frequencies. We also reveal the dynamic process of how Bitcoin's price is influenced by different factors in different phases.

3. Methodology

3.1. Bai-Perron Multiple Breakpoint Test

The Bai-Perron Multiple Breakpoint Test is a sophisticated econometric technique that detects several structural changes in a time-series dataset. Proposed by economists Jushan Bai and Pierre Perron, this test allows for multiple breakpoints, enhancing its utility in fields like economics, finance, and social sciences where data often exhibits structural shifts over time. The underlying principle of the Bai-Perron test revolves around identifying instances in a time-series where statistical properties such as mean and variance experience shifts. The algorithm executes this by iteratively checking for structural breaks at all feasible time points and subsequently selecting the breakpoint that minimizes the sum of squared residuals. Overall, the Bai-Perron Multiple Breakpoint Test serves as a robust tool for detecting multiple structural breaks in time-series data, facilitating deep insights into the temporal evolution of data trends (Bai, 1997; Bai & Perron, 1998; Bai & Perron, 2003).

The advantages of the Bai-Perron Multiple Breakpoint Test can be summarized into at least the following three points. First, unlike the Chow-Type Test which can only test for a single break, the Bai-Perron Multiple Breakpoint Test can handle multiple structural breaks. Second, the Bai-Perron Multiple Breakpoint Test can endogenously determine the optimal break dates without needing to know the break dates in advance. Third, the Bai-Perron Multiple Breakpoint Test provides a framework for testing the null hypothesis of no structural breaks against an alternative hypothesis of an unknown number of breaks.

This study employed EViews to conduct a Global Bai-Perron L Breaks VS. None on ten years of Bitcoin price data. Based on the value of the Weighted F-Statistic, we believe the optimal number of breakpoints is 4. These four breakpoints are: May 23rd 2016, Dec 17th 2017, Mar 13th 2020, and Oct 21st 2021.

3.2. The three-stage analysis method

3.2.1. First stage with ICEEMDAN

We employ various advanced signal processing techniques. Initially, we used the Empirical Mode Decomposition (EMD) method, which is ideal for non-linear and non-stationary data analysis (Huang et al., 1998). However, due to its mode mixing limitations, where a single IMF might contain multiple modes, we integrate the Ensemble EMD (EEMD) approach (Wu & Huang, 2009), which adds white noise to the data, thereby facilitating better mode separation. To further refine this process, Complementary EEMD is applied, using dual noise additions for improved accuracy. Later, we incorporate the Complete Ensemble EMD with Adaptive Noise (CEEMDAN) method, an advancement over EEMD that addresses the inconsistency in mode numbers and minimizes reconstruction error, providing a more robust and precise decomposition (Torres et al., 2011). Lastly, Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (ICEEMDAN) is an improved version of CEEMDAN (Colominas et al., 2014). These methodologies collectively enhance our data analysis, ensuring a more accurate interpretation of complex signals.

We extensively utilize the Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (ICEEMDAN) technique. Building upon the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) approach, this advanced method introduces significant improvements in signal decomposition, particularly beneficial in analyzing complex and non-linear data. The main purpose of ICEEMDAN is to address the issues of residual noise and spurious modes in CEEMDAN.

Let $E_k(\cdot)$ be the operator that produces the k-th mode obtained by EMD and let $\mathrm{M}(\cdot)$ be the operator that produces the local mean of the signal that is applied to. It can be noticed that $E_1(x) = \mathrm{x} - \mathrm{M}(x)$. Let $w^{(i)}$ be a realization of zero mean unit variance white noise, $x^{(i)} = \mathrm{x} + w^{(i)}$, and $\langle\cdot\rangle$ the action of averaging throughout the realizations. For the first EEMD and original CEEMDAN modes we have:

$$\widetilde{d}_1 = \langle E_1(x^{(i)}) \rangle = \langle x^{(i)} - M(x^{(i)}) \rangle = \langle x^{(i)} \rangle - \langle M(x^{(i)}) \rangle.$$

By estimating only the local mean and subtracting it from the original signal, we have: $\widetilde{d}_1 = \mathrm{x} - \langle M(x^{(i)}) \rangle$.

In this way, we obtain a reduction in the amount of noise present in the modes.

In the initial approach of CEEMDAN, the extraction of the first mode is identical to that in EEMD, involving averaging the first modes from the combination of the signal and white noise. For our modes, a distinct process is employed where varying noise, specifically an EMD mode of white noise, is added to the residual component. This step is crucial for extracting the remaining modes effectively.

Here we propose a new algorithm for CEEMDAN, which is called ICEEMDAN. We will make use of the already introduced operators $M(\cdot)$, $E_k(\cdot)$. Let $w^{(i)}$ be a realization of white Gaussian noise with zero mean and unit variance. With this in mind, we propose the ICEEMDAN's algorithm as follows (Colominas et al., 2014; Wang & Yu, 2022):

Algorithm 1. Proposed framework for ICEEMDAN.

1: Calculate by EMD the local means of I realizations $x^{(i)} = x + \beta_0 E_1(w^{(i)})$ to obtain the first residue $r_1 = \langle M(x^{(i)}) \rangle$.
2: At the first stage (k = 1) calculate the first mode: $\widetilde{d}_1 = x - r_1$.
3: Estimate the second residue as the average of local means of the realizations $r_1 + \beta_1 E_2(w^{(i)})$. Define the second mode: $\widetilde{d}_2 = r_1 - r_2 = r_1 - \langle M(r_1 + \beta_1 E_2(w^{(i)})) \rangle$.
4: For k = 3, …, K, calculate the k-th residue $r_k = \langle M(r_{k-1} + \beta_{k-1} E_k(w^{(i)})) \rangle$.
5: Compute the k-th mode $\widetilde{d}_k = r_{k-1} - r_k$.
6: Go to step 4 and step 5 for next k.

In the original CEEMDAN approach, the constants $\beta_k = \epsilon_k \mathrm{std}(r_k)$ are selected to achieve a specific Signal-to-Noise Ratio (SNR) target for the noise addition in relation to the residue. For the initial mode, this is done by mirroring the EEMD process of averaging modes derived from the signal with added white noise. As the decomposition progresses to higher order residues, k > 1, the energy of the noise is just a portion of the initial added noise, reflecting the diminishing SNR. The initial β_0 is set inversely proportional to the intended SNR between the original noise and signal. This is calculated by the ratio of their standard deviations $\beta_0 = \epsilon_0 \mathrm{std}(x)/\mathrm{std}(E_1(w^{(i)}))$, facilitating lower amplitude noise realizations in later decomposition stages. For subsequent modes, the noise is adjusted without the normalization of its standard deviation, different from the initial mode. This parameter's influence is critical and further details and its algorithmic implementation can be found in referenced literature.

3.2.2. Second stage with Van der Waerden test

The Kruskal-Wallis test is a non-parametric method suited for comparing more than two independent groups without assuming a normal distribution. It ranks all group data together and tests for significant differences between group ranks (Kruskal & Wallis, 1952). The Kruskal-Wallis test can be considered as a generalization of the Wilcoxon rank-sum test. Specifically, the Wilcoxon rank-sum test is a non-parametric method used to compare whether the medians of two samples are significantly different (Mann & Whitney, 1947; Wilcoxon, 1945). The Kruskal-Wallis test extends this idea to handle comparisons among multiple groups. Conversely, the Van der Waerden test transforms these ranks into normal scores before analysis, providing a more powerful test when data distributions are close to normal but imperfect. It offers the robustness of non-parametric tests with increased efficiency similar to ANOVA, making it particularly useful when normality is approximately, but not exactly, met. The Van der Waerden test, therefore, may yield more sensitive results in detecting group differences when the data distribution is symmetrical or nearly normal (Connover, 1999; Van der Waerden, 1952; Van der Waerden, 1953).

Due to its non-parametric nature, the Van der Waerden test provides a valuable tool for statistical inference, particularly effective in handling data with outliers or ordinal characteristics. It converts rank into scores to assess the differences across multiple samples. The distribution of the test statistic, which asymptotically approaches u_p, is used to evaluate the significance of rank differences among groups. This method is extensively utilized in various scientific research disciplines, allowing for data analysis unsuitable for parametric tests.

The test methods and steps are as follows (Connover, 1999; Van der Waerden, 1952; Van der Waerden, 1953):

Algorithm 2. Proposed methodology for Van der Waerden test.

1: Null hypothesis H_0: There is no significant difference among groups;
Alternative hypothesis H_1: There is a significant difference among groups.
2: Calculate the test statistic T : $P = \frac{R(X_{ij})}{N+1}$.
$R(X_{ij})$ represents the rank of each observed value within the entire dataset, while N signifies the total count of observations. P reflects the probability or area under the curve of the normal distribution after rank transformation. For practical purposes, especially when referencing tables, it is advisable to retain the P value to three decimal places for precision and ease of lookup.
$A_{ij} = u_p$, A_{ij} is the z-score, which is equal to the u value when the area is P.
$\overline{A_i} = \frac{1}{n_i}\sum_{j=1}^{n_i} A_{ij}$, i = 1, 2, …, K, $\overline{A_i}$ is the average normal score of each sample.
$S^2 = \frac{1}{N-1}\sum A_{ij}^2$, where S^2 represents the variance across all normalized scores.
It's important to recognize that the aggregate mean of these scores is zero, assuming no repetition of data in the sample set. In instances of data repetition, the mean is effectively zero. Consequently, the overall mean can be disregarded in calculations, simplifying the sum of squared deviations from the mean, $\sum (A_{ij} - 0)^2$ to $\sum A_{ij}^2$.
$T = \frac{1}{S^2}\sum_{i=1}^{K} n_i \overline{A_i}^2$, here n_i represents the sample size for each of the K groups in the data.
3: The principle of decision-making is as follows: One should consult the chi-square distribution table using the degrees of freedom $K-1$ and the significance level α to determine the critical chi-square threshold. If the calculated T value exceeds the critical chi-square value at α, then $P < \alpha$. At this α level, we reject the null hypothesis H_0 and accept the alternative hypothesis H_1.
In the referenced test, the pairwise comparison of population distributions leads to a consideration of rejecting hypothesis H_0. For a thorough pairwise comparison of overall distributions, we examine the hypothesis H_0, proposing that the two populations in question share the same distribution, against H_1, suggesting they differ. Should the established inequality hold true, we reject H_0, accept H_1, and accordingly draw the pertinent conclusion.
Two populations are different if the following inequality is satisfied:
$$\left|\overline{A_{j_1}} - \overline{A_{j_2}}\right| > t_{1-\frac{\alpha}{2}}\left(S^2\frac{N-T-1}{N-K}\right)^{\frac{1}{2}}\left(\frac{1}{n_{j_1}} + \frac{1}{n_{j_2}}\right)^{\frac{1}{2}}.$$
The $t_{1-\frac{\alpha}{2}}$ value can be obtained by referring to the t-distribution table.

3.2.3. Third stage with elastic net

Elastic Net is a regression method widely used in statistics and machine learning. It combines two types of regularization, $L1$ regularization (LASSO regressions) and $L2$ regularization (Ridge regressions), balancing the advantages of these two methods within a unified model. Elastic Net is an effective tool for feature selection, especially when dealing with highly correlated predictor variables. By combining the feature selection capability of the LASSO regression and the ability of the Ridge regression to handle multicollinearity, Elastic Net can effectively manage complex datasets. The algorithm we used is Elastic NetCV.

Algorithm 3. Proposed framework for Elastic NetCV.

1: Data Preprocessing: Normalize the data to ensure that the features are on the same scale. Initially, we standardize (subtracting the mean and dividing by the standard deviation) the decomposition curves of Bitcoin's price at different frequencies and phases and the influencing factors of Bitcoin's price selected from the literature before inputting them into the Elastic Net regression.
2: Set up a series of testable α values and l_1 − ratio values. α is the regularization strength parameter in the Elastic Net model and l_1 − ratio is the parameter used to balance between $L1$ and $L2$ regularization.
3: Create an ElasticNetCV regression model. The parameters 'α' and 'l_1-ratio' receive the α and l_1-ratio values set earlier, respectively, and the 'cv' parameter specifies the number of folds for cross-validation, set here as 10-fold.
4: Fit the ElasticNetCV model using the fit method. During this step, ElasticNetCV will calculate the prediction error for each (α, l_1-ratio) combination using cross-validation.
5: After the model training, the optimal α and l_1-ratio values that minimize the cross-validation prediction error can be output.
6: Finally, the coefficients of the optimal model can be extracted.

Since we standardized both the dependent variables (high-frequency, low-frequency, and trend curves of the five phases) and the 47 potential factors influencing Bitcoin's price before applying Elastic Net regression, we can utilize the coefficients from the Elastic Net regression to calculate the factor weights for these 47 factors. Let the coefficients from the Elastic Net regression be denoted as

$\beta_{ij}(C_k), i = 1, 2, \ldots, 5, j = high, low, trend, k = 1, 2, \ldots, 47.$

The calculation formula of the factor weights is as follows:

$$w_{ij}(c_k) = \frac{|\beta_{ij}(c_k)|}{\sum_{k=1}^{47}|\beta_{ij}(c_k)|}, i = 1, 2, \ldots, 5, j = high, low, trend, k = 1, 2, \ldots, 47.$$

In the Data section, we categorize the 47 factors influencing Bitcoin's price into 5 categories: Factors of Bitcoin's Production and Transaction, Factors of Bitcoin's Supply-demand Dynamics, Factors of Bitcoin Market Conditions, Factors of Macroeconomic Environment, and Factors of Global Geopolitical Risks. The partial weight for each category is the sum of the factor weights of all its constituent factors.

$$W_{ij}(C_{k'}) = \sum\nolimits_{c_k \in C_{k'}} w_{ij}(c_k), i = 1, 2, \ldots, 5, j = high, low, trend, k' = 1, 2, \ldots, 5.$$

When calculating the overall weights of the 5 categories in Bitcoin's price for each phase, we multiply the variance proportions $\gamma_{ij}, i = 1, 2, \ldots, 5, j = high, low, trend$, of the high-frequency, low-frequency, and trend curves by the partial weights of the 5 categories in the three frequency curves.

$$W_i(C_{k'}) = \sum\nolimits_{j=high,low,trend} \gamma_{ij} W_{ij}(C_{k'}), i = 1, 2, \ldots, 5, k' = 1, 2, \ldots, 5.$$

3.2.4. General framework

The proposed ICEEMDAN-Van der Waerden Test-Elastic Net method includes three steps:

1. Utilize the ICEEMDAN method to decompose Bitcoin's daily closing price in each phase.
2. Apply the Van der Waerden Test to synthesize the IMFs into high-frequency, low-frequency and trend curves.
3. Employ the Elastic Net regression to identity the top ten factors influencing the high-frequency, low-frequency and trend curves.

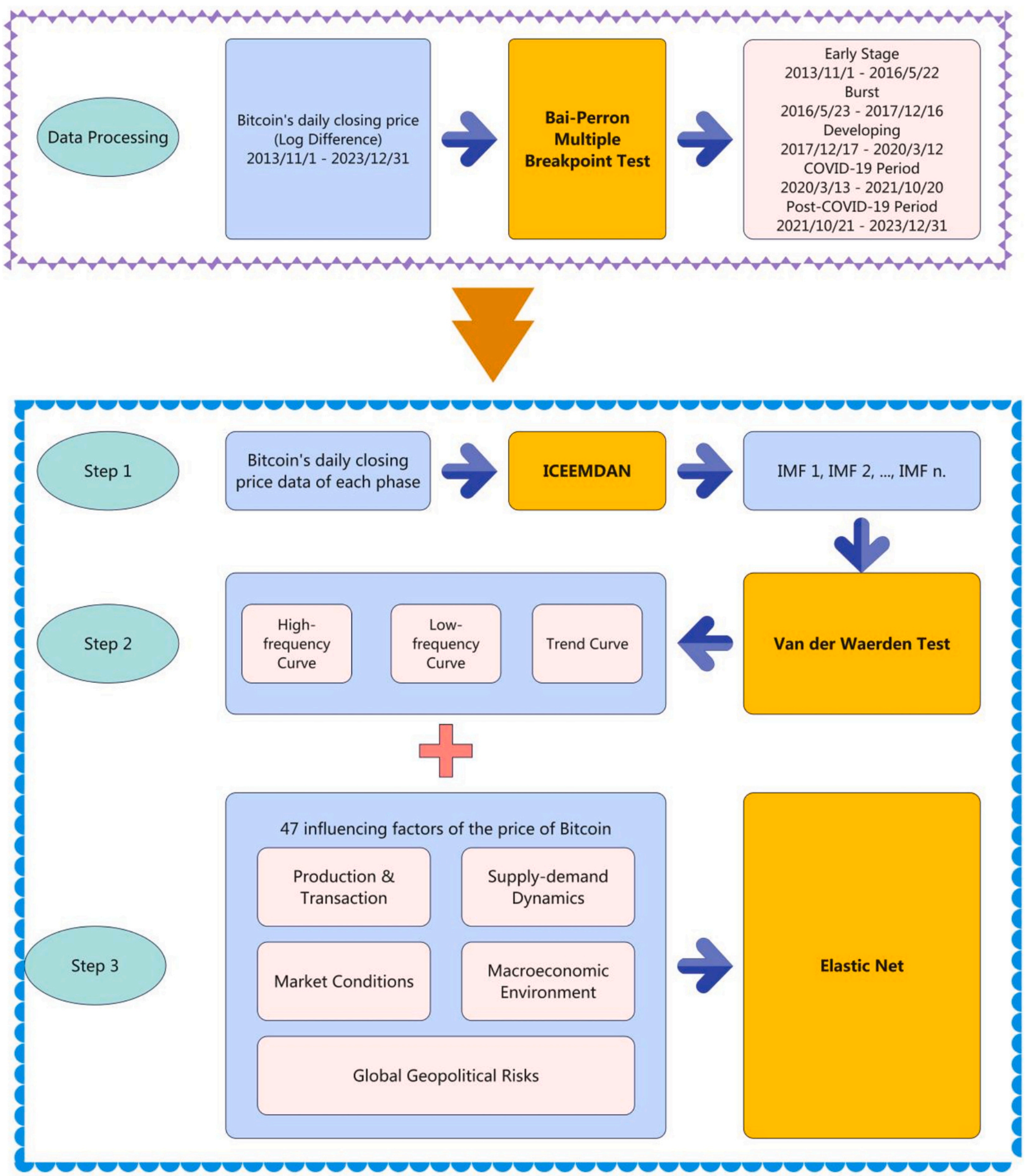

Fig. 1. The general layout of the experiment procedure.

Fig. 1 shows the general layout of our experiment procedure. The premise of this three-stage analysis is that we ignore the interactions between factors.

4. Data

4.1. Bitcoin data

This paper obtained the daily closing price for Bitcoin on Bitfinex from November 1, 2013, to December 31, 2023, from the Investing.com website. We selected November 1, 2013, as the starting date because Bitcoin's price surpassed $1000 per unit for the first time on November 28, 2013, attracting significant global attention.

4.2. Influencing factors

We download daily data for the following 47 factors covering November 1, 2013, to December 31, 2023. These factors are categorized into 5 categories: Factors of Bitcoin's Production and Transaction (Table 1), Factors of Bitcoin's Supply-demand Dynamics (Table 2), Factors of Bitcoin Market Conditions (Table 3), Factors of Macroeconomic Environment (Table 4), and Factors of Global Geopolitical Risks (Table 5).

Factors of Bitcoin's Production and Transaction (Table 1), Factors of Bitcoin's Supply-demand Dynamics (Table 2), and Factors of Bitcoin Market Conditions (Table 3) are derived from the CoinMetrics.com website. Our explanations of these factors are based on the definitions provided on the CoinMetrics.com website. Data related to the GPR Index (Table 5) is sourced from matteoiacoviello.com website. The daily closing prices of the macroeconomic financial factors (excluding JPY/USD) and the CBOE Volatility Index (VIX) are obtained from the Investing.com website. The daily closing price of JPY/USD is sourced from the official website of the Bank of Japan.

5. Empirical study

We employ EViews software to conduct Bai-Perron Multiple Breakpoint Test on the ten-year Bitcoin price data, dividing it into five phases. The start and end dates for each of these five phases are as follows (Table 6):

Although we identified these four breakpoints (May 23rd, 2016; Dec 17th, 2017; Mar 13th, 2020; and Oct 21st, 2021) using the Bai-Perron Multiple Breakpoint Test, they also coincide with the timing of significant global events or major developments within the Bitcoin market. Dividing the Bitcoin market from November 1st, 2013, to December 31st, 2023, into five developmental phases based on these four breakpoints is supported by strong economic reasoning.

The first breakpoint (May 23rd, 2016) exists because Bitcoin's second halving event was set to occur in July 2016. Consequently, in May 2016, Bitcoin investors began adjusting their strategies in anticipation of the event, leading to a price increase (Fig. 2).

The second breakpoint (Dec 17th, 2017) marks the peak of Bitcoin's 2017 bull market, driven by the launch of Bitcoin futures by the Chicago

Table 1
Factors of Bitcoin's production and transaction.

Factor name	Explanation
Hash Rate	The mean rate at which miners are solving hashes in a day
Mining Difficulty	The mean difficulty of finding a hash that meets the protocol-designated requirement (i.e., the difficulty of finding a new block) in a day.
Transaction Fee	The USD value of the mean fee per transaction in a day.
Block Size	The mean size (in bytes) of all blocks created in a day.
Mean Block Weight	The mean weight of all blocks created in a day.
Sum Block Weight	The sum of the weights of all blocks created in a day.
Miner Revenue	The su USD value of all miner revenue (fees plus newly issued Bitcoins) in a day.
Miner Revenue Per Hash Unit	The USD value of the mean daily miner reward per estimated hash unit performed during the period, also known as hash price.

Table 2
Factors of Bitcoin's supply-demand dynamics.

Factor name	Explanation
1-Day Active Supply	The sum of unique Bitcoins that are transacted at least once in a day. Bitcoins that are transacted more than once are only counted once.
7-Day Active Supply	The sum of unique Bitcoins that are transacted at least once in the trailing 7 days up to the end of a day. Bitcoins that are transacted more than once are only counted once.
30-Day Active Supply	The sum of unique Bitcoins that were transacted at least once in the trailing 30 days up to the end of a day. Bitcoins that are transacted more than once are only counted once.
Free Float Supply	Free float supply refers to the number of Bitcoins that are readily available to trade in open markets (i.e., not restricted) at the end of a day.
Current Supply	The sum of all Bitcoins ever created and visible on the ledger (i.e., issued) at the end of a day.
10-Year Expected Supply	The sum of all Bitcoins counting current supply and including all those expected to be issued over the next 10 years from that day if the current down continuous issuance schedule is followed. Future expected hard-forks that will change the continuous issuance are not considered until the day they are activated/enforced.

Table 3
Factors of Bitcoin market conditions.

Subcategory	Factor name	Explanation
Factors of Bitcoin Market Vitality	Market Capitalization	The sum USD value of the current supply in the Bitcoin market.
	Free Float Market Capitalization	The sum USD value of the current free float supply in the Bitcoin market.
	Realized Market Capitalization	The sum USD value is based on the USD closing price on the day that a Bitcoin last transacted for all Bitcoins.
Factors of Bitcoin Asset Valuation	MVRV	The ratio of the sum USD value of the current supply to the sum realized USD value of the current supply.
	Free Float MVRV	The ratio of the free float market capitalization to the sum realized USD value of the current supply.

Table 4
Factors of macroeconomic environment.

Subcategory	Factor name
Factors of Stock Markets	CBOE Volatility (VIX) Index, S&P 500 Index, Dow Jones Industrial Average, Nasdaq Composite Index, FTSE China A50 Index, Hong Kong Hang Seng Index, Euro Stoxx 50 Index, DAX 40 Index, FTSE 100 Index, Cotation Assistée en Continu 40 (CAC 40) Index, MOEX Russia Index, Nikkei 225 Stock Index.
Factors of Exchange Rates	U.S. Dollar Index Futures, CNY/USD, EUR/USD, GBP/USD, RUB/USD, JPY/USD, CAD/USD, CHF/USD.
Factors of Commodity Markets	Gold Futures, WTI Crude Oil Futures, Brent Oil Futures.

Table 5
Factors of global geopolitical risks.

Factor name	Explanation
Daily GPR Index	A score reflecting overall geopolitical risk on a specific day.
Daily GPR Acts	This subindex focuses on the number of news articles related to actual events like war beginnings, war escalations, and terror acts.
Daily GPR Threats	This subindex focuses on the number of news articles related to potential risks, including war threats, peace threats, military buildups, nuclear threats, and terror threats.
7-Day Moving Average of Daily GPR	An average of the daily GPR Index over the past 7 days, smoothing out short-term fluctuations.
30-Day Moving Average of Daily GPR	An average of the daily GPR Index over the past 30 days, highlighting longer-term trends.

Table 6
The five phases of the ten-year Bitcoin price data.

Phase	Start	End
Early Stage	Nov 1st 2013	May 22nd 2016
Burst	May 23rd 2016	Dec 16th 2017
Developing	Dec 17th 2017	Mar 12th 2020
COVID-19 Period	Mar 13th 2020	Oct 20th 2021
Post-COVID-19 Period	Oct 21st 2021	Dec 31st 2023

Board Options Exchange (CBOE) and the Chicago Mercantile Exchange (CME) in December 2017. This event signified mainstream financial recognition of Bitcoin, sparking heightened investor enthusiasm. However, the overheated Bitcoin market quickly faced downward pressure: in early 2018, Bitcoin prices fell below $10,000, initiating a year-long bear market.

The third breakpoint (Mar 13th, 2020) reflects the global financial turmoil caused by the rapid spread of COVID-19, which led to a sharp drop in the Bitcoin's price in early March 2020. This decline was driven by panic selling among investors. However, with the arrival of Bitcoin's May 2020 halving event, Bitcoin's price recovered and maintained an upward trajectory in the subsequent months.

The fourth breakpoint (Oct 21st, 2021) marks a significant phase in Bitcoin's 2021 autumn bull market. This price peak was catalyzed by ProShares launching the first Bitcoin ETF, a milestone indicating further mainstream financial acceptance of Bitcoin. Additionally, in the post-pandemic period, persistently high inflation rates across many global economies fueled greater expectations among investors for Bitcoin as "digital gold". However, following increased regulatory pressures on Bitcoin across various countries, its price began to decline significantly.

We analyze the different patterns of Bitcoin price fluctuations during five phases. The Elastic Net is employed to identify the most significant factors affecting Bitcoin's price in the five phases. These analytical results will reveal the secret of the formation of Bitcoin's price.

5.1. Early stage

Fig. 3 depicts the line chart of the daily closing price of Bitcoin in the Early Stage, along with the high-frequency, low-frequency and trend curves. Table 7 presents the Pearson correlation coefficient, Kendall correlation coefficient, coefficient of variation, relative range, variance as a percentage of ($\sum$IMFs + residue), and the top ten factors among the 47 influencing factors affecting the high-frequency, low-frequency and trend curves.

We observe that the high-frequency curve has the largest absolute values for both the coefficient of variation and relative range, indicating the most intense volatility. While the trend curve has the smallest absolute values for the coefficient of variation and relative range, the low-frequency curve's variance as a percentage of ($\sum$IMFs + residue) is the largest. This suggests that in this phase, although the high-frequency curve influences short-term (daily) fluctuations in Bitcoin's price, the general trajectory of Bitcoin's price is determined by the low-frequency curve.

When using Elastic Net to determine the influencing factors of the high-frequency curve, we observe the high-frequency curve is positively correlated with Bitcoin market vitality (market capitalization, free float market capitalization, realized market capitalization). The more heated the Bitcoin market, the more violent the fluctuations of the high-frequency curve. In terms of external macro finance, the high-frequency curve is also affected by the stock markets (MOEX Russia Index, S&P 500 Index, VIX Index) and the exchange rate RUB/USD. The high-frequency curve of Bitcoin's price is also influenced by factors of Bitcoin's production and transaction (Miner Revenue Per Hash Unit, Transaction Fee).

According to the results of the Elastic Net, we find that the factors that have the greatest impact on the low-frequency curve of Bitcoin's price in the Early Stage come from the Bitcoin market conditions: market capitalization, free float market capitalization, and realized market

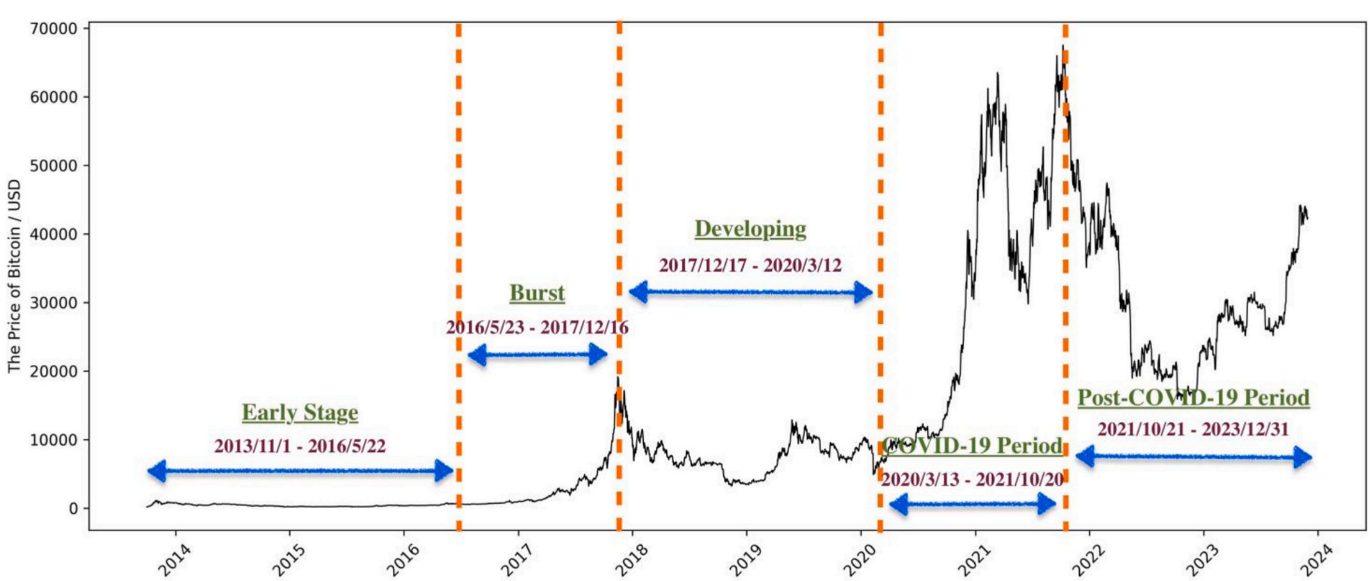

Fig. 2. The five phases of the ten-year Bitcoin price data.

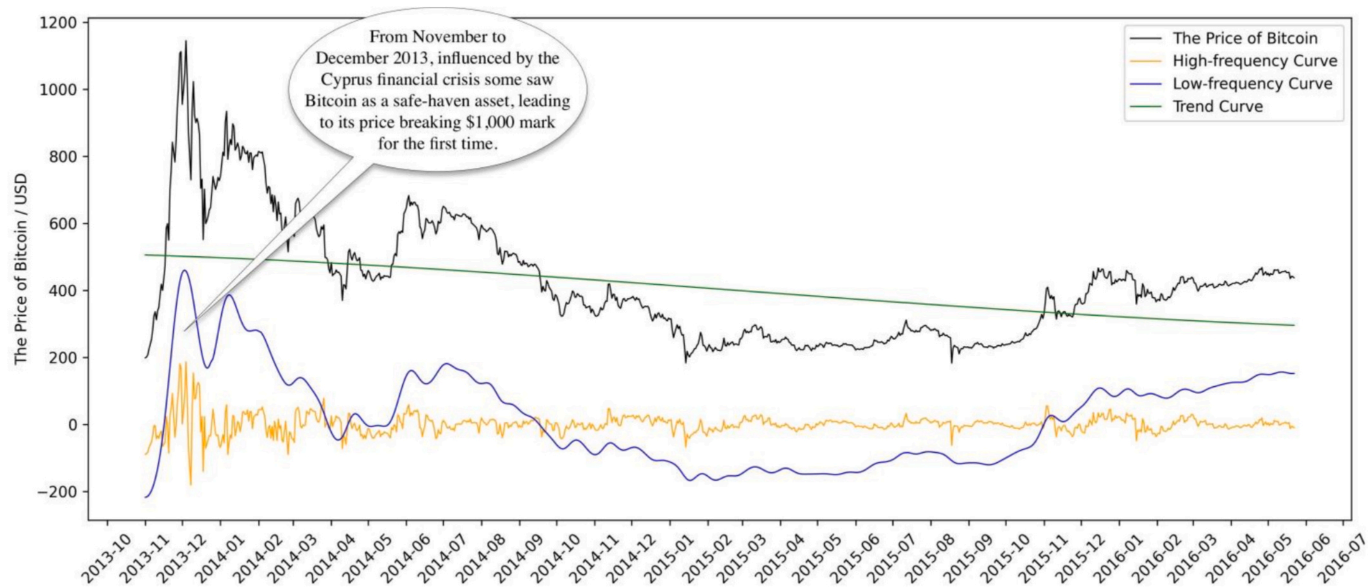

Fig. 3. Bitcoin's daily closing price and its three frequency curves of the Early Stage.

Table 7
The statistical metrics and major influencing factors of the high-frequency, low-frequency and trend curves of the Early Stage.

	High-frequency curve	Low-frequency curve	Trend curve
Pearson Correlation	0.301*	0.923*	0.574*
Kendall Correlation	0.171*	0.756*	0.322*
Coefficient of Variation	−184.07	8.22	0.16
Relative Range	−2414.84	39.74	0.52
Variance as % of (∑IMFs + residue)	3.16 %	79.36 %	17.48 %
Top 10 Contributing Factors (arranged in descending order of the factor weights of the coefficients according to Elastic Net)	Market Capitalization (11.13 %), Free Float Market Capitalization (10.42 %), MOEX Russia Index (8.73 %), JPY/USD (7.14 %), S&P 500 Index (6.32 %), Miner Revenue Per Hash Unit (6.02 %), Realized Market Capitalization (5.91 %), RUB/USD (5.87 %), VIX Index (4.31 %), Transaction Fee (3.33 %).	Market Capitalization (25.94 %), Free Float Market Capitalization (23.62 %), Miner Revenue (18.24 %), MOEX Russia Index (6.17 %), Free Float Supply (3.82 %), FTSE 100 Index (2.74 %), Realized Market Capitalization (2.29 %), Mining Difficulty (2.00 %), Dow Jones Industrial Average (1.68 %), JPY/USD (1.61 %).	Current Supply (13.33 %), 10-Year Expected Supply (12.18 %), Free Float Supply (9.90 %), Nasdaq Composite Index (7.11 %), CNY/USD (6.57 %), FTSE 100 Index (6.02 %), Hash Rate (5.47 %), Mining Difficulty (5.22 %), MOEX Russia Index (4.80 %), CAD/USD (4.16 %).

* Correlation is significant at the 0.05 level.

capitalization. Interestingly, we observed a jump in the low-frequency curve from November 2013 to January 2014: this is the impact of the Cyprus financial crisis on the Bitcoin market. This financial crisis led many people to regard the emerging financial asset Bitcoin as a safe-haven asset, and the sudden increase in market heat caused Bitcoin's price to break through $1000 per piece for the first time. Some scholars argue that the current high level of attention on Bitcoin is contributing to a bubble in its price (Cretarola & Figa-Talamanca, 2021). The low-frequency curve is also affected by Bitcoin blockchain factors: miner revenue and mining difficulty. In addition, the low-frequency curve is also affected by the Russian stock market (MOEX Russia Index), the UK stock market (FTSE 100 Index) and the US stock market (Dow Jones Industrial Average). In summary, the low-frequency of Bitcoin's price in the Early Stage is mainly influenced by factors of Bitcoin market vitality. When major events affect the investor sentiment of the Bitcoin market, the low-frequency curve shows a violent jump.

During this phase, the three factors that have the greatest impact on the trend curve are all related to the supply-demand dynamics of Bitcoin: current supply, future expected supply in the next 10 years, and free float supply. This implies that in the Early Stage, the biggest factors influencing the trend of Bitcoin's price come from changes in the supply-demand relationship of Bitcoin: the less the supply of Bitcoin, the higher the trend curve of Bitcoin's price. The trend curve is also influenced by the hash rate and mining difficulty. This suggests that the production process of Bitcoin has a certain long-term impact on its price. Additionally, the US stock market (Nasdaq Composite Index), UK stock market (FTSE 100 Index), and Russian stock market (MOEX Russia Index) all impact the trend curve of Bitcoin's price. Fluctuations in the exchange rates of CNY/USD and CAD/USD also affect the price of Bitcoin. Therefore, the long-term trend of Bitcoin's price in the Early Stage is mainly influenced by Bitcoin's supply-demand dynamics.

5.2. Burst

Fig. 4 and Table 8 depict the high-frequency, low-frequency and trend curves of Bitcoin's daily closing price of the Burst phase, obtained through ICEEMDAN decomposition and Van der Waerden Test reconstruction. We find that the absolute values of relative range and coefficient of variation of the low-frequency curve are the largest, while those of the trend curve are the smallest. The variance of the trend curve as a percentage of (∑IMFs + residue) is the highest, the high-frequency curve is the lowest. This indicates that, although the long-term trajectory of Bitcoin's price in this phase is primarily determined by the trend curve, the impact of the low-frequency curve's volatility on Bitcoin's price has decreased.

When using Elastic Net to determine the influencing factors of the

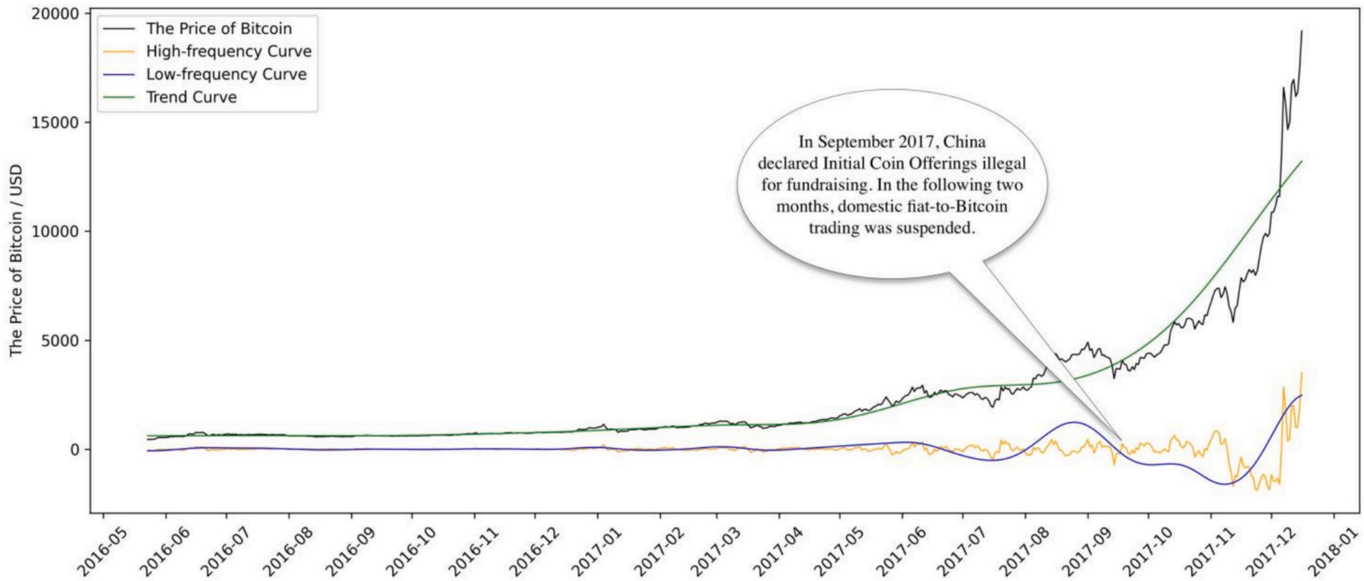

Fig. 4. Bitcoin's daily closing price and its three frequency curves of the Burst phase.

Table 8
The statistical metrics and major influencing factors of the high-frequency, low-frequency and trend curves of the Burst phase.

	High-frequency curve	Low-frequency curve	Trend curve
Pearson Correlation	0.118*	0.190*	0.964*
Kendall Correlation	0.063*	0.094*	0.908*
Coefficient of Variation	−26.24	−70.04	1.18
Relative Range	−350.04	−530.44	5.22
Variance as % of (∑IMFs + residue)	1.91 %	3.42 %	94.67 %
Top 10 Contributing Factors (arranged in descending order of the factor weights of the coefficients according to Elastic Net)	Transaction Fee (100.00 %).	30-Day Active Supply (10.19 %), Mining Difficulty (8.22 %), Miner Revenue (8.19 %), FTSE China A50 Index (6.76 %), Nikkei 225 Stock Index (6.08 %), Miner Revenue Per Hash Unit (5.29 %), Market Capitalization (5.13 %), Free Float Market Capitalization (5.11 %), Free Float Supply (4.68 %), Hash Rate (4.57 %).	Realized Market Capitalization (12.50 %), Free Float Market Capitalization (9.02 %), Market Capitalization (8.87 %), FTSE China A50 Index (7.50 %), Mining Difficulty (7.11 %), Nikkei 225 Stock Index (6.96 %), Miner Revenue (5.93 %), Hash Rate (5.86 %), RUB/USD (5.57 %), Free Float Supply (4.08 %).

* Correlation is significant at the 0.05 level.

high-frequency curve, we observe a positive correlation between the high-frequency curve and transaction fees during this phase. Bitcoin transaction fees are determined by the congestion level of the Bitcoin transaction network: when there is a large number of transactions awaiting confirmation on the Bitcoin network, transactions with higher fees are prioritized by miners (Easley et al., 2019; Huberman et al., 2021; Jiang et al., 2022; Tschorsch & Scheuermann, 2016). Therefore, the high-frequency curve is associated with the daily number of Bitcoin transactions, and the more daily Bitcoin transactions, the more pronounced the fluctuations in the high-frequency curve (Ibikunle et al., 2020).

The results of the Elastic Net indicate that during this phase, the low-frequency curve of Bitcoin's price is significantly influenced by the supply-demand dynamics of Bitcoin (30-day active supply, free float supply) and Bitcoin production factors (mining difficulty, miner revenue, miner revenue per hash unit, hash rate). The factors of Bitcoin market vitality (free float market capitalization, market capitalization) are also important factors affecting the low-frequency curve. In addition, the low-frequency curve is also influenced by the volatility of stock markets (FTSE China A50 Index, Nikkei 225 Stock Index). We observe a significant drop in the low-frequency curve from September 2017 to November 2017: in September 2017, China declared ICOs as illegal financing and shut down Bitcoin and RMB settlement services within the country. This was a major blow to the Bitcoin market.

The trend curve of Bitcoin's price in the Burst phase presents as an accelerating upward curve. The results of the Elastic Net regression tell us that during this phase, factors of Bitcoin market vitality (realized market capitalization, free float market capitalization, market capitalization) has the greatest impact on the trend curve: this implies that the continuous price rise comes from the increasing market vitality for Bitcoin. Bitcoin's production factors (hash rate, mining difficulty, miner revenue) still affect the trend curve of Bitcoin's price. As the difficulty of mining a Bitcoin increases, the cost required becomes higher and higher, leading to a long-term rising trend in Bitcoin's price. Stock markets and exchange rates around the world also affect the trend curve. In general, in the Burst phase, the continuous rise in Bitcoin market vitality and the increase of Bitcoin's mining difficulty lead to the rapid rise of (the trend curve of) Bitcoin's price.

5.3. Developing

Fig. 5 and Table 9 present the high-frequency, low-frequency and trend curves of Bitcoin's daily closing price of the Developing phase, utilizing ICEEMDAN decomposition and Van der Waerden Test synthetic reconstruction, along with their statistical metrics and major influencing factors. We observe that, the low-frequency curve exhibits the maximum variance as a percentage of (∑IMFs + residue). This indicates that, during this phase, the low-frequency curve, has the greatest impact on the volatility of Bitcoin's price.

From the results of the Elastic Net regression, we know that the high-

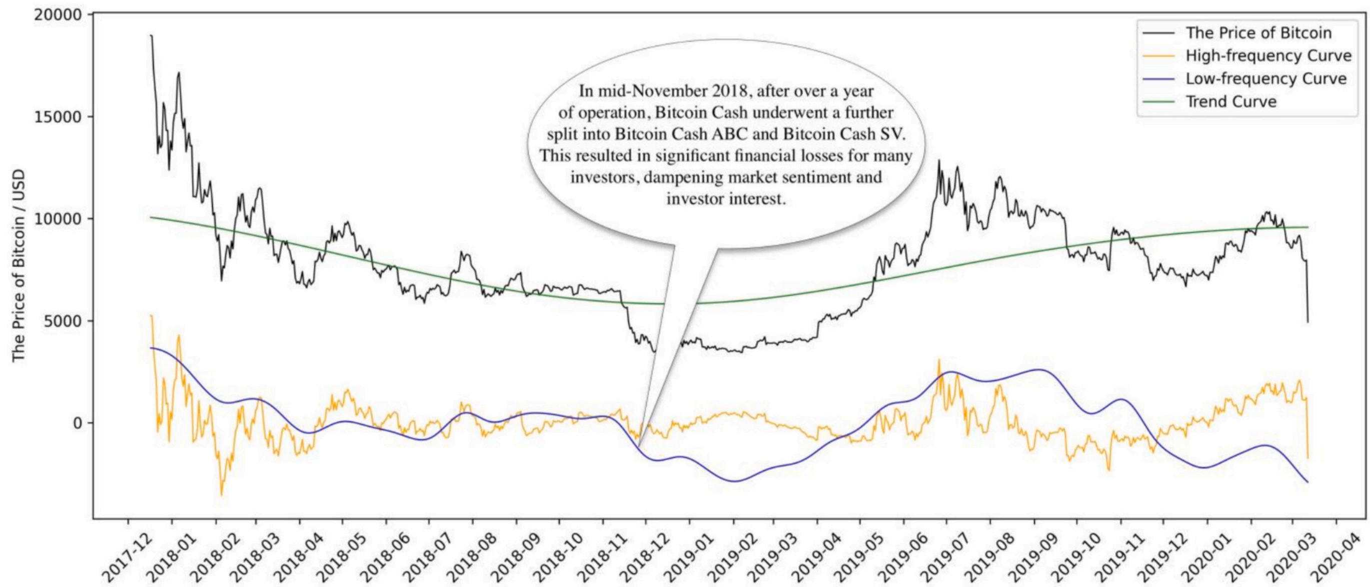

Fig. 5. Bitcoin's daily closing price and its three frequency curves of the Developing phase.

Table 9
The statistical metrics and major influencing factors of the high-frequency, low-frequency and trend curves of the Developing phase.

	High-frequency Curve	Low-frequency Curve	Trend Curve
Pearson Correlation	0.437*	0.782*	0.748*
Kendall Correlation	0.194*	0.567*	0.569*
Coefficient of Variation	37.96	−64.42	0.17
Relative Range	363.23	−271.27	0.55
Variance as % of (∑IMFs + residue)	16.61 %	47.63 %	35.76 %
Top 10 Contributing Factors (arranged in descending order of the factor weights of the coefficients according to Elastic Net)	MVRV (100.00 %).	GBP/USD (8.51 %), Market Capitalization (7.08 %), Free Float Market Capitalization (6.67 %), CNY/USD (6.48 %), FTSE China A50 Index (6.47 %), MVRV (5.55 %), Free Float MVRV (4.90 %), Nasdaq Composite Index (4.84 %), Gold Futures (4.82 %), WTI Crude Oil Futures (4.48 %).	Realized Market Capitalization (13.26 %), DAX 40 Index (8.02 %), Miner Revenue Per Hash Unit (7.77 %), Gold Futures (7.71 %), JPY/USD (6.98 %), FTSE China A50 Index (6.60 %), RUB/USD (6.21 %), Euro Stoxx 50 Index (6.18 %), Brent Oil Futures (5.36 %), GBP/USD (5.06 %).

* Correlation is significant at the 0.05 level.

frequency curve during the Developing phase is most significantly influenced by factors related to Bitcoin asset valuation (MVRV). MVRV is used to assess whether Bitcoin's value is overestimated or underestimated and is often seen as a signal for Bitcoin market transactions. Therefore, the high-frequency curve remains related to the daily trading frequency and investor sentiment in the Bitcoin market.

The impact of the low-frequency curve on the overall price of Bitcoin during the Developing phase has increased compared to the previous stage. The low-frequency curve at this phase began a trough lasting six months from November 2018: in mid-November 2018, Bitcoin Cash, which had been running for more than a year, further split into Bitcoin Cash ABC and Bitcoin Cash SV. This blockchain fork led to a significant reduction in the value of Bitcoin Cash, causing huge losses to investors. This damaged investor confidence and enthusiasm in the cryptocurrency market. The low-frequency curve in this stage is mainly influenced by factors related to Bitcoin's market conditions (MVRV, market capitalization, free float MVRV, free float market capitalization) and macro-financial factors (GBP/USD, CNY/USD, FTSE China A50 Index, Nasdaq Composite Index, Gold Futures, WTI Crude Oil Futures).

The trend curve in the Developing phase is greatly influenced by macro-financial factors. In the long term, the Bitcoin market is influenced by various countries' stock markets (DAX40 Index, FTSE China A50 Index, Euro Stoxx 50 Index), exchange rates (RUB/USD, JPY/USD, GBP/USD), and commodity prices (Brent Oil Futures, Gold Futures). Although the two influential factors on the trend curve of Bitcoin's price, realized market capitalization and miner revenue per hash unit, are related to Bitcoin market conditions and Bitcoin's production, the impact of macroeconomic factors on Bitcoin's price has increased in the Developing phase compared to the previous two phases.

5.4. COVID-19 period

Fig. 6 and Table 10 present the high-frequency, low-frequency and trend curves of Bitcoin's price of the COVID-19 Period, along with their statistical metrics and major influencing factors. We observe that the absolute values of relative range and coefficient of variation of the high-frequency curve are the highest, while those for the trend curve are the lowest. According to the variance as a percentage of (∑IMFs + residue) ranking from largest to smallest, the order is the trend, low-frequency, and high-frequency curves. This indicates that, during this phase, the trend curve has the greatest impact on the volatility of Bitcoin's price.

The results from Elastic Net indicate that factors influencing the high-frequency curve during the COVID-19 Period are related to Bitcoin market conditions (MVRV, free float MVRV), macroeconomic factors (Nikkei 225 Stock Index, Gold Futures), Bitcoin production factors (transaction fee, mining difficulty, miner revenue), and factors of Bitcoin's supply-demand dynamics (1-day active supply). The trend curve at this phase is mainly affected by the factors of Bitcoin's supply-demand dynamics (free float supply, 10-year expected supply, current supply) and Bitcoin market conditions (realized market capitalization, free float

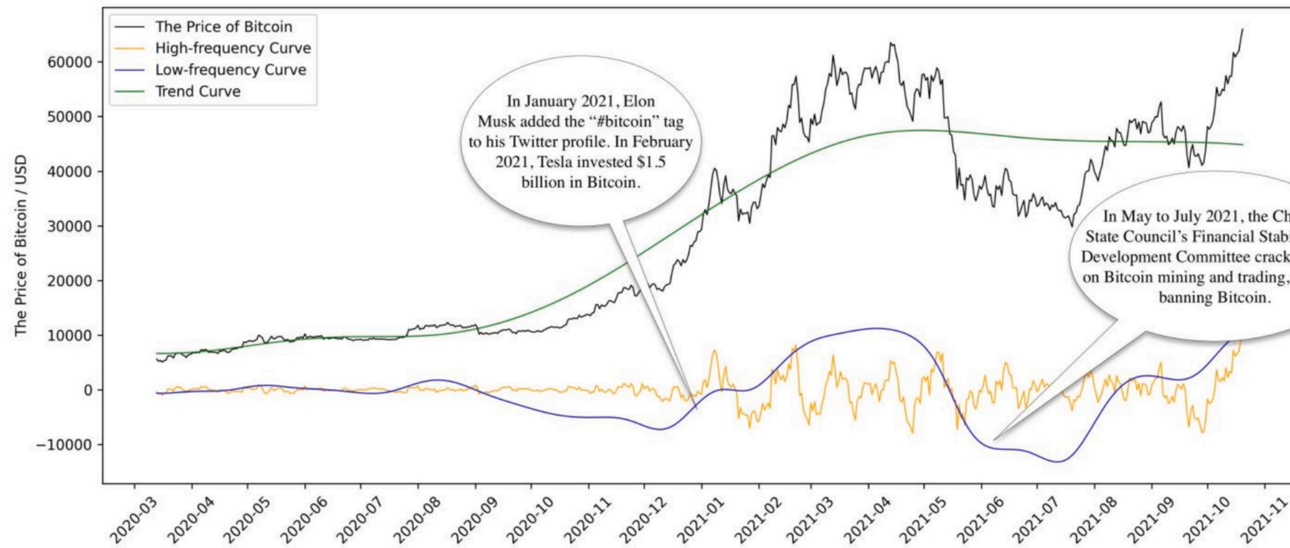

Fig. 6. Bitcoin's daily closing price and its three frequency curves of the COVID-19 Period.

Table 10
The statistical metrics and major influencing factors of the high-frequency, low-frequency and trend curves of the COVID-19 Period.

	High-frequency curve	Low-frequency curve	Trend curve
Pearson Correlation	0.169*	0.447*	0.934*
Kendall Correlation	0.121*	0.260*	0.727*
Coefficient of Variation	−1421.81	−16.16	0.57
Relative Range	−11,249.80	−66.40	1.41
Variance as % of (∑IMFs + residue)	1.81 %	11.42 %	86.77 %
Top 10 Contributing Factors (arranged in descending order of the factor weights of the coefficients according to Elastic Net)	JPY/USD (13.16 %), MVRV (9.77 %), Free Float MVRV (9.44 %), Nikkei 225 Stock Index (6.56 %), Mining Difficulty (5.73 %), 7- Day Moving Average of Daily GPR (5.62 %), Miner Revenue (5.30 %), Transaction Fee (4.96 %), Gold Futures (4.72 %), 1-Day Active Supply (4.48 %).	CNY/USD (8.65 %), Free Float Supply (8.52 %), Market Capitalization (7.08 %), MVRV (6.89 %), Free Float Market Capitalization (6.89 %), Free Float MVRV (6.60 %), Miner Revenue (5.75 %), Hash Rate (4.78 %), Transaction Fee (4.61 %), Mining Difficulty (4.53 %).	Free Float Supply (13.44 %), Realized Market Capitalization (11.60 %), CNY/USD (9.27 %), Hong Kong Hang Seng Index (6.35 %), Gold Futures (6.10 %), 10-Year Expected Supply (5.99 %), Miner Revenue Per Hash Unit (5.62 %), Current Supply (5.31 %), FTSE 100 Index (3.40 %), Free Float Market Capitalization (3.37 %).

* Correlation is significant at the 0.05 level.

market capitalization), and macroeconomic factors (CNY/USD, Hong Kong Hang Seng Index, Gold Futures, FTSE 100 Index).

Observing the general trajectory of the low-frequency curve of Bitcoin's price during the COVID-19 Period, we find a distinct peak and an obvious trough. The peak of the low-frequency curve is from January 2021 to April 2021, during which Elon Musk made a high-profile announcement about his interest in investing in Bitcoin and followed through with his actions. This led to a surge in investment enthusiasm in the cryptocurrency market. Subsequently, in May 2021, the Chinese government forcibly shut down all Bitcoin mining activities within its borders. This caused Bitcoin's price to drop rapidly, resulting in a trough period. According to the results from Elastic Net, we find that the low-frequency curve is most significantly influenced by factors of Bitcoin market conditions (MVRV, market capitalization, free float MVRV, free float market capitalization). This demonstrates that the emotional fluctuations in the Bitcoin market caused by these two events were the primary reasons for the significant mid-term fluctuations in Bitcoin's price during this phase. Additionally, the low-frequency curve at this phase was also influenced by the Bitcoin's supply-demand dynamics (free float supply) and Bitcoin production factors (miner revenue, hash rate, transaction fee, mining difficulty).

5.5. *Post-COVID-19 period*

Fig. 7 and Table 11 showcase the statistical metrics, major influencing factors, and the high-frequency, low-frequency, and trend curves of Bitcoin's price during the Post-COVID-19 Period. Our observations show that the high-frequency curve has the highest absolute values for relative range and coefficient of variation, while the trend curve has the lowest. As per the ranking of variance as a percentage of (∑IMFs + residue), which goes from largest to smallest, the sequence is the trend, low-frequency, and high-frequency curves. This suggests that the trend curve significantly influences Bitcoin's price volatility during this period.

The regression results of the Elastic Net tell us that the Russian stock market (MOEX Russia Index) significantly impacts the low-frequency curve and trend curve of Bitcoin's price in the Post-COVID-19 Period. We observed a significant drop in Bitcoin's low-frequency curve in February 2022: in February 2022, the Russia-Ukraine conflict broke out. This is a major and long-lasting international conflict that impacts the cryptocurrency market. The factors of Bitcoin market situations mainly influence the low-frequency curve of Bitcoin's price (MVRV, free float MVRV, market capitalization, realized market capitalization, free float market capitalization). The low-frequency curve of Bitcoin's price in this phase is also influenced by many external macro-financial factors: in addition to the Russian stock market (MOEX Russia Index), there is also the influence of the Chinese stock market (FTSE China A50 Index) and exchange rates (RUB/USD, GBP/USD).

The trend curve in the Post-COVID-19 Period shows a trend of first

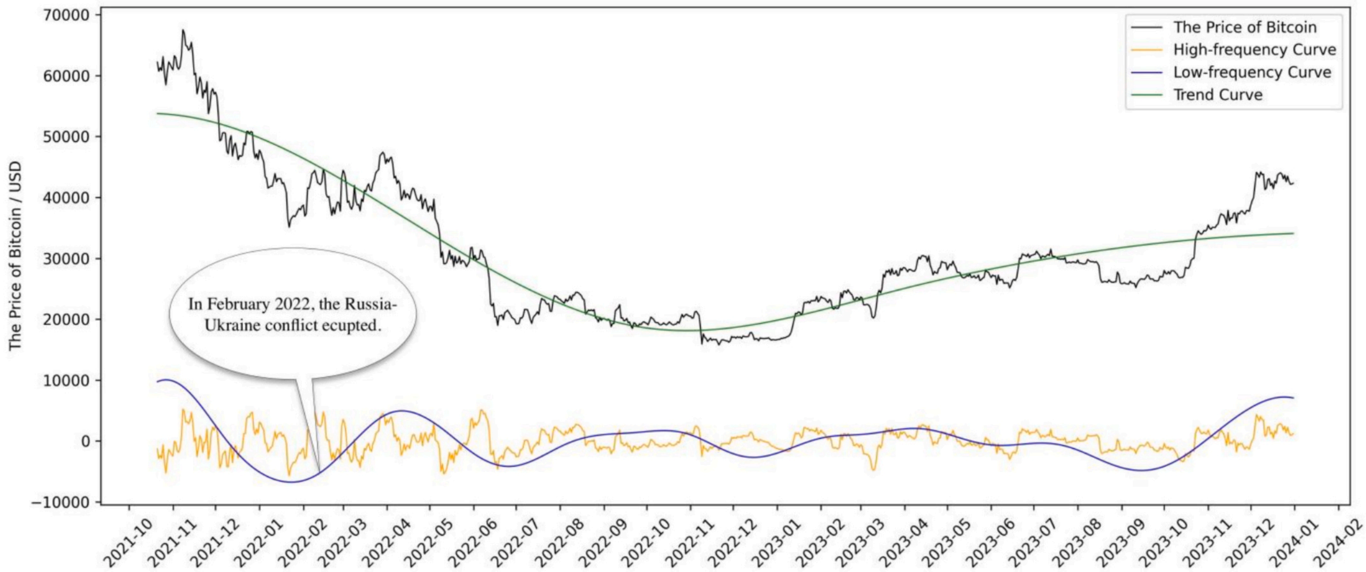

Fig. 7. Bitcoin's daily closing price and its three frequency curves of the Post-COVID-19 Period.

Table 11
The statistical metrics and major influencing factors of the high-frequency, low-frequency and trend curves of the Post-COVID-19 Period.

	High-frequency curve	Low-frequency curve	Trend curve
Pearson Correlation	0.187*	0.426*	0.929*
Kendall Correlation	0.165*	0.181*	0.765*
Coefficient of Variation	−81.37	94.33	0.33
Relative Range	−480.43	451.08	1.15
Variance as % of (∑IMFs + residue)	2.87 %	10.32 %	86.81 %
Top 10 Contributing Factors (arranged in descending order of the factor weights of the coefficients according to Elastic Net)		MOEX Russia Index (9.05 %), MVRV (7.76 %), Free Float MVRV (7.59 %), Miner Revenue Per Hash Unit (6.76 %), GBP/USD (6.19 %), FTSE China A50 Index (6.01 %), Market Capitalization (5.30 %), Realized Market Capitalization (5.28 %), Free Float Market Capitalization (5.01 %), RUB/USD (4.59 %).	MOEX Russia Index (19.68 %), Realized Market Capitalization (12.35 %), RUB/USD (7.99 %), FTSE China A50 Index (7.54 %), Nasdaq Composite Index (6.20 %), GBP/USD (5.63 %), Free Float Market Capitalization (4.83 %), Market Capitalization (4.36 %), EUR/USD (3.42 %), Miner Revenue Per Hash Unit (3.18 %).

* Correlation is significant at the 0.05 level.

falling and then rising. The main factors affecting the trend curve are related to Bitcoin market conditions (realized market capitalization, free float market capitalization, market capitalization). In addition to the Russian stock market (MOEX Russia Index), the trend curve of Bitcoin's price at this phase is also affected by the Chinese stock market (FTSE China A50 Index), the US stock market (Nasdaq Composite Index), and exchange rates (RUB/USD, GBP/USD, EUR/USD). In general, in the Post-COVID-19 Period, Bitcoin's price is mainly influenced by the factors of Bitcoin market conditions and the external macro-financial environment. The Bitcoin market is greatly affected by the Russia-Ukraine conflict.

5.6. *A summary of the five phases*

Overall weights offer a more direct approach to analyzing the changing influence of various factors on Bitcoin's price. Employing Elastic Net regression coefficients, we calculated overall weights of the five categories across the five phases: Factors of Macroeconomic Environment, Factors of Bitcoin Market Conditions, Factors of Bitcoin's Production and Transaction, Factors of Bitcoin's Supply-demand Dynamics, and Factors of Global Geopolitical Risks.

Fig. 8 depicts the evolution of these overall weights across different phases. We observe an upward trend in the overall weights of Factors of Macroeconomic Environment, suggesting a strengthening link between Bitcoin and other financial assets such as stocks, currencies, and commodities. This indicates that macroeconomic environment is exerting a growing influence on Bitcoin's price, making it increasingly susceptible to economic fundamentals. While the overall weights of Factors of Bitcoin Market Conditions initially declined, they subsequently stabilized around a consistent value, signifying their enduring impact on Bitcoin's price. Conversely, the overall weights of Factors of Bitcoin's production and Transaction have steadily decreased, indicating that while these factors were initially critical to Bitcoin's pricing, their influence is diminishing. Factors of Bitcoin's Supply-demand Dynamics exerted a significant impact on Bitcoin's pricing during the COVID-19 Period. The influence of Factors of Global Geopolitical Risks on Bitcoin's price remains generally low.

Fig. 9 delves into the overall weight changes within Factors of Macroeconomic Environment, focusing on its three subcategories: Factors of Stock Markets, Factors of Exchange Rates, and Factors of Commodity Markets. Notably, the sustained growth in the overall weights of this category is primarily driven by the increasing overall weights of Factors of Stock Markets. This signifies that the interconnectedness of Bitcoin market to stock markets is strengthening faster than its interconnectedness to other financial markets.

The speculative or safe-haven nature of Bitcoin has changed as the market has evolved through different phases. In the Early Stage, despite some people considering Bitcoin a safe-haven asset following the Cyprus financial crisis, Bitcoin did not exhibit clear characteristics of a safe-haven asset. After its price exceeded $1000, it quickly fell. At this

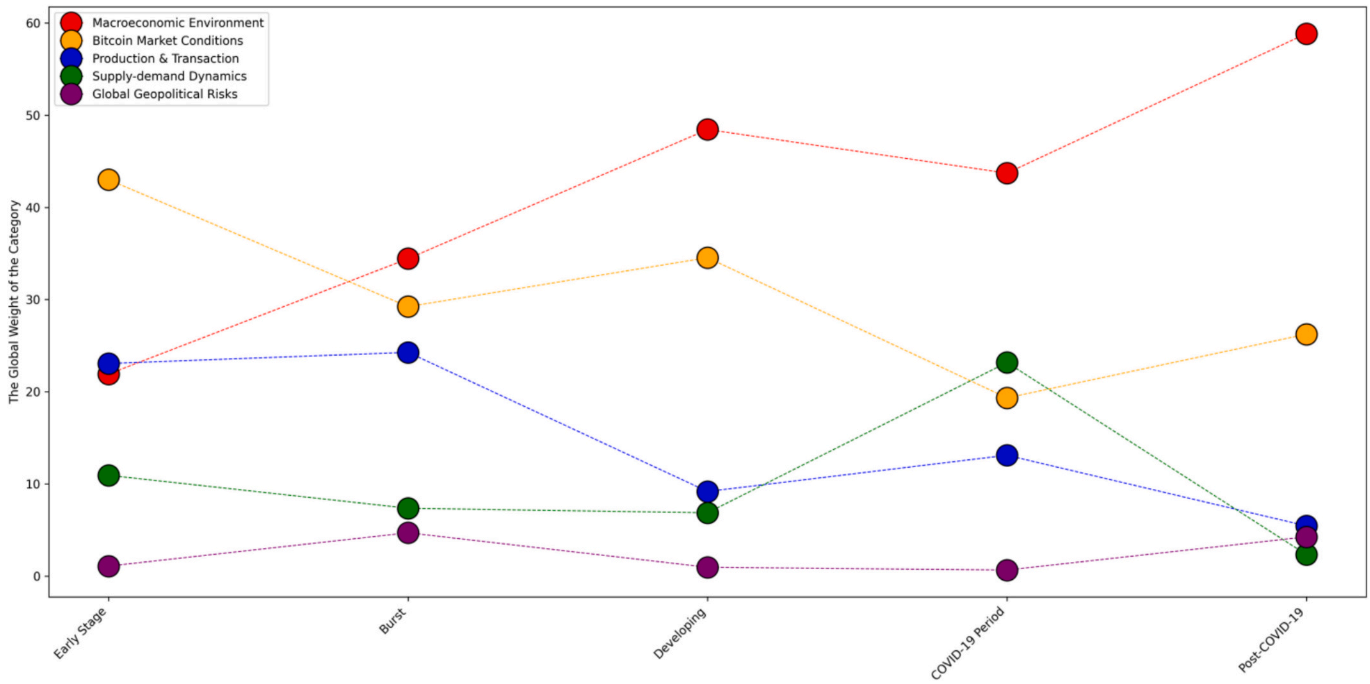

Fig. 8. Overall Weights of the five categories across the five phases.

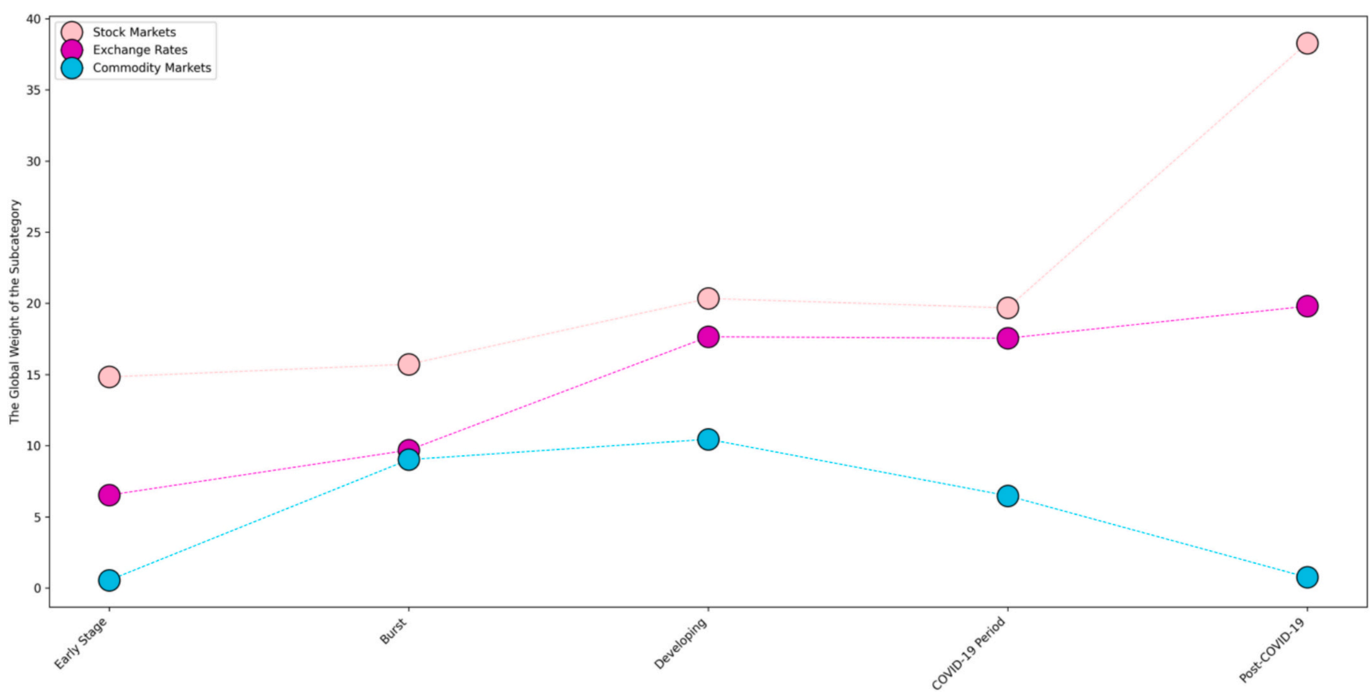

Fig. 9. Overall weights of the three subcategories of Factors of Macroeconomic Environment.

phase, Bitcoin's price was largely influenced by factors such as Bitcoin production and trading dynamics, as well as market conditions (such as market sentiment), and had low correlation with other financial assets. Therefore, Bitcoin in this phase displayed traits of a speculative asset. During the Burst and Developing phases, investor sentiment fluctuated significantly—initially rising sharply, catalyzed by the launch of Bitcoin futures by CBOE and CME in December 2017, and later dipping, influenced by the November 2018 Bitcoin Cash split into Bitcoin Cash ABC and Bitcoin Cash SV. After peaking at the end of 2017, Bitcoin's price rapidly dropped into a prolonged bear market that lasted over a year. Although Bitcoin's connection with the broader macro-financial environment strengthened during this period, it did not exhibit clear safe-haven characteristics and remained a speculative asset driven by short-term investor sentiment. In the COVID-19 Period, despite the rapid surge in Bitcoin's price in the first half of 2021, catalyzed by Elon Musk's strong interest in Bitcoin (which sparked similar strong interest from other investors), Bitcoin maintained a bull market throughout the pandemic. In this phase, Bitcoin could be viewed as a new emerging asset with both speculative and safe-haven properties. In the Post-COVID-19 Period, Bitcoin's correlation with the broader macro-financial environment continued to strengthen. During this phase, Bitcoin is often viewed as a tool for diversifying financial investment risks.

6. Conclusion

Using Bai-Perron Multiple Breakpoint Test, we have partitioned the daily closing price of Bitcoin spanning from November 1, 2013, to December 31, 2023, into five discernible temporal phases, namely Early Stage, Burst, Developing, COVID-19 Period and Post-COVID-19 Period. Within each distinct phase, the ICEEMDAN method has been employed for dissection Bitcoin's daily closing price, followed by applying the Van der Waerden Test to reconstruct high-frequency, low-frequency, and trend curves synthetically. Key statistical metrics, including Pearson coefficient, Kendall coefficient, variance as a percentage of (IMFs + residue), coefficient of variation, and relative range, were calculated for each of the three curves in every phase. In conjunction with an exhaustive review of Bitcoin literature spanning the last ten years, encompassing a spectrum of 47 influencing factors, the Elastic Net regression technique was implemented to discern the ten most impactful factors for the high-frequency, low-frequency, and trend curves during each phase. This three-stage analysis is based on the assumption that interactions between factors are not considered. The analytical examination of Bitcoin's price engendered distinctive revelations pertaining to the dynamics of the high-frequency, low-frequency, and trend curves within the confines of each discerned temporal phase.

When examining the five distinct phases, it becomes evident that, with the exception of the Burst stage, the high-frequency curve exhibits a higher coefficient of variation and relative range compared to the other two curves. However, across these five phases, the high-frequency curve's variance accounts for the lowest percentage of (IMFs + residue). This meticulous observation suggests that, despite the high-frequency curve's greater dispersion around its mean, its influence on the overall trend of Bitcoin prices is relatively minor. The Elastic Net regression analysis results reveal a notable positive correlation between the high-frequency curve and factors such as MVRV and transaction fees. This indicates that fluctuations in the high-frequency curve often align with investor sentiment and daily trading frequency within the Bitcoin market. Notably, the volatility of the high-frequency curve is more pronounced during periods of elevated investor sentiment, increased market activity, and a higher frequency of daily transactions. Furthermore, the high-frequency curve can serve as a suggestive indicator of speculative behavior within the dynamic environment of the Bitcoin market.

In our analysis of the low-frequency curve, we observe that significant fluctuations in the curve often coincide with major global political and economic events or significant events within the cryptocurrency market. These events that impact the Bitcoin market include the Cyprus financial crisis, the Chinese government's declaration of ICO financing as illegal, the Bitcoin Cash blockchain fork, Tesla's substantial investment in Bitcoin, the Chinese government's closure of all Bitcoin mining activities within its borders, and the outbreak of the Russia-Ukraine conflict. These events can be categorized as follows: policies and regulatory measures taken by national institutions regarding Bitcoin, stances adopted by prominent companies (such as Tesla) towards Bitcoin, unpredictable global events (such as the COVID-19 pandemic and the Russia-Ukraine conflict), changes in macroeconomic and financial landscapes (such as the Cyprus financial crisis), and Bitcoin's security issues and blockchain stability (such as exchange hacks and the Bitcoin Cash fork event). Results from the Elastic Net regression analysis indicate that the low-frequency curve is influenced by factors of Bitcoin market conditions, factors of Bitcoin's supply-demand dynamics, factors of Bitcoin's production and transaction, global stock markets, and exchange rates. This highlights that Bitcoin's medium-term fluctuations are not solely linked to internal factors related to Bitcoin's production and transaction and Bitcoin market conditions but also exhibit a correlation with broader macroeconomic and financial indicators on a global scale.

In the Burst, COVID-19 Period, and Post-COVID-19 Period phases, the percentage of variance accounted for by the trend curve in relation to (IMFs + residue) is most pronounced among the three curves resulting from the decomposition and reconstruction of Bitcoin's price. This underscores the dominant role played by the trend curve in determining the primary trajectory of Bitcoin's price during these phases. The Elastic Net regression analysis reveals the factors influencing the trend curve, with factors of Bitcoin market vitality, factors of Bitcoin's supply-demand dynamics, Bitcoin production factors, and macroeconomic factors (including factor of stock markets, exchange rates, and commodity markets) emerging as the four most significant drivers. In the Early Stage, factors of supply-demand dynamics are the most prominent factors influencing the trend curve, followed by macroeconomic factors and Bitcoin production factors. During the Burst phase, factors of Bitcoin market vitality significantly impact the trend curve, followed by macroeconomic factors and Bitcoin production factors. In the Developing phase, macroeconomic factors become the most prominent influence on the trend curve of Bitcoin's price, followed by factors of Bitcoin market vitality and Bitcoin production factors. In the COVID-19 Period, factors of supply-demand dynamics have the most pronounced effect on the trend curve, followed by macroeconomic factors and factors of Bitcoin market vitality. In the Post-COVID-19 Period, the most influential factors on the trend curve for Bitcoin's price are macroeconomic factors, followed by factors of Bitcoin market vitality. Overall, among the factors influencing the long-term trend of Bitcoin's price, the influence of macroeconomic factors is increasing, while the impact of Bitcoin production factors is diminishing. This suggests that the interconnectedness between Bitcoin and other financial assets (stocks, exchange rates, commodities) is strengthening as the cryptocurrency market matures further.

To gain a deeper understanding of how various factors impact Bitcoin's price over time, we employ a novel approach utilizing overall weights. These weights, derived from Elastic Net regression coefficients, provide a more direct measure of the changing influence of different categories of factors. We categorize these factors into five distinct categories: Factors of Macroeconomic Environment, Factors of Bitcoin Market Conditions, Factors of Bitcoin's Production and Transaction, Factors of Bitcoin's Supply-demand Dynamics, and Factors of Global Geopolitical Risks. Analyzing these categories across five distinct phases revealed notable trends. The overall weights attributed to Factors of Macroeconomic Environment show a consistent upward trend. This suggests a strengthening link between Bitcoin and traditional financial markets, indicating that macroeconomic forces are increasingly influencing Bitcoin's price. Notably, the growth in this category's overall weight is primarily driven by the increasing influence of Factors of Stock Markets, highlighting the accelerating interconnectedness between Bitcoin and stock markets. Factors of Bitcoin Market Conditions initially see a decline in the overall weights, but eventually stabilized at a consistent level, indicating the sustained influence on Bitcoin's price. Conversely, the overall weights of Factors of Bitcoin's Production and Transaction have been steadily decreasing. This suggests that while these factors were initially crucial in determining Bitcoin's price, their impact is diminishing over time. This analysis provides valuable insights into the evolving dynamics of Bitcoin's price, highlighting the growing importance of macroeconomic factors and the persistent influence of factors of Bitcoin market conditions. It also reveals the diminishing impact of factors of Bitcoin's production and transaction, suggesting a shift in the factors driving Bitcoin's price fluctuations.

The speculative and safe-haven properties of Bitcoin vary at different phases of its market development. During the Early Stage, Burst, and Developing phases, Bitcoin had a weak connection with the external financial environment, and its price movements were often influenced by short-term investor sentiment, typically catalyzed by significant events such as the Cyprus financial crisis, the launch of Bitcoin futures by CBOE and CME, and the Bitcoin Cash fork. In the COVID-19 Period, although Bitcoin still exhibited some speculative characteristics (such as Elon Musk's interest in Bitcoin, which fueled enthusiasm among other investors in the market), its price remained in a bull market throughout this phase, serving as a potential safe-haven asset. In the Post-COVID-19 Period, as Bitcoin's connection with the broader financial environment strengthened further, it began to be increasingly viewed as a tool for diversifying investment risk.

Hence, our recommendations for Bitcoin investment are as follows: Firstly, from a long-term perspective, it is anticipated that Bitcoin's price will positively correlate with the escalating market vitality. The periodic halving of Bitcoin production introduces alterations in supply-demand dynamics, thereby contributing to an elevation in Bitcoin's price. Secondly, in the short-term or mid-term perspectives, Bitcoin can be strategically incorporated into investment portfolios as a risk-diversifying asset alongside traditional assets (Alexander et al., 2023; Anyfantaki et al., 2021; Baur, Dimpfl, & Kuck, 2018; Bouri, Gupta, et al., 2017; Briere et al., 2015; Corbet, Meegan, et al., 2018; Frikha et al., 2023; Guesmi et al., 2019; He et al., 2024; Kayla et al., 2023; Klein et al., 2018; Mariana et al., 2021). Thirdly, during periods of global upheaval and instability, Bitcoin's price is subject to a myriad of influencing factors, resulting in heightened volatility and challenging predictability. Consequently, it is not advisable to categorize Bitcoin as a safe-haven asset during such tumultuous times (Chen et al., 2020; Conlon & McGee, 2020; Corbet et al., 2020).

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Data availability

No.

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