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Research Article

The impact of fundamental factors and sentiments on the valuation of cryptocurrencies

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A B S T R A C T

The valuation of cryptocurrencies is important given the increasing significance of this potential asset class. However, most state-of-the-art cryptocurrency valuation methods only focus on one of the fundamental factors or sentiments and use out-of-date data sources. In this study, a robust cryptocurrency valuation method is developed using up-to-date datasets. Using various panel regression models and moving-window regression tests, the impacts of fundamental factors and sentiments in the valuation of cryptocurrencies are explored with data covering from January 1, 2009 to April 30, 2023. The research shows the importance of sentiments and suggests that the fear and greed index can indicate when to make a cryptocurrency investment, while Google search interest in cryptocurrency is crucial when choosing the appropriate type of cryptocurrency. Moreover, consensus mechanism and initial coin offering have significant effects on cryptocurrencies without stablecoins, while their impacts on cryptocurrencies with stablecoins are insignificant. Other fundamental factors, such as the type of supply and the presence of smart contracts, do not have a significant influence on cryptocurrency. Findings from this study can enhance cryptocurrency marketisation and provide insightful guidance for investors, portfolio managers, and policymakers in assessing the utility level of each cryptocurrency.

1. Introduction

1.1. Research purpose

This study examines the valuation of cryptocurrencies (cryptocurrency). There is a growing interest in cryptocurrency, and many existing studies [1–3] have explored its nature and characteristics. Two important aspects of the debate on cryptocurrency relate to whether they are a distinctive asset class and the way in which they are valued. The valuation of cryptocurrency is important given its increasing significance as an emerging new asset class. However, because there is a lack of an effective valuation method for cryptocurrency, it can be difficult for investors to evaluate them and determine their utility and potential to generate high investment returns. For this reason, it is vital to develop useful and effective valuation methods for cryptocurrencies so that investors are better informed and are not investing in cryptocurrencies that have low returns. Clarifying the valuation of cryptocurrency can enhance its transfer and marketisation.

1.2. Gaps in the literature

One of the major drawbacks of previous research is that they evaluated the impacts of individual fundamental factors and sentiments without a comprehensive consideration of the different fundamental factors and sentiments. For example, although Hayes [4] investigated the impacts of the applied algorithm, coin production rate, computational power, marginal costs of production, and mining potential on various cryptocurrencies, the author did not consider the types of supply (i.e., inflationary, deflationary, or limited). However, types of supply could be predictive of price because investors may have a higher valuation on a cryptocurrency if its supply is limited. For example, Bitcoin has a higher value due to its scarcity. Thus, this study will include supply factors to further expand on research regarding the supply fundamentals of cryptocurrencies. Furthermore, consensus mechanisms are key fundamentals of cryptocurrencies that could have price predictive power because they determine mining priorities. However, Hayes's studies did not consider the consensus mechanism. Extant studies also relied on very old data, with most of the data collected before 2018. Moreover, the majority of the extant studies also used a simple regression model setup

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without exploring the dynamic relationship between the independent and dependent variables. For example, Hayes [4] investigated the fundamental factors on the 66 most widely used cryptocurrencies in 2014, a time when smart contracts had not been developed. Smart contracts are now a common feature of cryptocurrencies. Liebi [5] specified active addresses-to-network value as a valuation metric that captures transaction benefits. He found that a high active addresses-to-network value ratio yields on average 3.7% higher weekly returns than cryptocurrency assets with a low active addresses-to-network value ratio. Furthermore, cryptocurrencies with stablecoins were not considered in previous studies. Cryptocurrencies with stablecoins are pegged to non-volatile assets, and their price volatility could be quite different from those without stablecoins. Thus, it is important to include the top 100 cryptocurrencies of today's market whilst considering the influence of stablecoin on cryptocurrency value and other different fundamental factors that have not been considered in the extant studies (e.g., consensus mechanism, supply types, presence of smart contract, and initial coin offerings) to gain a more comprehensive evaluation of the fundamental factors.

Furthermore, although Google search and the pandemic fears have been considered in the evaluation of the role of sentiments in the valuation of cryptocurrency, the cryptocurrency market has grown significantly since these investigations. Last year alone, the total cryptocurrency market cap grew by over 880% [6]. In addition, Bitcoin is now being adopted as a legal tender in countries like El Salvador [7]; therefore, a reassessment of the claim that Bitcoin and other cryptocurrencies are a bubble is expedient. Moreover, most sentiment studies only focused on popular cryptocurrencies such as Bitcoin and Ethereum, while other altcoins have not been considered. Our study extends the literature on the bubble behavior in cryptocurrency markets by using the Google search interest index (GSI) as an indicator of market sentiment. This extends the literature on the impacts of sentiment on the value of cryptocurrency. It is important to build a critical mass of evidence on the best valuation techniques for cryptocurrencies involving an extensive number of cryptocurrencies. In a recent theoretical exposition, Burda [8] suggested that cryptocurrency could be evaluated by a demand fundamental (i.e., driven by present and expected future convenience opportunity costs in each period), a supply fundamental (i.e., algorithmic coin issue trajectory), and a bubble component (i.e., the deviation of the observed price from its fundamental, driven solely by expectations of future appreciation). Our study extends the literature by providing empirical evidence of the valuation of cryptocurrency and taking into account various fundamental factors.

Our analysis is based on data from January 1, 2009 to April 30, 2023, using panel regression models and moving-window regression tests to comprehensively assess cryptocurrency valuation. This study explores three hypotheses and provides novel insights into cryptocurrency valuation. It found that the cryptocurrency Fear and Greed Index (FGI) and GSI are two of the most significant factors affecting the values of cryptocurrencies. The fact that the FGI has a vital influence on cryptocurrency returns demonstrates the importance of market sentiments and their predictive value. The importance of GSI shows that cryptocurrencies remain susceptible to bubbles. However, only consensus mechanisms and Initial Coin Offering (ICO) have significant effects on cryptocurrencies without stablecoins, while none of the fundamental factors has significant impacts on cryptocurrencies with stablecoins. These findings provide significant insights to investors, fund managers, policymakers, and other stakeholders on the valuation and marketisation of cryptocurrencies.

1.3. Contribution

This study makes four unique contributions to the cryptocurrency literature regarding their valuation and marketisation. Although there is growing interest in cryptocurrencies, investors are allocating their portfolios with limited knowledge of the principles and intrinsic values of blockchain. There is inadequate clarity on the selection criteria for cryptocurrency, which often exacerbates investors' risk exposure. This study first addresses the valuation of cryptocurrency, which is crucial to its acceptance on a global scale. The top 100 cryptocurrencies are investigated to evaluate cryptocurrency daily return features. Second, it provides an alternative valuation method of cryptocurrencies that considers both fundamental factors and market sentiments, including consensus mechanism, ICO, the presence of smart contract, the presence of stablecoin, the supply type, FGI and Google search index. This extends the previous literature on the valuation approaches to cryptocurrencies. Third, it uses moving-window regression tests to demonstrate the dynamic relationship between different fundamental factors, sentiments and cryptocurrency's daily returns. Finally, this study recognises the alternative context in cryptocurrency valuation by focusing on the period between 2009 and 2023, thereby providing the most up-to-date assessment of the valuation for cryptocurrencies. The rest of the study is presented in four sections. Section 2 presents the theoretical context and the literature review. Section 3 presents the study design, and Section 4 presents the findings and discussion. Section 5 illustrates the practical implications, while the conclusion and future study are discussed in Section 6.

2. Literature review

2.1. A brief background to techniques in cryptocurrency

Cryptocurrencies are digital assets that have become a new global frontier where technology meets finance [9]. Blockchain technology can be described as a digital public ledger of transactions that exist across a network [10]. Several previous studies have provided basic introductions and background information about cryptocurrencies [11–13]. The blockchain processes transactions by sorting them into blocks of data, with each block having a specified capacity for transactions. Once the block's capacity is filled, it is timestamped, encrypted, and added to the previous block via hash codes. Every block contains a unique hash code that allows blocks to connect in chronological order. Before blocks are added to the blockchain, they need to be verified via a consensus mechanism, for example, through a proof-of-work (PoW). This requires miners to use computational power to solve the hash function of the next block to be added to the chain. The miner that computes the correct hash is then rewarded with cryptocurrency as payment for their work. The security of the PoW consensus mechanism relies on the inability of a bad actor to acquire control of 51% of the network's computational power to double-spend funds. Without control of this percentage of the network, transactions that double-spend funds are invalidated by honest miners.

The PoW consensus mechanism was first adopted by Adam Back in 1997, who invented Hashcash, which was used as a security measure to limit unwanted emails and denial-of-service attacks within a network [14]. Just over ten years later, Satoshi Nakamoto adapted this system and created Bitcoin [15]. Bitcoin is the first decentralised cryptocurrency to solve the double-spend problem using blockchain technology. An attractive feature of Bitcoin from an investor's perspective is its finite supply; only 21,000,000 Bitcoins can ever be mined. Therefore, Bitcoin is scarce, and for this reason, it has the potential to become a store of value assets in the future [16].

Since the creation of Bitcoin, the cryptocurrency market has grown significantly, as there are now over 6000 cryptocurrencies with a total market capitalisation of approximately USD 2 trillion as of Q4 2021 [17, 18]. All cryptocurrencies created after Bitcoin have been termed Altcoins, short for alternative coins [19]. The first altcoin was Namecoin, developed by the pseudonym Vincent Durham in 2011 [20]. Shortly after, Buterin [21] created the largest altcoin to date, by market cap, called Ethereum [22]. Ethereum presently utilises a PoW protocol, although it planned to transition to a proof-of-stake (PoS) consensus mechanism. PoS is commonly adopted by cryptocurrency because it changes the way blocks are verified to increase scalability and reduce the environmental concerns of PoW protocols [23]. Validators are paid for using their staked coins to verify blocks and add them to the blockchain. If they behave dishonestly, they are penalised via partial removal of their staked coins (i.e., slashing) [24]. In this way, validators are incentivised to be honest actors in the network. Such consensus mechanisms can be seen as key fundamentals of a cryptocurrency valuation.

Ethereum is the first altcoin to develop smart contracts, a term that was initially proposed by Szabo [25]. Smart contracts replicate tangible contracts except that they are programmed to automatically execute an agreement once the predefined conditions are met [26]. This removes the need for an intermediary such as a bank [27]. Decentralised finance (Defi) services such as collateralised loans and yield farming from cryptocurrency assets are possible through smart contracts. They have also enhanced the development of decentralised applications (DApps), which are digital programs that run autonomously on the blockchain [28]. One application of DApps is peer-to-peer marketplaces, where users can buy and sell Non-Fungible Tokens. Due to the versatility of the Ethereum blockchain, it behaves like a digital ecosystem [29]. Users can trade NFTs, make or validate transactions, stake coins, partake in yield farming and use other Defi services, all whilst transacting in the native cryptocurrency (i.e., Ether). Consequently, the ecosystem has a wide range of users that use blockchain for different purposes, interacting daily in a multitude of ways [30]. Unlike the stock market, where investors use financial ratios such as the price-to-earnings ratio [31] to find undervalued stocks, cryptocurrency investors lack a consensus valuation method. Previous studies [32,33] have revealed a wide range of fundamental factors that can determine and influence the value of cryptocurrencies. However, there is no consensus on their usefulness.

2.2. Fundamental factor valuation

The fundamental factors of a cryptocurrency refer to the asset's primary characteristics that determine its stability as an asset. Existing studies [4,34] on cryptocurrency have identified supply factors, the algorithms used and the longevity of a cryptocurrency as fundamental value drivers. For example, Hayes [4] explored the fundamental factors that enhance the value of a cryptocurrency using cross-sectional empirical data and regression analysis. He examined 66 of the most widely used cryptocurrencies in 2014 and suggested that when valuing a cryptocurrency, supply factors are important, as they can affect the price. Hayes [4] also found that the type of algorithm (i.e., Scrypt and SHA-256) also affects the value of a cryptocurrency. The Scrypt algorithm appeared to have more value in altcoins than the SHA-256 algorithm. This is because the Scrypt algorithm requires more computing power, meaning the cryptocurrency is less susceptible to hacks, which is evidently a trait that investors value. He also concluded that the longevity of a cryptocurrency is positively related to its price. This is because the longevity of cryptocurrency demonstrates its stability and intrinsic value. In other words, it is not just a pump and dump.

Sharif et al. [35] adopted a quantile spillover index approach to examine the relationship between green economy performance and the mode of cryptocurrency consensus. They found a stronger overall linkage between green economy indices and cryptocurrencies with PoS than those with PoW. They also found that the overall spillover effect of cryptocurrencies with PoS was quite high, indicating the safe harbour property for diversification purposes. Furthermore, Hayes [32] considered the impact of the marginal cost of production on the value of a Bitcoin and found that 81% of the price of the cryptocurrency is associated with its marginal cost of production. Evidence over five years showed that Bitcoin had been relatively efficient because the standard deviation between the model created and the price of Bitcoin was just USD 0.33. Hayes [32], therefore, disputed critics who suggested that Bitcoin is worthless. For example, Cheah and Fry [36] argued that Bitcoin has no fundamental value.

Thus, the extant literature has focused predominantly on Bitcoin whilst neglecting other fundamental factors, such as consensus mechanisms, supply types, the presence of smart contracts, and ICOs. Consequently, one of the objectives of this study is to explore the impacts of the fundamental factors of cryptocurrency on its investment returns. Based on the above-mentioned research [32,36], we predict that cryptocurrency's fundamental factors affect their daily returns. The hypothesis is formulated as follows.

Hypothesis 1. There is an association between a cryptocurrency's fundamental factors and its daily returns.

2.3. Market sentiment value

The speculative feature of cryptocurrencies has been a concern of many stakeholders. Many investors have argued that cryptocurrencies such as Bitcoin and Ethereum do experience speculative bubbles. A speculative bubble is a sharp rise in prices that is fuelled by market sentiments instead of the underlying fundamentals. Bubbles have been measured using different variables and indexes. Glaser et al. [37] found that new users tend to trade Bitcoin as a speculative investment and have little intention of using Bitcoin as a means of payment. Mai et al. [38] used social media forum posts that include the term 'Bitcoin' to find a relationship between forum posts and Bitcoin price. Mai et al. found that one positive forum post is associated with an increase in Bitcoin's price by 0.00353% the next day. This shows that social media and investor sentiment cause Bitcoin volatility because the price reacts to sentiment rather than fundamentals. This means that sentiment can predict the value of a cryptocurrency in the short term. However, Corbet et al. [39] used a Generalised Supremum Augmented Dickey-Fuller in a recursive backward regression analysis to test and timestamp the presence of bubbles in Bitcoin between 2010 and 2017 and Ethereum between 2015 and 2017. They did not find any clear evidence that Bitcoin and Ethereum experienced persistent bubbles. Instead, they found that there are distinct short-term periods where fundamentals influence the price dynamics of both cryptocurrencies.

Kyriazis et al. [40] investigated the nonlinear causality of the cryptocurrency mean and Twitter-derived economic and market uncertainty index during the COVID-19 pandemic. They established a non-linear relationship between the mean value of selected cryptocurrencies (including Bitcoin, Ethereum, Bitcoin Cash, and Litecoin) and the Twitter-derived economic uncertainty index. This is because low-priced cryptocurrencies generally present modest levels of volatility, even when modest levels of economic uncertainty or investor optimism exist. These types of cryptocurrencies are found to be unaffected by volatile investor sentiment or financial crises. Similarly, Papadamout et al. [41] examined the relationship between the Economic Policy Uncertainty index and cryptocurrency prices. They found that the Economic Policy Uncertainty index influences the means of almost half of the investigated cryptocurrencies and demonstrated significant non-linear effects in every quantile of cryptocurrency volatilities. This indicates that the speculative motivation of cryptocurrency investment is not affected by the economic environment. Using a backward superior covariate-augmented Dickey-Fuller test, Agosto et al. [42] demonstrated that the effects of a polarised version of investors' sentiment on cryptocurrency are more significant than news volume and Google queries, especially in providing an early warning signal of market bubble episodes in cryptocurrencies.

Gaies et al. [43] analysed the impact of Bitcoin sentiment on its returns in both the short and long term. They used the Kansas City Financial Stress Index to represent sentiment, and other variables in their analysis include the Bitcoin Misery Indicator, the 10-year nominal interest rate, and the US volatility Index. One key finding of their study was that the long-run coefficient of the Financial Stress Index was positively correlated with Bitcoin returns, showing that in the long term, investors will disinvest in Bitcoin in the event of financial stress or bad news. However, in the short term, Bitcoin is seen as a safe haven for investors to increase returns. Hoang and Baur [44], on the other hand, contradicted these findings when examining the effects of coronavirus fears on volatility and returns of major cryptocurrencies during the COVID-19 outbreak. They used five different cryptocurrencies in their analysis and found that cryptocurrency prices fell, and volatility increased during times of extreme fear, as measured by the abnormal Google search volume index. However, when fear disappeared, prices rallied and became more stable, thus contradicting Gaies et al.'s conclusion that investors react to financial stress by buying Bitcoin and treating it as a safe haven [43]. Hoang and Baur's research appears more credible, as they used Google search volume to measure fear, which is inclusive of the world population [44]. Whereas Gaies et al. [43] used the Financial Stress Index based on the US which may not be a representative indicator.

Overall, the extant literature focused on the Economic Policy Uncertainty index or Financial Stress Index to represent market sentiments, while only the top 5 cryptocurrencies have been investigated. There is a lack of study on the dynamic relationship between cryptocurrency's daily returns and its FGI on a broad selection of cryptocurrencies. In this paper, we used the cryptocurrency FGI ranging from 2018 to 2023 and explored the issue with the hypothesis below.

Hypothesis 2. There is an association between the cryptocurrency FGI and its daily returns.

Furthermore, studies have explored the impact of social media trends on the value of cryptocurrency. For example, Kristoufek [45] used Google trend searches and Wikipedia searches to determine sentiments in their exploration of the relationship between Bitcoin's price and search interest. Both variables were proven to be statistically correlated to price between 2011 and 2013, thus supporting the claim that social media and internet trends can be predictive of future Bitcoin prices. Similarly, Cheah and Fry [36] valued Bitcoin as a speculative bubble by using the GSI index as the variable affecting price between July 2010 and November 2013. They found that the bubble accounted for around 48.7% of the observed daily prices and concluded that Bitcoin's fundamental value is zero.

However, the above-mentioned studies focused on Bitcoin only and with data collection before 2014. Our study aims to evaluate the dynamic relationship between the Google search index and daily investment returns for various cryptocurrencies and to explore whether speculative bubbles are applicable to each cryptocurrency. Thus, our third hypothesis is formulated as follows.

Hypothesis 3. There is an association between GSI in each cryptocurrency and their corresponding daily returns.

3. Methodology

3.1. Research design

There are 22,904 cryptocurrencies in existence as of March 2023 [46], while there are only 8832 active cryptocurrencies. An initial sample of 100 cryptocurrencies was chosen according to their market capitalisation (Coinmarketcap.com) on May 10, 2022. The sample is further reduced to 42 due to the availability of historical cryptocurrency prices [47]. Given that our regression models are developed using panel data, daily data of 42 cryptocurrencies over the period between January 1, 2009 and April 30, 2023 give us a total of 79,445 observations, which should be sufficient to achieve insightful outcomes. Historical cryptocurrency prices of these 42 cryptocurrencies are collected from Messari.io, information regarding fundamental factors is extracted from Coinmarketcap.com, and information on FGI is collected from the Alternative.me website [48], and information on the GSI of each cryptocurrency is obtained from Google Trend [49]. Alternative.me, Coinmarketcap.com, and Messari.io are the most reliable and frequently used websites in the study of cryptocurrency. We have cross-checked information from these websites against one another to ensure that they are up-to-date and the most reliable. The detailed data collection sources, time span and frequency are summarised in Table 1.

After data collection, this study adopts a deductive research approach and a quantitative research strategy. Various regression models and statistical tests were conducted to evaluate the three hypotheses. The daily return price of each cryptocurrency is calculated as follows:

$$RTN_i = \frac{P_i - P_{i-1}}{P_{i-1}} \tag{1}$$

where

RTN_i represents daily return on the ith day, and P_i represents cryptocurrency price on the ith day.

Additional information about the detailed data collection sources and data analytics methods are presented in the following subsections based on the related hypotheses tested. Most of the regression analyses were based on panel data analysis [50] given that our data were composed of a panel of cryptocurrencies explored over a reasonable length of time.

3.2. Fundamental factors analysis

The definition and data sources for each of the fundamental factors are summarised in Table 1. To test Hypothesis 1 on the association between cryptocurrency fundamental factors and daily returns, we used a panel regression model approach on the 42 sampled cryptocurrencies over the scope of the study. The dependent variable is the daily return on investment (RTN) in cryptocurrency, whilst the independent variables include various fundamental factors, including the adoption of PoW consensus mechanism, the adoption of PoS consensus mechanism, the presence of smart contract (SC), ICO, the adoption of inflationary with unlimited supply (IS) and the adoption of limited supply (LS). We used these fundamental factors due to their importance in cryptocurrency mining. We control whether a cryptocurrency is a stablecoin or not. We present the definition, measurement and importance of each variable in Table 2. These factors are dummy-coded for regression analysis. Regression model 1 is shown in Eq. (2) below, where i is the cryptocurrencies and t is the time frame:

$$\begin{aligned}\mathrm{RTN}_{it} = {} & \beta_0 + \beta_1 \mathrm{PoW}_{it} + \beta_2 \mathrm{PoS}_{it} + \beta_3 \mathrm{SC}_{it} + \beta_4 \mathrm{ICO}_{it} + \beta_5 \mathrm{IS}_{it} + \beta_6 \mathrm{LS}_{it} \\ & + \beta_7 \mathrm{NSC}_{it} + \varepsilon_{it}\end{aligned} \tag{2}$$

3.3. Market sentiment and interest analysis

Regression model 2 tests Hypothesis 2 on the association between market sentiment and cryptocurrency daily returns. Market sentiment is measured by FGI, where 0–24 represents extreme market fear, 25–49 indicates market fear, 50–74 represents market greed, and 75–100 indicates extreme market greed. Regression model 2 is shown in Eq. (3), with cryptocurrency's FGI adopted as the independent variable and daily cryptocurrency return as the dependent variable.

$$\mathrm{RTN}_{it} = \beta_0 + \beta_1 \mathrm{FGI}_t \tag{3}$$

RTN_{it} represents the daily return of different types i of cryptocurrencies at different time steps t, while FGI_t indicates the FGI at corresponding time steps t.

Regression model 3 tests Hypothesis 3 on the association between GSI and cryptocurrency daily returns. The GSI for each cryptocurrency is collected from Google Trends and scaled between 0 and 100 on a rolling basis. GSI 100 means the peak search volume for the name of a certain cryptocurrency, while 0 means lack of data for the term. Regression model 3 is shown in Eq. (4), with GSI as an independent variable and daily cryptocurrency return as the dependent variable.

Table 1
Summary of data collection sources, time span, and frequency.

Item	Data sources	Time span	Frequency	Different among different cryptocurrencies?
Cryptocurrency prices	Messari.io	From the birth of each cryptocurrency till April 30, 2023	Daily	Yes
Fundamental factors of each cryptocurrency	Coinmarketcap.com	Almost constant, except consensus mechanism of Ethereum and related cryptocurrencies till April 30, 2023		Yes
Fear and Greed Index (FGI)	Alternative.me	Feb 1, 2018 till April 30, 2023	Daily	No
Google search interest index (GSI)	Google trend	From the birth of GSI for each cryptocurrency till April 30, 2023	Daily	Yes

Table 2
The definition, measurement and importance of fundamental factors.

Type	Variables	Definition	Measurement	Importance
Dependent variable	**Daily return**	The daily return price of each cryptocurrency	As defined above	Used by investors and other stakeholders to measure return on investments and value of such investment.
Independent variables	**Proof-of-work (PoW) consensus mechanism**	Virtual miners around the world racing to be the first to solve a math puzzle [51].	A cryptocurrency is awarded 1 if it uses PoW consensus and 0 otherwise.	A fault-tolerant mechanism for transaction verification. It is important in maintaining adversity tolerance, failure resilience, partitioning throughout the network, delay perseverance, and other important properties [52].
	Proof-of-stake (PoS) consensus mechanism	It employs a network of “validators” who contribute their own cryptocurrency in exchange for a chance of getting to validate new transaction, update the blockchain, and earn a reward. (Sriman., 2021)	A cryptocurrency is awarded 1 if is uses PoS and 0 otherwise.	
	Presence of smart contracts (SC)	A self-executing protocol that facilitates the automatic actions required in an agreement or contract [53].	A cryptocurrency is awarded 1 if it has a smart contract and 0 if otherwise.	It allows for more complex transactions than simply exchanging digital tokens for a product or service [54].
	Initial Coin Offering (ICO)	Public offers of new cryptocurrencies in exchange of existing ones, which aims at financing projects in the blockchain development arena [55].	A cryptocurrency is awarded 1 if it has initial coin offerings and 0 if otherwise.	Early investors in an ICO are usually motivated by the expectation that the tokens will gain value after the cryptocurrency launches.
	Limited supply (LS)	The total supply of this cryptocurrency is fixed [56].	A cryptocurrency is awarded 1 if it has a token supply cap and 0 if otherwise.	Cryptocurrency with limited supply has halving cycles. Until certain point, the miners will not receive some reward for mining [57].
	Inflationary with unlimited supply (IS)	There’s a steadily increasing supply of coins entering the cryptocurrency market [58].	A cryptocurrency is awarded 1 if its supply is added to the network and 0 if otherwise.	It encourages spending and discourages hoarding [59].
Control variables	**Presence of native stable coin**	A native stablecoin is designed to maintain a stable value relative to a specific asset or currency.	This is a dummy variable. A cryptocurrency is awarded 1 if it has its own stable coin and 0 if otherwise.	Stablecoins may be pegged to a currency like the USD or to the price of a commodity such as gold.

$$\mathrm{RTN}_{it} = \beta_0 + \beta_1 \mathrm{GSI}_{it} \tag{4}$$

RTN_{it} represents the daily return of different types i of cryptocurrencies at different time steps t, while GSI_{it} indicates the GSI of the corresponding type i of cryptocurrencies at corresponding time steps t.

4. Results and discussion

We used the outcome of the regression analysis to test the hypotheses. The results section proceeds with explanations of the descriptive statistics followed by the presentation of the hypothesis testing.

4.1. Descriptive statistics of collected data

Descriptive statistics are presented to gain better insight into the collected data. Given that fundamental factors are based on dummy variables, Table 3 reports the descriptive statistics for the dependent variables, FGI, and GSI, respectively. A total count of 79,445 represents the total observations of daily returns for each cryptocurrency at different available time steps. The minimum, average, and maximum values of daily return are −0.6752, 0.0033, and 3.1879, respectively. The same dataset of daily returns of cryptocurrency prices is adopted for sentiment analysis. The descriptive statistics show that the minimum, average, and maximum values of FGI are 5.0, 42.7, and 95.0, respectively. Most of the FGI values are lower than 58.00. In terms of market interest analysis, due to the lag between the birth of a cryptocurrency

Table 3
Descriptive statistics.

	For fundamental factors	For fear and greed index		For Google search index	
	Daily return of cryptocurrency price	Daily return of cryptocurrency price	Fear and greed index	Daily return of cryptocurrency price	Google search index
Count	79,445	79,445	1914	64,810	64,810
Mean	0.0033	0.0033	42.70	0.0021	43.50
Std	0.0704	0.0704	22.04	0.0622	22.60
Min	−0.6752	−0.6752	5.00	−0.5684	5.00
25%	−0.0202	−0.0202	24.00	−0.0197	24.00
50%	5×10^{-6}	5×10^{-6}	39.00	1.1×10^{-5}	40.00
75%	0.0207	0.0207	58.00	0.01984	60.00
Max	3.1879	3.1879	95.00	3.0839	95.00

and people beginning to search it on Google, there are fewer available timesteps (i.e., 64,810) of the Google search index than of the daily return for each cryptocurrency (i.e., 79,445). Thus, the total number of observations for daily returns is also reduced to 64,810. The minimum, average, and maximum values of GSI are 5.0, 43.5, and 95.0, respectively, while the minimum, average, and maximum values of the adjusted daily return are −0.5684, 0.0021, and 3.0839, respectively.

4.2. Evaluation of fundamental factors

Table 4 reports the regression outcome for the fundamental factors. Given that we controlled for the presence of stablecoin, we partitioned the regression model into 2 sub-samples. One with stablecoin and another without stablecoin. For each regression model, 67.7% and 33.3% of the dataset are used for training and testing purposes, respectively. The adjusted R^2 for non-stable coins and stable coins are 0.003 and 0.000, respectively. The *F*-statistics are 19.40 and 8.86 for the training and testing datasets of non-stable coins, while 1.051 and 0.3786 for the training and testing datasets of stablecoins, respectively. The Log-Likelihood are 41,754 and 22,294 for the training and testing datasets of non-stable coins, while 23,946 and 12,134 for the training and testing datasets of stablecoins, respectively.

Table 5 presents the regression outcomes for the fundamental factors, including the coefficients, standard error, *t*-statistics, and *p*-value. Both the testing and training results are similar, especially in terms of coefficients and *p*-values. For cryptocurrencies without native stablecoins, only the consensus mechanism and the adoption of ICOs have significant effects on cryptocurrency daily returns, with *p*-values being 0.007 and 0.004 for the training and testing cases, respectively. Moreover, PoS has a similar coefficient but is slightly more significant than PoW, with a coefficient of 0.0019 and *p*-value of 0.037 for PoS, while 0.0022 and 0.002 for PoW, respectively. For cryptocurrencies with native stablecoin, none of the fundamental variables have a significant effect on cryptocurrency daily returns. Therefore, Hypothesis 1 is not fully supported.

Cryptocurrencies without native stablecoin tend to have higher price volatility. The fact that consensus mechanisms have significant effects on cryptocurrency daily returns implies that different consensus mechanisms have various trade-offs in terms of security, scalability, and efficiency [24]. The regression results also indicate that PoS and PoW have a similar effect on cryptocurrency daily returns, which is consistent with the suggestion that switching from PoW to PoS does not have a significant impact on cryptocurrency prices [60]. Alternatively, it might be because PoS is relatively new, and the data sample for PoS cryptocurrencies is much smaller than that of PoW cryptocurrencies. Also, only 4 of the 41 cryptocurrencies adopted their unique consensus mechanism, namely, a combination of PoW and PoS for the DASH coin; nominated PoS for the Palkadot coin; proof-of-reserve for the Tether; and Ripple Protocol consensus algorithm for the Ripple coin.

ICO also has a significant positive effect on the daily return of cryptocurrency without stablecoins. Although not directly supply-related, ICOs allow venture capitalists to purchase large portions of the supply at a discounted price. Early investors in an ICO are usually motivated by the anticipation that the value of the tokens will be increased after the launch of cryptocurrency [61]. The regression results align well with the finding that listing ICOs during the bubble period resulted in significantly higher initial returns, while cryptocurrencies launched with ICO regulations have higher initial returns than those launched elsewhere [62].

However, the other fundamental factors do not have significant

Table 4
Summary of regression statistics of fundamental factors.

Statistics	Non-stable coins		Stable coins	
	Training	Testing	Training	Testing
R-squared	0.002	0.003	0.000	0.001
Adj. *R*-squared	0.002	0.003	0.000	0.000
F-statistic	17.97	11.61	0.7437	1.140
Prob (*F*-statistic)	$7.56e \times 10^{-18}$	3.19×10^{-11}	0.591	0.337
Log-Likelihood	43,853	20,156	24,137	11,934
AIC	-8.770×10^4	-4.030×10^4	-4.826×10^4	-2.386×10^4
BIC	-8.765×10^4	-4.026×10^4	-4.822×10^4	-2.382×10^4
No. observations	37,182	18,314	16,045	7904

Table 5
Summary of regression results of fundamental factors.

	Independent variables	Coefficient	Std error	*t*-statistic	*p*-value
Training of non-stable coins	PoS	0.0019	0.001	2.087	0.037**
	PoW	0.0022	0.001	3.083	0.002***
	Smart contract	−0.0004	0.001	−0.389	0.697
	ICO	0.0026	0.001	2.684	0.007***
	Inflationary supply	0.0009	0.001	1.113	0.266
Testing of non-stable coins	PoS	2.657×10^{-5}	0.001	0.019	0.985
	PoW	0.0036	0.001	3.260	0.001***
	Smart contract	−0.0010	0.001	−0.656	0.512
	ICO	0.0044	0.002	2.581	0.004***
	Inflationary supply	0.0005	0.001	0.448	0.654
Training of stable coins	PoS	0.0016	0.001	1.239	0.215
	PoW	0.0006	0.002	0.351	0.726
	Smart contract	0.0004	0.002	0.152	0.879
	ICO	−0.0003	0.001	0.241	0.810
	Inflationary supply	−0.0009	0.001	−0.681	0.496
Testing of stable coins	PoS	−0.0015	0.002	−0.853	0.394
	PoW	−0.0008	0.003	−0.317	0.751
	Smart contract	0.0012	0.003	0.345	0.730
	ICO	−0.0017	0.002	−0.901	0.368
	Inflationary supply	−0.0034	0.002	−1.943	0.052**

Where *, **, *** represent significance at 10%, 5%, and 1%, respectively. PoS: proof-of-stake, PoW: proof-of-work, ICO: initial coin offering.

Table 6
Sliding window regression results for cryptocurrency with non-stable coins.

Fundamental factors	Time period	Coefficient	Std error	*t*-statistic	*p*-value
PoS	1/1/2009–8/8/2015	–	–	–	–
	9/8/2015–31/12/2017	0.0049	0.002	2.034	0.042**
	1/1/2018–31/12/2019	−0.0009	0.007	−0.127	0.899
	1/1/2020–31/12/2021	0.0028	0.002	1.759	0.079*
	After January 1, 2022	0.0034	0.001	2.849	0.004***
PoW	1/1/2009–8/8/2015	0.0094	0.003	3.483	0.001***
	9/8/2015–31/12/2017	0.0083	0.002	3.540	0.000***
	1/1/2018–31/12/2019	0.0032	0.002	1.489	0.137
	1/1/2020–31/12/2021	0.0013	0.001	1.074	0.283
	After January 1, 2022	0.0035	0.001	2.993	0.003***
Smart contract	1/1/2009–8/8/2015	–	–	–	–
	9/8/2015–31/12/2017	0.0083	0.002	3.540	0.000***
	1/1/2018–31/12/2019	−0.0116	0.007	−1.613	0.107
	1/1/2020–31/12/2021	0.0019	0.002	1.158	0.247
	After January 1, 2022	−0.0001	0.001	−0.122	0.903
ICO	1/1/2009–8/8/2015	–	–	–	–
	9/8/2015–31/12/2017	−0.0005	0.003	−0.147	0.883
	1/1/2018–31/12/2019	0.0211	0.007	2.921	0.003***
	1/1/2020–31/12/2021	−0.0011	0.002	−0.599	0.549
	After January 1, 2022	0.0028	0.001	2.183	0.029**
Inflationary supply	1/1/2009–8/8/2015	–	–	–	–
	9/8/2015–31/12/2017	–	–	–	–
	1/1/2018–31/12/2019	0.0064	0.002	2.699	0.007***
	1/1/2020–31/12/2021	−0.0022	0.001	−1.699	0.089*
	After January 1, 2022	0.0015	0.001	1.324	0.185

Where *, **, *** represent significance at 10%, 5%, and 1%, respectively. PoS: proof-of-stake, PoW: proof-of-work, ICO: initial coin offering.

effects on cryptocurrency daily returns. In terms of the supply type, i.e., either inflationary supply or deflationary supply, the lack of significance may be because both inflationary supply and deflationary supply have unique advantages. For example, cryptocurrency with deflationary supply has halving cycles, which implies that the reward for new cryptocurrency entering circulation as a block is cut in half. For example, the reward for mining Bitcoin is reduced by 50% every 4 years. Meanwhile, inflationary cryptocurrencies have higher supply than demand; therefore, they encourage investors to spend more, which could stimulate their daily return at early stages [58]. Moreover, it is interesting to find that the presence of smart contracts had no impact on daily returns, with *p*-values higher than 0.5. These may be due to two main reasons. Smart contracts have become more of a common feature in recent cryptocurrencies and therefore may have become an expectation and no longer seen as a unique feature for investors. Second, the sample may be biased towards new coins that have smart contracts, as many older coins without smart contracts have fallen out of the top 100 cryptocurrency rankings.

On the other hand, none of the fundamental factors has a significant effect on the daily return of cryptocurrency with stablecoins. This may be because cryptocurrency with stablecoins is designed to minimise price volatility by pegging its price to the USD [63]. On the other hand, there are only 14 stablecoins in the chosen cryptocurrency sample, which may make the regression results less representative.

To better understand the varying impacts of the fundamental factors on daily cryptocurrency returns, we used a sliding-window regression analysis. The dataset is divided into five sub-samples to recognize the different time spans: 1 January, 2009–8 August, 2015; 9 August, 2015–31 December, 2017; 1 January, 2018–31 December, 2019; 1 January, 2020–31 December, 2021; and after January 1, 2022. As there were fewer types of cryptocurrencies before 2015, 1 January, 2009–8 August, 2015 is selected as the first window of the time span. Ethereum is the second-largest cryptocurrency in terms of market capitalisation and is the first cryptocurrency to adopt smart contracts. As August 9, 2015 is the date when the data of the Ethereum daily return became available, it is chosen as a slot to divide the time span. After that, the time window is roughly equally divided. The regression results for non-stable cryptocurrency during different time windows are summarised in Table 6. There are no meaningful regression results for PoS, smart contract, and ICO between January 1, 2009 and August 8, 2015, and inflationary supply between January 1, 2009 and December 31, 2017. This is due to the lack of sufficient data for certain types of cryptocurrencies. Furthermore, it shows that the adoption of PoS and PoW has significant effects on the daily return of cryptocurrency, especially between January 1, 2013 and December 31, 2017 and after January 1, 2022. ICO also has a significant effect on the daily return of cryptocurrency, especially between August 1, 2018 and December 31, 2019 and after January 1, 2022, with *p*-values being 0.003 and 0.029, respectively. Moreover, both smart contracts and inflationary supply have significant effects on cryptocurrency daily returns during its early stages. For example, smart contracts have a *p*-value smaller than 0.000 between 9 August, 2015 and 31 December, 2017. Inflationary supply has a *p*-value smaller than 0.007 between 9 August, 2018 and 31 December, 2019.

The regression results of stable cryptocurrency during different time windows are summarised in Table 7. Interestingly, consensus mechanism, smart contract, and ICO all have significant positive effects on cryptocurrency daily return between 9 August, 2015 and 31 December, 2017, while inflationary supply has a significant negative effect. This might be because this is the period when most of the new cryptocurrencies were born, which may enhance investor trust, thereby leading to an increase in the purchased cryptocurrencies with PoS or PoW consensus mechanisms, smart contracts, ICOs, and limited supply.

To further validate the relationship between cryptocurrency fundamental factors and its daily return, we implemented three nonlinear regressions to test whether there is any nonlinear relationship between each fundamental factor and cryptocurrency daily return. We used the random forest regression, decision tree regression, and polynomial regression models with a degree of 2. The regression results are summarised in Table 8. The R^2 scores for all the regression models are lower than 0.001, demonstrating that there is no significant nonlinear relationship between fundamental factors and cryptocurrency daily returns.

4.3. Evaluation of market sentiment and interests

The discussion of cryptocurrencies on social media communities can influence cryptocurrency returns because of their large audiences. Lemon et al. [64] found that Reddit and Twitter communities [65] can

Table 7
Sliding window regression results for cryptocurrency with stable coins.

Fundamental factors	Time period	Coefficient	Std error	*t*-statistic	*p*-value
PoS	1/1/2009–8/8/2015	3.989×10^{-19}	4.15×10^{-19}	0.961	0.337
	9/8/2015–31/12/2017	2.315×10^{11}	9.03×10^{10}	2.564	0.010**
	1/1/2018–31/12/2019	0.0016	0.002	0.650	0.516
	1/1/2020–31/12/2021	0.0016	0.002	0.894	0.372
	After January 1, 2022	−0.0008	0.002	−0.477	0.633
PoW	1/1/2009–8/8/2015	0.0009	0.001	0.961	0.337
	9/8/2015–31/12/2017	2.314×10^{11}	9.03×10^{10}	2.564	0.010**
	1/1/2018–31/12/2019	0.0007	0.003	0.226	0.821
	1/1/2020–31/12/2021	0.0033	0.002	1.340	0.180
	After January 1, 2022	−0.0020	0.002	−0.917	0.359
Smart contract	1/1/2009–8/8/2015	0.0009	0.001	0.961	0.337
	9/8/2015–31/12/2017	2.314×10^{11}	9.03×10^{10}	2.564	0.010**
	1/1/2018–31/12/2019	−0.0073	0.005	−1.491	0.136
	1/1/2020–31/12/2021	0.0010	0.003	0.321	0.749
	After January 1, 2022	0.0017	0.003	0.623	0.534
ICO	1/1/2009–8/8/2015	0.0009	0.001	0.961	0.337
	9/8/2015–31/12/2017	2.315×10^{11}	9.03×10^{10}	2.564	0.010**
	1/1/2018–31/12/2019	0.0007	0.002	0.305	0.761
	1/1/2020–31/12/2021	0.0005	0.002	0.291	0.771
	After January 1, 2022	−0.0008	0.002	−0.515	0.606
Inflationary supply	1/1/2009–8/8/2015	0.0009	0.001	0.961	0.337
	9/8/2015–31/12/2017	-2.359×10^{11}	9.20×10^{10}	−2.564	0.010**
	1/1/2018–31/12/2019	0.0031	0.003	1.191	0.234
	1/1/2020–31/12/2021	−0.0033	0.002	−2.124	0.034
	After January 1, 2022	−0.0004	0.001	−0.305	0.760

Where *, **, *** represent significance at 10%, 5%, and 1%, respectively. PoS: proof-of-stake, PoW: proof-of-work, ICO: initial coin offering.

Table 8
Regression results (R^2 score: $\times 10^{-4}$) using nonlinear regression models.

Nonlinear regression models	Cryptocurrency with non-stable coins		Cryptocurrency with stablecoins	
	Training	Testing	Training	Testing
Random forest regression	5.83	−12.56	1.14	2.15
Decision tree regression	2.68	−0.70	1.13	2.94
Polynomial regression (degree = 2)	3.55	−0.68	1.06	18.79

influence short-term price movements due to herd investing. Bikhchandani and Sharma also supported this by claiming that there is an obvious intent by investors to learn the behaviours from investors [66]. The existence of herd investing was supported by Ante [67], who demonstrated that celebrity figures on social media, such as Elon Musk, can have a significant impact on cryptocurrency returns through tweeting about Bitcoin and Dogecoin. Therefore, in some circumstances, fundamental factors of a cryptocurrency do not matter, while a 'halo effect' is created by the influential figure that leads to herd investing. The herd investing concept is common in cryptocurrencies because they are emerging assets in a premature market, and there is a lack of consensus on how to value them.

Further investigation is conducted to analyse whether cryptocurrencies are purely speculative. FGI values are used as the independent variables resembling sentiment in the regression analysis, while RTN values are used as dependent variables. As FGI data are collected from February 1, 2018, there are fewer data samples (i.e., 64,810) than that of fundamental factors analysis (i.e., 79,455). Similarly, 67.7% of the dataset is selected for training purposes, while the other 33.3% of the dataset is chosen for testing purposes. The regression statistics of the FGI analysis are summarised in Table 9. The R^2 value, *F*-statistics, Log-Likelihood, AIC, and BIC are 0.002, 87.87, 59459, -1.189×10^5, and -1.189×10^5 for the training dataset, respectively, while 0.002, 41.03, 21388, -5.730×10^4 and -5.729×10^4 for the testing dataset, respectively.

The regression results for the FGI analysis are summarised in Table 10. It is seen that FGI has a significant positive effect on cryptocurrency daily returns for both training and testing datasets, as the *p*-values are 0.000. It supports Hypothesis 2. When FGI is below 25, cryptocurrency returns are mainly negative because investors have higher risk aversion and become cautious, withdrawing capital with the expectation of other investors mirroring these actions [68]. This causes cryptocurrency prices and daily returns to drop, portraying the importance of behaviours and emotions in cryptocurrency markets. This phenomenon supports the existence of market momentum and is corroborated by Caporale and Plastun [69], who found that market momentum is more powerful when the price is decreasing as opposed to when the price increases because investors become wary of a pullback so purchase power slows down. As the same set of FGI values is adopted to indicate the FGI for all cryptocurrencies, it cannot infer which cryptocurrency would have a higher daily return. However, it is also important to indicate when to make a cryptocurrency investment.

The regression results of the FGI analysis during different time windows are summarised in Table 11. To represent the latest effect of FGI on cryptocurrency value, a broader window is given to the period before June 30, 2021. After that, a half-year window is adopted to gain insight into the dynamic effects of FGI for the past two years. It shows that FGI has a constant significant effect on cryptocurrency daily returns, with 1 February, 2018–31 December, 2021 and later than January 1, 2023 having a positive effect and 1 January, 2022–31 January, 2022 having a negative effect. This might be because FGI values are smaller than 49 most of the time in 2022, which indicates that extreme fear exists in the cryptocurrency market.

GSI, the phrase searched for in web search engines, is another important sentiment factor [70]. The regression statistics of GSI are summarised in Table 12. The R^2 value, *F*-statistics, Log-Likelihood, AIC,

Table 9
Summary of regression statistics of Fear and Greed Index (FGI) analysis.

Statistics	Training	Testing
R-squared	0.002	0.002
Adj. *R*-squared	0.002	0.002
F-statistic	87.87	41.03
Prob (*F*-statistic)	7.31×10^{-21}	1.53×10^{-10}
Log-Likelihood	59,459	21,388
AIC	-1.189×10^5	-5.730×10^4
BIC	-1.189×10^5	-5.729×10^4
No. observations	43,422	21,388

Table 10
Summary of regression results of Fear and Greed Index (FGI) analysis.

Datasets	Coefficient	Std error	*t*-statistic	*p*-value
Training	5.331×10^{-5}	1.92×10^{-6}	8.999	0.000***
Testing	6.405×10^{-5}	9.19×10^{-6}	6.968	0.000***

Where *, **, *** represent significance at 10%, 5%, and 1%, respectively.

Table 11
Sliding window regression results of Fear and Greed Index (FGI) analysis.

Time period	Coefficient	Std error	*t*-statistic	*p*-value
Before June 30, 2021	7.90×10^{-5}	6.81×10^{-6}	11.60	0.000***
30/6/2021–31/12/2021	3.71×10^{-5}	1.15×10^{-5}	3.24	0.001***
1/1/2022–30/6/2022	-1.00×10^{-4}	2.14×10^{-5}	−5.53	0.000***
30/6/2022–31/12/2022	-5.09×10^{-5}	1.81×10^{-5}	−2.81	0.005***
Later than January 1, 2023	2.10×10^{-5}	9.26×10^{-6}	2.27	0.023**

Where *, **, *** represent significance at 10%, 5%, and 1%, respectively.

Table 12
Summary of regression statistics of Google search index analysis.

Statistics	Training	Testing
R-squared	0.002	0.001
Adj. *R*-squared	0.002	0.001
F-statistic	94.66	31.26
Prob (*F*-statistic)	2.36×10^{-22}	2.28×10^{-8}
Log-Likelihood	64,601	33,558
AIC	-1.292×10^{5}	-6.711×10^{4}
BIC	-1.292×10^{5}	-6.711×10^{4}
No. observations	53,228	26,217

and BIC are 0.002, 94.66, 64601, -1.292×10^5, and -1.292×10^5 for the training dataset, respectively, while 0.002, 31.26, 33558, -6.711×10^4 and -6.711×10^4 for the testing dataset, respectively.

The regression results of GSI analysis are summarised in Table 13 below. It shows that GSI has a significant positive effect on cryptocurrency daily returns for both training and testing datasets, as the *p*-value is 0.000. It supports Hypothesis 3. This might be because cryptocurrencies are inherently speculative in nature [71]. Therefore, a higher number of web searches may be linked to increased speculation, while the number of searches decreases as the bubble comes to an end. It aligns well with the findings of Refs. [72,73], that GSI can determine and predict short-term price bubbles. As each cryptocurrency has its individual GSI value, GSI is crucial when choosing the appropriate type of cryptocurrency for investment. Both FGI values and GSI values are in the range of 0–100, while the coefficients of GSI values (i.e., 0.0001 for the training dataset and 8.972×10^{-5} for the testing dataset) are slightly higher than those of FGI values (i.e., 5.331×10^{-5} for the training dataset and 6.405×10^{-5} for the testing dataset), the impacts of GSI are slightly higher than those of FGI.

The regression results of GSI analysis during different time windows are summarised in Table 14. The window is the same as that of FGI analysis to gain insight into the dynamic effects of GSI for the past two

Table 13
Summary of regression results of Google search index analysis.

Cases	Coefficient	Std error	*t*-statistic	*p*-value
Training	0.0001	1.19×10^{-5}	9.729	0.000***
Testing	8.972×10^{-5}	1.60×10^{-5}	5.591	0.000***

Where *, **, *** represent significance at 10%, 5%, and 1%, respectively.

Table 14
Sliding window regression results for Google search index analysis.

Time period	Coefficient	Std error	*t*-statistic	*p*-value
Before June 30, 2021	8.43×10^{-5}	1.29×10^{-5}	6.52	0.000***
30/6/2021–31/12/2021	2.00×10^{-4}	3.04×10^{-5}	5.89	0.000***
1/1/2022–30/6/2022	1.00×10^{-4}	3.36×10^{-5}	3.09	0.002***
30/6/2022–31/12/2022	4.52×10^{-5}	2.26×10^{-5}	2.00	0.045**
Later than January 1, 2023	-2.33×10^{-5}	1.17×10^{-5}	−2.00	0.046**

Where *, **, *** represent significance at 10%, 5%, and 1%, respectively.

years. It shows that GSI has a constant significant effect on cryptocurrency daily returns. The impact is positive from February 1, 2018 to December 31, 2022. After that, it becomes negative after January 1, 2023. This might be because cryptocurrencies have grown substantially in the last couple of years. Moreover, there are more use cases for cryptocurrencies now than ever before. For example, Bitcoin is now used as a legal tender in El Salvador [7]. Thus, the cryptocurrency market has become less impacted by Google searches and has become less susceptible to bubble behaviour.

5. Practical implication

Cryptocurrencies, as digital assets, represent a new frontier in the world of technology and financial markets. With every new industry and technology comes the opportunity for investors to take part in growth and subsequently obtain abnormal returns. For example, in the 1990s, the Internet revolutionised interactions between people and changed ideas of the future. This led to immense speculation, creating the dot-com bubble whereby many companies behaved irrationally [74]. However, this resulted in the opposite consequences, as growth unaccompanied by profits was proven unsustainable when the market crashed due to an extended sell-off period, causing a USD 5 trillion drop in market value [75]. Due to this, over 800 Internet companies became insolvent [76], and some of the companies that survived are now worth billions today, such as Amazon, clearly showing that some of these companies had intrinsic value despite arising during a financial bubble. Cryptocurrencies have also been suggested to be in a bubble [36]; by analogy, it can be assumed that similar to companies during the dot-com bubble, some cryptocurrencies have intrinsic value and may survive the bursting of the bubble they are in to become industry leaders in the future.

Cryptocurrencies lack correlation to traditional assets such as stocks [77], therefore supporting the notion of a distinct new asset class [78]. In order to determine the value of these new assets, the framework used to value traditional assets should be reassessed to determine the effectiveness of its application to cryptocurrencies. For example, stock market investors generally use fundamental analysis and financial ratios to determine whether a stock is undervalued or if its price is inflated without merit. In addition, some companies behave as networks, for example, Facebook, and these companies can be valued in accordance with Metcalfe's law. Other assets such as gold and real estate can serve as a store of value by maintaining their value over time. This study provides a comprehensive performance evaluation of different cryptocurrencies' valuation methods and provides insights into what factors need to be considered when making cryptocurrency investments.

6. Conclusions and future studies

This paper presents a comprehensive evaluation of the impacts of fundamental factors and sentiments on cryptocurrency daily returns.

Up-to-date historical datasets (i.e., 2009–2023) of cryptocurrency price data, FGI data, and GSI index data have been used. The key conclusion from this research is that the GSI of cryptocurrency are crucial when choosing the appropriate type of cryptocurrency for investment, although its effects have become less important recently. This indicates that advancement in technology has made cryptocurrencies less susceptible to bubble behaviour. The FGI is also important in choosing when to make a cryptocurrency investment. For example, periods of fear and extreme fear, such as 2022 due to the pandemic, are associated with negative cryptocurrencies.

Overall, consensus mechanism and ICO have significant effects on cryptocurrencies without stablecoins, while their impacts on cryptocurrencies with stablecoins are insignificant. Other fundamental factors, including the type of supply and the presence of smart contracts, do not have significant impacts on cryptocurrency, irrespective of whether they have stablecoins or not. Thus, investors should consider the consensus mechanism and the ICO of a cryptocurrency when investing irrespective of whether the cryptocurrency has a stablecoin or not. We also showed that consensus mechanisms, smart contracts, and ICOs all have significant positive impacts on cryptocurrencies daily returns, while inflationary supply has a significant negative effect between 9 August, 2015 and 31 December, 2017, a period when most new cryptocurrencies were born while investors trusted and purchased cryptocurrencies with PoS or PoW consensus mechanisms, smart contracts, ICOs, and limited supply. This indicates that a dynamic relationship might exist between fundamental factors and cryptocurrency daily returns. When a new technology or concept is implemented in a cryptocurrency, it may attract investment and stimulate daily returns.

In conclusion, this study provides a robust valuation method for cryptocurrencies by evaluating the effects of fundamental factors and sentiments on cryptocurrency daily returns. The findings from the study can enhance cryptocurrency marketisation and provide insightful guidance for investors, portfolio managers, and policymakers to assess the utility level of each cryptocurrency.

However, this study was limited by the lack of public data. As the cryptocurrency market matures and more data become available, future studies should explore the effects of other fundamental factors and transaction features. Similarly, some recent studies have started to explore the hedging potential [79] and herding behaviours of cryptocurrencies [80,81], and whether there are spillovers within and across cryptocurrencies markets and exchanges [82,83]. However, the findings in these directions are tentative and require additional studies to build a strong and critical mass of evidence to ascertain these phenomena. A potential aspect of such investigation could be to explore the circumstances in which cryptocurrencies could be used to hedge and enhance portfolio diversification. Such studies would be of utmost importance to fund managers and investment analysts. Extending studies on the spillover effects between traditional and cryptocurrency markets would be of interest to regulators who are still behind the curve with regulating cryptocurrencies.

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Abbreviations

FGI	Fear and Greed Index
GSI	Google Search Interest index
ICO	Initial coin offering
IS	Inflationary with unlimited supply
LS	Limited supply
PoS	Proof-of-stake
PoW	Proof-of-work
RTN	Return on investment
SC	Smart contract

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