DOI: https://doi.org/10.4038/ijcbr.v4i1.32

International Journal of Contemporary Business Research
Volume 4, Issue 1_2025

Cryptocurrency Returns, Investor Attention and Market Conditions

M.S.F. Nasrifa[1], R.P.D.M. Amarasinghe[2], W.M.P.K. Weerasinghe[3]

Department of Industrial Management, University of Moratuwa

nasrifamsf.20@uom.lk[1], amarasingherpdm.20@uom.lk[2], poornimaw@uom.lk[3]

Abstract

The purpose of this research is to explore how investor attention, measured by GSVI, influences cryptocurrency market behavior under varying conditions. For this the study examines the impact of Google Search Volume Index (GSVI) on cryptocurrency returns, considering market uncertainty, news sentiment, and the COVID-19 pandemic. A regression analysis was conducted using datasets covering BNB, Bitcoin, Dogecoin, Solana, and Tether from 2015 to 2022. Stata was used to estimate the relationships between cryptocurrency returns and key variables, ensuring accurate and reliable results to quantify the relationships. Our findings indicate that abnormal increases in GSVI positively affect cryptocurrency returns, particularly during high uncertainty periods and when news sentiment is favorable. Moreover, the effect of investor attention on returns was significantly amplified during the COVID-19 pandemic, suggesting that global crises has heightened the role of behavioral factors in cryptocurrency markets. This research contributes to the literature by integrating investor attention with uncertainty and sentiment measures, offering a comprehensive view of cryptocurrency price dynamics. Unlike previous studies that examine these factors in isolation, our study highlights their combined effect, providing valuable insights for investors, policymakers, and analysts in understanding market trends and decision-making strategies.

Keywords: *Google SVI, Covid-19 pandemic, investor attention , Cryptocurrency returns, news sentiment , market uncertainty.*

1. Introduction

The cryptocurrency market is a dynamic ecosystem of digital currencies and derivative assets driven by blockchain technology that function independently of a centralized authority like banks or governments (Da et al., 2011). This decentralization guarantees that the system is not governed by a single body. Rather, cryptocurrencies use a dispersed user base to validate and log transactions on a blockchain, which is a public digital ledger. Similar to stocks or precious metals, cryptocurrencies are frequently seen as speculative investment assets. The market is highly unpredictable, characterized by significant price fluctuations influenced by global factors, shifts in regulation, and the mood of the economy. Given the high volatility resulting in large gains, cryptocurrencies have gained attention from investors, companies, and governments resulting in fast growth of the asset class.

However, because of the influence of numerous factors, forecasting cryptocurrency returns is still difficult (Almeida et al., 2022). Prior studies (Da et al., 2011) have looked at the correlation between cryptocurrency returns and factors like investor attitude, market uncertainty, and world events. For instance, research suggests that Bitcoin returns may be adversely affected by the constant changes in economic policy . Additionally, studies show that the Fear and greed index, which gauges market sentiment, might have an impact on bitcoin values. Cryptocurrency markets have been further influenced by the COVID-19 outbreak, which has changed investment behavior and increased volatility.

As cryptocurrencies continue to evolve, several emerging trends are shaping their future. Regenerative Finance (Refi) and green crypto projects are gaining momentum, focusing on sustainability by integrating blockchain with ecological restoration efforts (Schletz et al., 2023). The rise of decentralized identity (DID) solutions is transforming online security by giving individuals control over their personal data, while decentralized AI (deAI) is revolutionizing machine learning by enhancing transparency and privacy in data usage (Kang & Lemieux, 2021). Additionally, central bank digital currencies (CBDCs) are expected to modernize global financial systems, offering financial inclusion and efficiency in digital transactions. Advances in blockchain-based dispute resolution are also improving governance in decentralized ecosystems, ensuring greater security and transparency (Gabuthy, 2023). These trends highlight how cryptocurrencies are moving beyond speculative trading and becoming key drivers of financial innovation and economic transformation.

1.1. Problem Statement

Cryptocurrency markets remain less developed compared to other financial markets which are driven by individual investors who are more prone to behavioral biases. Attention theory states that investors have limited attention spans, and assign attention based on various factors (Da et al., 2011). The study also states that investors are likely to change their behavior during periods of high uncertainty and changing market sentiments. The impact of the changes in investor behavior on cryptocurrency returns remains an unexplored issue. Focusing on this, our research problem spans over understanding the impact GSVI and cryptocurrency returns, using the UCRY to determine how market uncertainty affects crypto returns. Additionally, we examine how the pre & post covid periods affect crypto returns through abnormal searches. Previous research has stated that investor attention, measure in terms of search volume index (SVI) has positive impacts on the value of cryptocurrency, and when more attention is directed toward a particular cryptocurrency, its price tends to increase (Da et al., 2018).

Moreover, the interaction of investors in Bitcoin with the market prior to and during the Covid 19 period. Furthermore, the study mainly examines how investor fear in the cryptocurrency market interacted with Bitcoin prices before and during the ongoing COVID-19 pandemic. (Sah & Patra, 2023). In parallel, we aim to explore the role of uncertainty in shaping cryptocurrency returns through the Cryptocurrency Uncertainty Index (UCRY). UCRY leverages data-driven methodologies to quantify the level of uncertainty in the cryptocurrency market, taking into account factors such as news coverage, regulatory developments, and technological advancements. By incorporating the UCRY into our analysis, we aim to uncover how fluctuations in uncertainty impact cryptocurrency returns, shedding light on the underlying drivers of market volatility and investor decision-making.

1.2. Research Hypotheses

This research ascertains the coefficient correlation between market uncertainty, market sentiment, covid-19 pandemic with cryptocurrency returns through the google search volume index (GSVI) from 2015 to 2022 using regression analysis and statistical modeling techniques using Stata. Accordingly. For this, the following hypotheses were set,

H1: There is a significant association between the weekly cryptocurrency returns and the abnormal google search.

H2: The strength of association between weekly cryptocurrency returns and the abnormal searches is moderated by the degree of uncertainty.

H3: The strength of association between the weekly cryptocurrency returns and the abnormal google searches is moderated by the market sentiment.

H4: The strength of the association between the weekly cryptocurrency returns and the previous week's abnormal google search is moderated with Covid 19 impact

1.3. Scope of the study

The study investigates the relationship between market uncertainty, market sentiment, Google SVI, and the impact of COVID-19 on cryptocurrency returns. It analyzes whether changes in Google SVI can predict cryptocurrency price fluctuations and examines how market uncertainty, measured by the Uncertainty Index (UCRY), affects cryptocurrency returns. Additionally, the research explores the influence of market sentiment, indicated by the Fear and greed index, on cryptocurrency market behavior and prices. The study also examines the effects of the COVID-19 pandemic and regulatory responses on cryptocurrency performance and volatility, by analyzing data from 2015 to 2022.

1.4. Significance of the study

Investor behavior and predictability of cryptocurrency returns

The cryptocurrency markets are still underdeveloped and are driven by individual investors/traders. Individual investors are prone to behavioral biases, especially during market uncertainty, and market moods. Therefore, the factors that predict cryptocurrency returns remain unexplored. The results of this study will explain whether the cryptocurrency returns can be predicted using Google searches, during uncertain periods, and when the market mood changes. Investor communities will find these results useful when forming profitable trading strategies. The findings will be valuable for investor communities in developing profitable trading strategies based on investor attention and sentiment indicators.

Regulatory implications and market stability

Regulators are closely watching cryptocurrency markets, due to their decentralized nature. The results of this study will show regulators whether the abnormal patterns in future cryptocurrency prices are predictable based on market conditions or investor behaviors/patterns. These behavioral insights will be beneficial when developing suitable regulations. The study contributes to potential investors by revealing how market fluctuations and uncertainty affects cryptocurrency returns.

Market uncertainty, sentiment, and post-COVID-19 impacts

For this study, the fear and greed index is used to measure market sentiment. Many of the investors in Binance may be spot traders and future traders and stakeholders investing in proof of stake consequences mechanisms, and miners. Our research is more beneficial for future traders among them. So small changes of the market can make a big impact on their capital.

As market uncertainty influences investor behavior traders should monitor uncertainty indicators and adjust their positions accordingly. Understanding sentiment and navigating uncertainty are essential skills. Cryptocurrencies may serve as safe havens during uncertain times and the pandemic reshaped financial landscapes, including cryptocurrencies.

Further, traders should analyze how pandemic-related factors impact returns. Factors such as behavioral shifts, government stimulus packages, and remote work trends all play a role in financial markets. Being adaptable and informed about post-COVID dynamics is vital for traders.

Practical and Theoretical Importance of Study

This research provides actionable insights for investors, analysts, and policymakers navigating the dynamic financial landscape of cryptocurrencies. By understanding the impact of sentiment and uncertainty on cryptocurrency returns and the size of market fluctuations, the study equips stakeholders with the knowledge and tools necessary to make informed investment decisions, manage risk effectively, and capitalize on opportunities in the cryptocurrency market. Furthermore, this research contributes to advancing the academic understanding of cryptocurrency market dynamics and informs practical strategies for navigating this rapidly evolving asset class.

2. Literature Review

2.1. Investor attention

Da et al. (2011) explains investor attention as the level of interest and focus that investors have on a particular stock or opportunity. Attention can be influenced by various factors such as news articles, advertising, and the frequency of searches for information about stock on platforms like Google. Understanding investor attention is important because it can impact on the prices of stocks and the behavior of investors in the stock market. For example, higher levels of attention from investors might lead to increased buying or selling of a stock, which can affect its price.

Da et al. (2011) further states that market attention is a powerful mechanism that defines how people, and particularly investors, analyze and respond to information instances. Since investors have short-term memory horizons, investors often tend to focus on the noteworthy and outstanding aspects rather than the reliability of information. Collective attention can result in occurrences such as under reaction and post announcement price drifts. Indicators such as the GSVI capture the attention given to retail investors and associate it with price actions on stocks and have a negative bias on the investors, which means that investors give a stronger response to negative information that leads to fluctuations in the market price.

Investor attention, especially among individual investors can significantly influence market behavior, often leading to irrational decisions and market anomalies. Specifically, it highlights that by understanding how investors allocate their attention, it becomes possible to predict certain market phenomena, such as the post-revision drift (a delayed price reaction after analysts revises their recommendations). This reflects how investors' actions, reactions, and the flow of information in the market are deeply interconnected, demonstrating the complexity and uniqueness of investor behavior in financial markets.

2.2. **Google searches and direct investment attention**

Google search volume index (GSVI), which is highly related to our study, is a measurement of the popularity of a term, which is computed using a sample of searches. SVI captures investor attention on a timelier basis. Da et al. (2011) proposes a direct measure of investor demand for attention - active attention - using search frequency in GSVI. They have established a strong and direct link between SVI changes and trading by less sophisticated individual investors. Increased retail attention as measured by SVI during the Initial Public offering (IPO) contributes to the large first-day return and long-run underperformance of IPO stocks. They have found strong evidence that increases in SVI temporarily push up stock prices, especially in the context of an IPO. Further, it was examined that stronger price momentum among stocks with high SVI, supporting the "momentum effect

Furthermore, (Cai et al.,2018) studied the effects of Google search on the return and risk of 268 cryptocurrencies over 181 trading days. Results indicate that the SVI of a given cryptocurrency exerts a significant and positive impact on its price and turnover. Additionally, (Li et al., 2014) employs machine learning techniques to predict cryptocurrency returns, where neural networks outperform random forest algorithms when predicting returns. Accordingly, the study emphasized enhanced predictability of machine learning models compared to traditional stock markets. Portfolios based on neural networks achieve the highest cumulative returns, providing valuable insights for investors, traders, and financial analysts navigating the complex cryptocurrency market.

2.3. Factors affecting Cryptocurrency Returns

2.3.1. Common risk factors

There could be a number of risk factors impacting cryptocurrency returns. Among them (Li et al., 2014) examined the common risk factors and their relationship with cryptocurrency returns. The study presents a three-factor model that captures the cross-section of expected cryptocurrency returns, including the cryptocurrency market, size, and momentum factors. The study analyzes various price and market-related factors in the cryptocurrency market and constructs their cryptocurrency counterparts. It also identifies successful long-short strategies that generate significant excess returns and shows that these strategies are accounted for by the cryptocurrency three-factor model.

2.3.2. Other risks factors

Kufo et al. (2024) have identified additional risks factors, namely, trading volume, information demand, stock returns, and exchange rates on the volatility of returns for decentralized and unbacked cryptocurrencies from 2016 to 2022 by employing the Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) model.

The findings of this paper help investors in the decision-making process related to the behavior of cryptocurrency return volatility and portfolio optimization in the new and highly unpredictable crypto market. The cryptocurrency policy uncertainty (UCRY Policy) and cryptocurrency price uncertainty (UCRY Price) are captured by the newly developed Cryptocurrency Uncertainty Index (UCRY). The index is intended to demonstrate the impact of market and regulatory uncertainties on cryptocurrency markets. Further Colak et al. (2023) examines the relationship between financial uncertainty and cryptocurrency returns. By analyzing the impact of financial uncertainty on the cross-section of cryptocurrency returns, the study uncovers a systematically priced risk factor in the cryptocurrency market. This finding provides valuable insights for market participants looking to understand the dynamics of cryptocurrency returns and how they can be influenced by financial uncertainty.

2.3.3. Investor fear in the cryptocurrency market

Nikhil et al. (2023) examines the relationship between investor fear in the cryptocurrency market and Bitcoin prices by considering the potential effects of the COVID-19 pandemic during the period of May 5, 2018, and December 10, 2020. Their results show that both negative and positive interactions between fear sentiment and Bitcoin prices occur during several subperiods. The nature of these interactions changes significantly before and during the pandemic.

2.3.4. Investor attention and cryptocurrency return

Prior literature has examined the relationship between investor attention and cryptocurrency returns and findings show investors underreact after recommendation upgrades. The cumulative abnormal returns are positive and significant even after 10 days following the revision. However, price reactions are faster for downgrades. Furthermore, the relationship between uncertainty levels and cryptocurrency returns also has been established and the impact of sentiment on cryptocurrency returns has been examined. The majority of the studies utilize pre-COVID sample periods.

The mediating impact of uncertainty and sentiment on the relationship between investor attention and cryptocurrency returns has been unexplored by prior literature. Our study aims to bridge this by investigating the impact of sentiment and uncertainty on cryptocurrency returns, utilizing innovative approaches such as the fear and greed index and the UCRY. The fear and greed index captures the general attitude of investors toward cryptocurrency assets and offers a thorough picture of market sentiment. This study attempts to comprehend how shifts in investor emotion, from extreme fear to extreme greed, impact market dynamics and investor behavior by examining the fear and greed index in conjunction with bitcoin returns.

Through the bitcoin UCRY, the influence of uncertainty on bitcoin returns will be studied. In order to measure the degree of uncertainty in the cryptocurrency market, UCRY uses data-driven approaches that take into consideration news reports, legislative changes, and technological advancements. Through this, the study attempts to clarify how changes in uncertainty impact cryptocurrency returns, market volatility, and the fundamental factors influencing investor decision-making by including UCRY in our analysis.

3. Data and Methodology

3.1. **Selection of variables**

This study follows a systematic approach to examining the relationship between cryptocurrency returns, investor attention, and market conditions. The selection of variables was guided by previous research. Investor attention is measured using the GSVI, which has been widely used to study its impact on asset prices (Da et al., 2011). Market uncertainty is represented by the UCRY developed by Lucey et al. (2022), which captures fluctuations in crypto-market stability. News sentiment is included as an explanatory variable, given its significant influence on financial markets (Tetlock, 2007). Additionally, the impact of COVID-19 is accounted for using a dummy variable, as prior research has shown the pandemic's substantial effect on financial markets (Sah & Patra, 2023). Control variables such as market capitalization (SIZE), momentum (CMOM), and excess market return (CMKT) are included, following the three-factor model proposed by Liu et al. (2021).

3.1.1.Data sources

Cryptocurrency transaction data for this study is extracted from the coin market cap website (https://www.investing.com/crypto/bitcoin/historical-data).

Furthermore, GSVI related data will be collected from the google trend site (https://trends.google.com/trends/). The uncertainty index developed by (Lucey et al., 2022) will be incorporated by the study to collect data regarding markets. (https://brianmlucey.wordpress.com/2021/03/16/cryptocurrency-uncertainty-index-dataset/).

Data on market sentiment, which is the general outlook or attitude of investors toward a particular security or the overall financial market. will be collected from the website named Daily News Sentiment Index (https://www.frbsf.org/research-and-insights/data-and-indicators/daily-news-sentiment-index/).

The World Health Organization officially declared COVID-19 as a pandemic on March 11, 2020, and ended its status as a public health emergency of international concern on June 12, 2023. We use data from both the post COVID-19 period and the pre-COVID-19 period to measure how weekly cryptocurrency returns relate to the previous week's abnormal Google searches, considering the impact of COVID-19

3.1.2. Data cleaning and preparation procedure

After the data was collected, the log return was calculated by using Stata. Then, R software was used to process them to weekly data. Stata was used to take abnormal Google search values related to the topic. Log uncertainty and log sentiment values were also calculated using same method. Finally, we run the regression model in Stata to obtain the final results for our analysis.

3.2. Variable definition

We analyze the impact of various factors such as abnormal Google search activity, market uncertainty, investor sentiment, and the effects of the COVID-19 pandemic on cryptocurrency returns. Additionally, we control general market conditions, size metrics, and momentum to provide a comprehensive understanding of cryptocurrency behavior during different periods and events. Table 4 under in appendices summarizes the variable definitions that will be used in this study.

3.2.1. Investor attention Variables

Google search volume data involves selecting relevant keywords, extracting search volumes from Google Trends, and creating a composite index. Abnormal search volume is then calculated by comparing actual search volumes to historical baselines and standardizing the results (Da et al., 2011).

3.2.2. Cryptocurrency market variables

In analyzing the cryptocurrency market, key variables such as market size, momentum, trading volume, and volatility are essential, as highlighted by (Li et al., 2014) who demonstrated their significance in explaining cryptocurrency returns. An analysis of the cryptocurrency market has shown that the size and momentum factor that conventional asset pricing model has indicated could be used in anticipation of returns. This paper observes that smaller cryptocurrencies measured by their market capitalizations– provides greater excess returns to the smaller firms when compared to larger cryptocurrencies like bitcoins. Further, Investing in cryptocurrencies with strong recent performance while selling underperformers a strategy known as relative strength often yields notable short-term gains.

3.3. Empirical Model

Based on previous literature, the following models were formed to test the hypotheses.

Model 1

Model 1 was formed to test the relationship between cryptocurrency returns and the variables, namely, abnormal GSVI index , UCRY index, impact of Covid -19, cryptocurrency market , size and momentum.

$$\boldsymbol{R_{i,t}} = \alpha_i + \beta_1 ABGSVI_i + \beta_2 log(UCRY)_{i,t} + \beta_3 log(SENT)_{i,t} + \beta_4 COVR_t + \beta_5 Size_t + \beta_6 CMOM_t + \beta_7 CMKT_t + \in$$

Beta $\beta \neq 0$

The following models were formed using interaction variables to test the relationship between the cryptocurrency returns with each variable.

Model 2

$$\boldsymbol{R_{i,t}} = \alpha_i + \beta_1 ABGSVI_i + \beta_2 log(URCY)_{i,t} + \beta_3 log(SENT)_{i,t} + \beta_4 COVR_t + \beta_5 Size_t + \beta_6 CMOM_t + \beta_7 CMKT_t + \beta_8 (ABGSVI \times log(URCY))_{i,t} + \in$$

Model 3

$$\boldsymbol{R_{i,t}} = \alpha_i + \beta_1 ABGSVI_i + \beta_2 log(URCY)_{i,t} + \beta_3 log(SENT)_{i,t} + \beta_4 COVR_t + \beta_5 Size_t + \beta_6 CMOM_t + \beta_7 CMKT_t + \beta_8 (ABGSVI \times log(SENT))_{i,t} + \in$$

Model 4

$$\boldsymbol{R_{i,t}} = \alpha_i + \beta_1 ABGSVI_i + \beta_2 log(URCY)_{i,t} + \beta_3 log(SENT)_{i,t} + \beta_4 COVR_t + \beta_5 Size_t + \beta_6 CMOM_t + \beta_7 CMKT_t + \beta_8 (ABGSVI \times COVR)_{i,t} + \in$$

4. Results and Discussions

4.1. Summary Table

Table 1 Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
log return	697	-.001	.424	-10.485	1.191
Abnormal GSVI	697	.059	.474	-2.267	2.398
CMKT	697	.02	.123	-.353	.377
SIZE	697	.031	.136	-.232	1.319
CMOM	697	.011	.111	-.429	.708
New sentiment	697	-.214	1.435	-4.599	2.315
log avg uncertainty	697	0	.007	-.015	.039

4.1.1. Analysis and Interpretation of Results

The data analysis is carried out in three stages, namely, a quantitative analysis of the variables based on their descriptive statistics, an exploration of the correlation matrix to assess relationships between the variables, a comprehensive presentation of the results, with a focus on the dependent and independent variables, encapsulated in the final results table.

4.2. **Descriptive Statistics**

4.2.1. Log return

Log return, or continuously compounded return, is calculated as the natural logarithm of the ratio of consecutive asset prices. This measure is additive over time, facilitating the analysis of returns across multiple periods. As indicated in Table 2, the mean log return of -0.001 suggests a negligible average decline in asset value over the observed period. However, the substantial standard deviation of 0.424 indicates significant volatility.

Normal distribution for log returns is shown in Figure 1. The minimum value of -10.485 reflects a severe drop in asset prices at least once, while the maximum value of 1.191 denotes the highest observed gain. These statistics highlight the asset's exposure to extreme fluctuations, which is crucial for risk assessment and portfolio management.

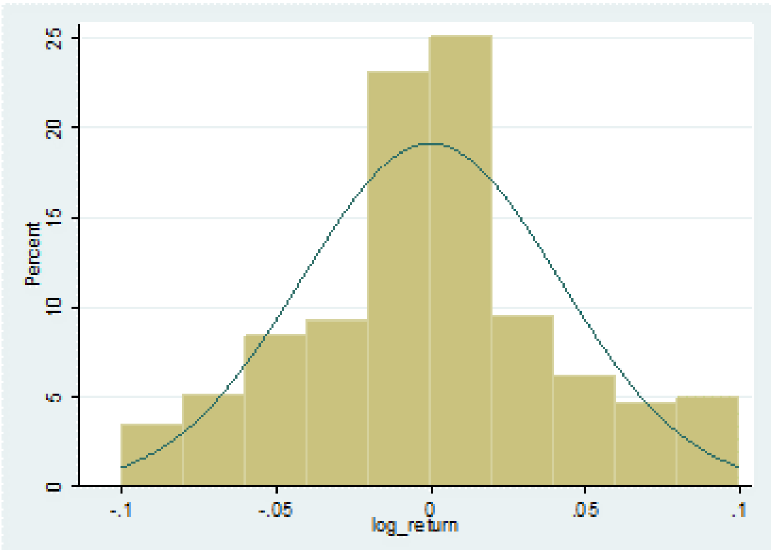

Figure 1 Distribution for log return

4.2.2. Abnormal GSVI

Abnormal GSVI measures deviations in the SVI from expected levels, indicating unusual public interest in a particular asset or topic. Table 1 indicates a positive mean of 0.059 and suggests a slight overall increase in search activity, implying heightened investor attention.

Normal distribution for Abnormal GSVI shown Figure 2. The standard deviation of 0.474 reflects variability in search interest, with values ranging from -2.267 to 2.398. This range indicates periods of both lower and higher-than-expected search volumes, which can be associated with market events or news affecting investor sentiment.

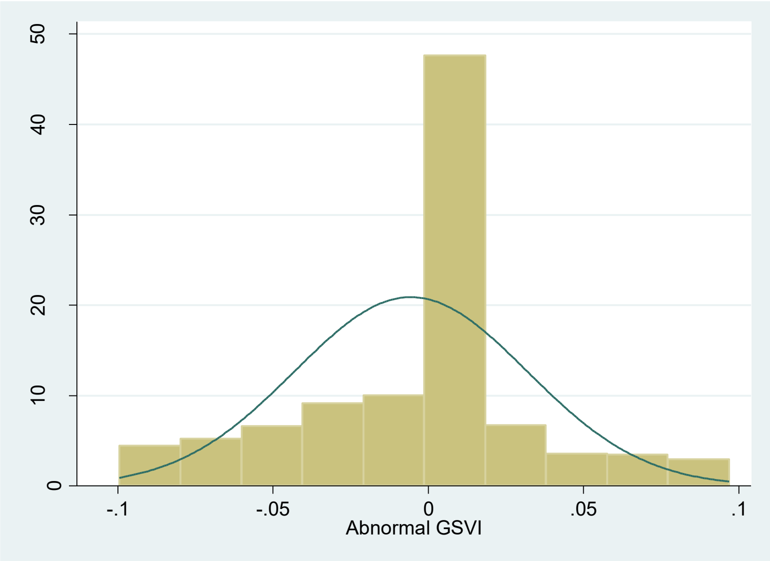

Figure 2 Distribution of Abnormal GSVI

4.2.3. Excess market return (CMKT)

CMKT represents the excess return of the market over a risk-free rate, serving as a benchmark for evaluating asset performance. The positive means of 0.020 in Table 1 indicates that, on average, the market outperformed the risk-free rate during the period. The standard deviation of 0.123 signifies moderate variability in excess returns, with a minimum of -0.353 and a maximum of 0.377. These figures reflect the market's performance in comparison to a risk-free benchmark, essential for assessing the attractiveness of investments.

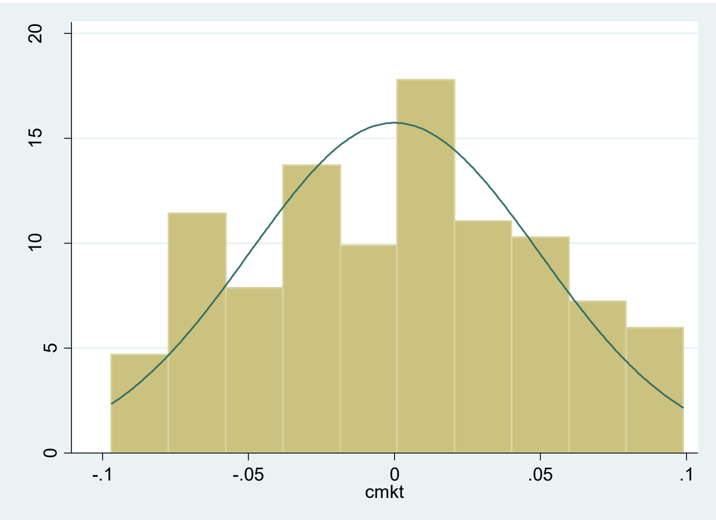

Figure 3 Distribution of Excess market return

4.2.4. Market capitalization (SIZE)

In financial analysis, 'SIZE' often refers to the natural logarithm of a firm's market capitalization, representing the company's scale. In Table 1, the mean value of 0.031 suggests a slight growth in firm size. The standard deviation of 0.136 indicates some dispersion in firm sizes, with values ranging from -0.232 to 1.319. Normal distribution Market capitalization shows in figure 4.

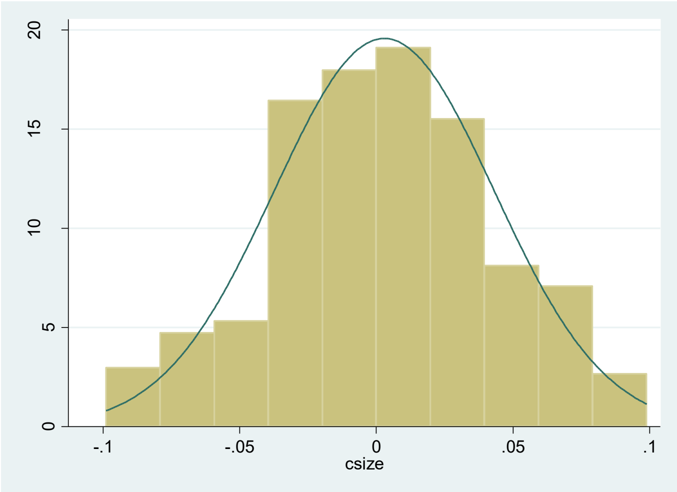

Figure 4 Distribution Market capitalization

4.2.5. Cumulative momentum (CMOM)

Momentum measures the rate of acceleration of a security's price or volume, indicating the tendency of assets to continue in their current price trend. The positive mean of 0.011 in Table 1 suggests a slight upward momentum on average. The standard deviation of 0.111 reflects variability in momentum, with a minimum of -0.429 and a maximum of 0.708. These statistics show the extent of upward and downward trends during the period, which are critical for momentum-based trading strategies. Distribution cumulative momentum shows in figure 5.

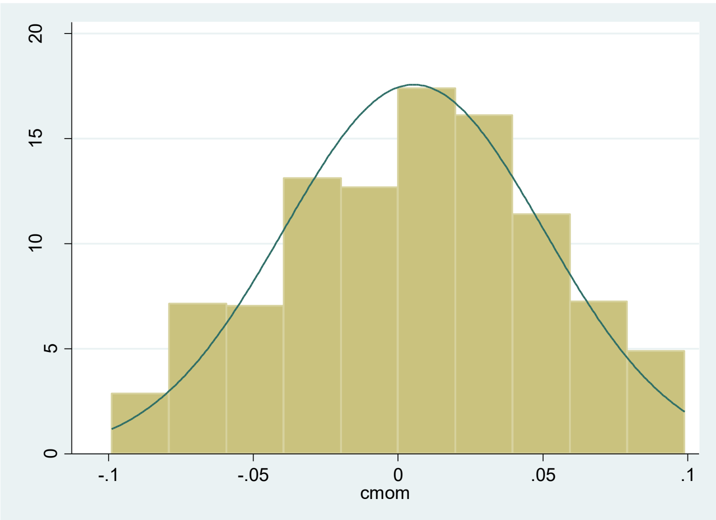

Figure 5 Distribution of cumulative momentum

4.2.6. News sentiment

News sentiment quantifies the tone of news articles related to an asset, with negative values indicating unfavorable sentiment and positive values indicating favorable sentiment. The negative mean of -0.214 as shown in Table 1 suggests that the overall news sentiment was slightly unfavorable during the observed period. The high standard deviation of 1.435 indicates significant variability in sentiment, with values ranging from -4.599 to 2.315. This wide range reflects diverse media perspectives, which can influence investor behavior and

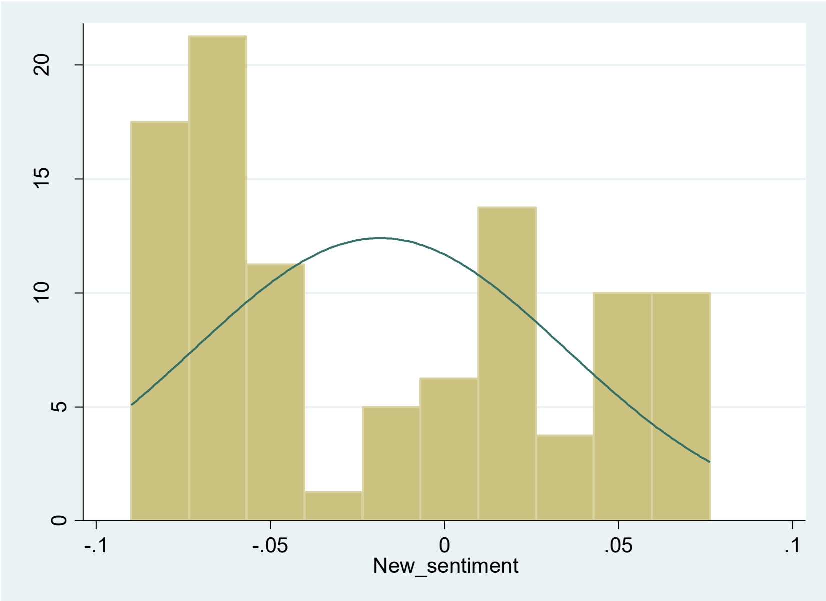

Figure 6 Distribution of News sentiment

4.2.7. Log average uncertainty

Log average uncertainty represents the logarithm of the average uncertainty in the market or specific asset, potentially derived from economic indicators or market volatility measures. Table 1 shows a mean value of 0.000 suggesting a neutral average uncertainty level. The low standard deviation of 0.007 indicates minimal variability in uncertainty, with a narrow range between -0.015 and 0.039. This implies relatively stable market conditions concerning uncertainty during the period, which is vital for risk assessment and strategic planning.

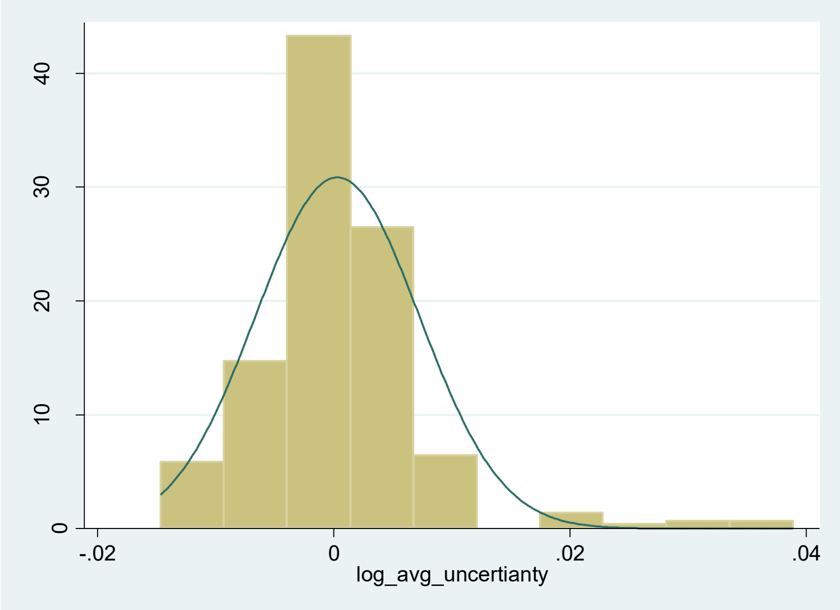

Figure 7 Distribution of Log average uncertainty

4.3. **Pairwise correlations**

Table 2 Correlation Metrix

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
(1) log return	1.000						
(2) Abnormal GSVI	0.055	1.000					
	(0.064)						
(3) CMKT	0.101	0.078	1.000				
	(0.001)	(0.009)					
(4) SIZE	0.028	0.022	0.124	1.000			
	(0.347)	(0.466)	(0.000)				
(5) CMOM	0.042	0.053	-0.002	0.125	1.000		
	(0.162)	(0.076)	(0.944)	(0.000)			
(6) New sentiment	0.054	-0.029	0.014	0.143	0.034	1.000	
	(0.068)	(0.328)	(0.645)	(0.000)	(0.254)		
(7) log avg	-0.008	0.039	0.115	-0.080	0.015	0.000	1.000
uncertainty	(0.835)	(0.295)	(0.002)	(0.033)	(0.681)	(0.996)	

4.4. **Correlation Matrix Analysis**

The correlation matrix offers a detailed overview of the relationships between the key variables in this study, providing valuable insights into their associations and potential interactions.

Log returns exhibit a weak positive correlation with abnormal GSVI (**0.055**, p = 0.064), suggesting that investor attention has a limited impact on cryptocurrency returns. They also show a significant positive correlation with cumulative market returns (**CMKT**, 0.101, p = 0.001), indicating that broader market trends moderately influence individual asset performance. However, correlations with other variables, such as market size (**CSIZE**, 0.028), momentum (**CMOM**, 0.042), news sentiment (**0.054**), and uncertainty (**Log Avg uncertainty**, -0.008), are weak and statistically insignificant, implying minimal direct effects on returns.

Abnormal GSVI demonstrates a weak positive correlation with cumulative market returns (**0.078**, p = 0.009), indicating that heightened investor attention aligns with broader market activity during active trading periods. The weak correlations with momentum (**0.053**, p = 0.076) and uncertainty (**0.039**, p = 0.295) reflect marginal associations. The near-zero and negative correlation with news sentiment (**-0.029**, p = 0.328) implies that news sentiment does not strongly influence search behavior, although isolated events may deviate from this trend.

Cumulative market returns show a moderate and significant positive correlation with market size (**Csize**, 0.124, p < 0.001), highlighting the role of large-cap cryptocurrencies in driving market-wide movements. However, market returns exhibit no meaningful association with momentum (**-0.002**, p = 0.944) or news sentiment (**0.014**, p = 0.645), indicating that these factors may not significantly impact aggregate returns in the cryptocurrency space. A significant positive correlation between cumulative market returns and uncertainty (**0.115**, p = 0.002) suggests some level of interdependence between regulated and unregulated markets.

The relationship between news sentiment and market size (**0.143**, p < 0.001) underscores a tendency for larger cryptocurrencies to receive more favorable media coverage. However, correlations between news sentiment and momentum (**0.034**, p = 0.254) remain weak, further reinforcing the limited influence of sentiment on short-term market dynamics.
The uncertainty index exhibits a significant positive correlation with cumulative market returns (**0.115**, p = 0.002), indicating that periods of heightened market uncertainty tend to align with aggregate market movements, possibly reflecting investor behavior during volatile conditions. However, its weak positive correlation with abnormal GSVI (**0.039**, p = 0.295) and near-zero relationship with log returns (**-0.008**, p = 0.835) suggest a limited direct influence on individual cryptocurrency performance or investor attention. Additionally, the index shows no significant correlation with news sentiment (**0.000**, p = 0.996) and a weak negative association with market size (**-0.080**, p = 0.033), implying that uncertainty is not strongly tied to sentiment-driven factors or larger-cap assets.

The correlation matrix highlights that the cryptocurrency market is influenced by greater market trends and investor attention. Strong associations between cumulative market returns, abnormal GSVI, and log returns reinforce these dynamics. However, the weak correlations with news sentiments suggest that media coverage may not drive the market directly, although its impact cannot be disregarded either. Furthermore, limited momentum across variables reflects the volatile and unpredictable nature of the cryptocurrency market.

These findings suggest that further analysis is required to uncover nonlinear relationships or lagged effects in understanding the dynamics of cryptocurrency markets. Thus, this provides a strong platform for further research in this area, focusing on the interplay between market trends, investor behavior, and external influences.

Table 3 Average return across Google Search Volume groups

Weekly Google Search Tercile	Full Sample (%)	BNB (%)	Bitcoin (%)	Dogecoin (%)	Solana (%)	Tether (%)
1 (Lowest)	-1.56**	-0.42	-0.35	-5.23***	-1.60***	-0.00
	(-2.45)	(-0.26)	(-0.01)	(-2.99)	(-6.10)	(-1.40)
2	0.60	-1.53	1.85	2.75	2.40 (0.72)	-0.00
	(1.14)	(-0.88)	(0.06)	(0.92)		(-0.14)
3 (Highest)	4.71***	6.82***	3.65***	11.77***	7.83***	0.00
	(7.09)	(3.60)	(4.27)	(3.65)	(2.87)	(0.62)
Highest - Lowest	**6.27*** (6.93)**	**7.24*** (2.99)**	**3.99*** (3.36)**	**17.01*** (5.23)**	**9.42*** (2.70)**	**0.00 (1.05)**

Table 3 presents average weekly returns for various cryptocurrencies—Binance Coin (BNB), Bitcoin (BTC), Dogecoin (DOGE), Solana (SOL), and Tether (USDT), categorized into three groups (terciles) based on daily Google search volumes, serving as a proxy for investor attention. The returns are reported for the full sample and individually for each cryptocurrency, with t-statistics indicating statistical significance provided in parentheses. The analysis reveals a positive correlation between Google search volumes and cryptocurrency returns. For the full sample, the lowest tercile (indicating the least search interest) has an average return of -1.56%, with a t-statistic of -2.45, signifying statistical significance at the 5% level. The middle tercile shows an average return of 0.60% (t-statistic: 1.14), which is not statistically significant. In contrast, the highest tercile exhibits an average return of 4.71%

(t-statistic: 7.09), significant at the 1% level. The difference between the highest and lowest terciles is 6.27% (t-statistic: 6.93), underscoring a strong association between increased search interest and higher returns.

Examining individual cryptocurrencies, a similar trend emerges. For instance, BNB's highest tercile shows an average return of 6.82% (t-statistic: 3.60), while the lowest tercile has -0.42% (t-statistic: -0.26). Bitcoin's highest tercile records a 3.65% return (t-statistic: 4.27), compared to -0.35% (t-statistic: -0.01) in the lowest. Dogecoin demonstrates a pronounced disparity, with the highest tercile at 11.77% (t-statistic: 3.65) and the lowest at -5.23% (t-statistic: -2.99). Solana follows this pattern, with the highest tercile at 7.83% (t-statistic: 2.87) and the lowest at -1.60% (t-statistic: -6.10). Tether, designed as a stablecoin, shows negligible returns across all terciles, aligning with its purpose of maintaining price stability.

4.5. Regression analysis

Table 4 Abnormal Search Volume and Returns

	(1)	**(2)**	**(3)**	**(4)**
	Ret	Ret	Ret	Ret
Abnormal Search	0.0430^{***}	0.0165^{**}	0.0194^{***}	0.0222^{***}
	(4.67)	(2.37)	(2.69)	(3.23)
News Sentiment		0.00889	0.00796	0.00318
		(1.63)	(1.51)	(-0.49)
Log(Uncertainty)		0.877	0.898	0.599
		(0.86)	(0.87)	(0.62)
Momentum		0.0600	0.0535	0.0612^{*}
		(0.97)	(0.86)	(1.80)
Market		0.232^{***}	0.231^{***}	0.191^{***}
		(3.78)	(3.74)	(3.20)

Size		-0.0509	-0.0478	0.0653*
		(-0.95)	(-0.91)	(-1.95)
Covid 19 Dummy		0.0507**	0.0503**	0.00401
		(2.12)	(2.30)	(-0.17)
_cons	0.0110**	-0.000175	0.000913	-0.0119
	(2.19)	(-0.03)	(0.05)	(-0.56)
N	695	695	695	695
Adj. R^2	0.020	0.093	0.094	0.166
Coin Fixed Effects	No	No	Yes	Yes
Year Fixed Effects	No	No	No	Yes

The regression analysis investigates the determinants of cryptocurrency returns across four models, each incorporating various independent variables and fixed effects to control for unobserved heterogeneity. In Model (1), Abnormal Search - representing deviations in search volume - exhibits a positive and statistically significant coefficient of 0.0430 (t-statistic: 4.67), indicating that heightened abnormal search activity correlates with increased returns. The intercept is also significant, suggesting a baseline return when all predictors are zero. However, the adjusted R^2 is 0.020, implying that only 2% of the variance in returns is explained by this model.

Model (2) introduces additional covariates: News Sentiment, Log (Uncertainty), Momentum, Market, Size, and a COVID-19 Dummy. Here, abnormal search remains significant with a reduced coefficient of 0.0165 (t-statistic: 2.37). The market variable shows a robust positive association with returns (coefficient: 0.232, t-statistic: 3.78), while the COVID-19 dummy indicates elevated returns during the pandemic period (coefficient: 0.0507, t-statistic: 2.12).

Other variables do not exhibit statistical significance. The adjusted R^2 improves to 0.093, suggesting enhanced explanatory power.

In Model (3), coin fixed effects are incorporated to account for unobserved heterogeneity across different cryptocurrencies. Abnormal Search remains significant (coefficient: 0.0194, t-statistic: 2.69), as does the Market variable (coefficient: 0.231, t-statistic: 3.74). The COVID-19 Dummy also retains significance (coefficient: 0.0503, t-statistic: 2.30). The adjusted R^2 is 0.094, comparable to Model (2).

Model (4) incorporates both coin and year fixed effects to control for time-specific factors. Abnormal Search continues to exhibit a positive and significant impact on returns (coefficient: 0.0222, t-statistic:

3.23). The Market variable remains significant, though its coefficient slightly decreases (0.191, t-statistic: 3.20). Momentum becomes marginally significant (coefficient: 0.0612, t-statistic: 1.80), and Size shows a negative relationship with returns (coefficient: -0.0653, t-statistic: -1.95). The COVID-19 dummy loses significance, suggesting its effect is captured by time-specific factors. The adjusted R^2 increases to 0.166, indicating the highest explanatory power among the models.

Abnormal search variable consistently demonstrates a positive and significant relationship with cryptocurrency returns across all models, underscoring the importance of investor attention. The Market variable also shows a strong positive association, highlighting the influence of broader market movements. The significance of the COVID-19 dummy varies, suggesting its impact is context-dependent. The inclusion of fixed effects enhances the models' explanatory power, accounting for unobserved heterogeneity and time-specific factors.

The regression analysis examines the determinants of cryptocurrency returns (Ret), focusing on the influence of abnormal search activity and its interactions with variables such as the COVID-19 dummy, Log(Uncertainty), and News Sentiment.

In Model (1), abnormal search exhibits a positive and statistically significant coefficient of 0.0198 (t-statistic: 2.08), indicating that increased investor attention, as proxied by abnormal search activity, correlates with higher cryptocurrency returns. The COVID-19 dummy, and News Sentiment variables are not statistically significant, suggesting that, in isolation, they do not have a discernible impact on returns.

Model (2) introduces an interaction term between Abnormal Search and Log (Uncertainty), yielding a coefficient of 0.697 (t-statistic: 0.42), which is not statistically significant. This implies that the effect of abnormal search activity on returns does not significantly change with varying levels of uncertainty. The main effect of Abnormal Search remains positive and significant (coefficient: 0.0229, t-statistic: 3.21), reinforcing its direct association with higher returns.

In Model (3), the interaction between Abnormal Search and News Sentiment is examined, resulting in a non-significant coefficient of 0.00308 (t-statistic: 0.96). This suggests that news sentiment does not significantly moderate the relationship between abnormal search activity and returns. The main effect of Abnormal Search continues to be positive and significant (coefficient: 0.0250, t-statistic: 3.07).

Table 5 Impact of Moderating factors

	(1)	(2)	(3)	(4)
	Ret	Ret	Ret	Ret
Abnormal Search	0.0198**	0.0229***	0.0250***	0.0142**
	(2.08)	(3.21)	(3.07)	(2.00)
Abnormal Search× COVID-19 Dummy	0.00517			0.0400**
	(0.36)			(1.98)
Abnormal Search× Log(Uncertainty)		0.697		0.548
		(0.42)		(0.32)
Abnormal Search× News Sentiment			0.00308	0.0113**
			(0.96)	(1.99)
COVID-19 Dummy	-0.00436	-0.00416	-0.00403	-0.00693
	(-0.18)	(-0.17)	(-0.17)	(-0.29)
News Sentiment	-0.00323	-0.00329	-0.00320	-0.00379
	(-0.50)	(-0.51)	(-0.49)	(-0.59)
Log (Uncertainty)	0.607	0.521	0.580	0.528
	(0.63)	(0.50)	(0.60)	(0.52)
Momentum	0.0619	0.0612	0.0594	0.0603*
	(1.60)	(1.13)	(1.10)	(1.89)
Market	0.191***	0.191***	0.189***	0.189***
	(3.20)	(3.21)	(3.17)	(3.19)
Size	-0.0654*	-0.0653	-0.0652	-0.0663*
	(-1.95)	(-1.58)	(-1.58)	(-1.80)
_cons	-0.0119	-0.0119	-0.0119	-0.0117
	(-0.56)	(-0.56)	(-0.56)	(-0.55)
N	695	695	695	695

Adj. R^2	0.165	0.165	0.166	0.185
Coin Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Model (4) incorporates interactions between Abnormal Search and both the COVID-19 Dummy and News Sentiment. The interaction term for Abnormal Search × COVID-19 Dummy is positive and significant (coefficient: 0.0400, t-statistic: 1.98), indicating that the positive effect of abnormal search activity on returns is amplified during the COVID-19 period. The interaction between Abnormal Search and News Sentiment is also positive and significant (coefficient: 0.0113, t-statistics: 1.99), suggesting that favorable news sentiment enhances the impact of abnormal search activity on returns. The main effect of Abnormal Search remains positive and significant (coefficient: 0.0142, t-statistic: 2.00). Across all models, the Market variable consistently shows a strong positive relationship with returns, with coefficients around 0.189 and t-statistics exceeding 3.17, indicating that broader market movements are closely tied to individual cryptocurrency returns. The Size variable exhibits a negative coefficient, reaching marginal significance in Models (1) and (4), suggesting that larger cryptocurrencies may experience slightly lower returns. Other variables, including Log(Uncertainty), Momentum, and the COVID-19 Dummy, do not show consistent statistical significance across models. The adjusted R^2 values range from 0.165 to 0.185, indicating that the models explain approximately 16.5% to 18.5% of the variability in cryptocurrency returns. The inclusion of interaction terms, particularly in Model (4), enhances the explanatory power, highlighting the importance of considering how factors like the COVID-19 pandemic and news sentiment interact with investor attention to influence returns. The analysis underscores the significant role of abnormal search activity in driving cryptocurrency returns, with its effect being further amplified during the COVID-19 period and in conjunction with positive news sentiment. These findings suggest that investor attention, especially during periods of heightened uncertainty or favorable news, can substantially influence cryptocurrency market performance.

5. Conclusion and Recommendations

This article singles out main cryptocurrency market features, i.e., investor sentiment, investor attention, and market volatility determine cryptocurrency return. Investor attention, as reflected in the GSVI, proved to be the major price driver of cryptocurrencies. High volumes of searches are connected with price movements, further verifying the prevalence of behavioural drivers in finance.

Besides, market uncertainty, as measured by UCRY, is also a significant driver of crypto volatility, with the times of higher uncertainty contributing more to price movement. This finding confirms the significance of understanding the uncertainty measures in making more informed risk management and investment choices. Similarly, sentiment measures, including the fear and greed index, are effective market trend indicators as investor sentiment is likely to be the cause for abnormal price behavior in cryptocurrencies. Another major contribution of this work is its analysis of the influence of exogenous shocks like the COVID-19 pandemic on cryptocurrency markets. Empirical evidence confirms that government stimulus packages, shifts in consumer behavior, and higher uncertainty due to the pandemic resulted in higher volatility and cryptocurrency trading. The current study is thus requesting investors and policy makers to factor macroeconomic variables and psychological factors in while making market trend analysis. Hence, the current paper presents a solid foundation for cryptocurrency price behaviors based on investor attention, market uncertainty, and sentiment. The findings indicate the contribution of behavioural finance to virtual asset markets and have implications for practitioners, traders, and policy makers in today's changing times of cryptocurrencies.

Based on these findings, investors are able to use GSVI and sentiment indicators for making trading decisions. Policymakers can detect investor activity and uncertainty within the market while policymakers are formulating policies to enhance stability within the market as well as protecting investors from extreme volatility.

References

Almeida, D., Dionísio, A., Vieira, I., & Ferreira, P. (2022). Uncertainty and Risk in the Cryptocurrency Market. *Journal of Risk and Financial Management*, *15*(11). https://doi.org/10.3390/jrfm15110532

Colak, G., Della Vedova, J., Foley, S., & Thoi Mai, S. (2023). *Financial Uncertainty and the Cross-Section of Cryptocurrency Returns* *. https://ssrn.com/abstract=4510856

Da, Z., Engelberg, J., Gao, P., Barberis, N., Battalio, R., Bodnaruk, A., Chen, Z., Conrad, J., Corwin, S., Hirshleifer, D., Hwang, B.-H., Jagannathan, R., Lou, D., Loughran, T., Schultz, P., Shive, S., Subrahmanyam, A., Tetlock, P., Tookes, H., & Yuan, Y. (n.d.-a). *In Search of Attention* *. http://ssrn.com/abstract=1364209Tel:

Da, Z., Engelberg, J., Gao, P., Barberis, N., Battalio, R., Bodnaruk, A., Chen, Z., Conrad, J., Corwin, S., Hirshleifer, D., Hwang, B.-H., Jagannathan, R., Lou, D., Loughran, T., Schultz, P., Shive, S., Subrahmanyam, A., Tetlock, P., Tookes, H., & Yuan, Y. (n.d.-b). *In Search of Attention* *. http://ssrn.com/abstract=1364209Tel:

Gabuthy, Y. (2023). Blockchain-Based Dispute Resolution: Insights and Challenges. *Games*, *14*(3). https://doi.org/10.3390/g14030034

Kang, M., & Lemieux, V. L. (2021). A decentralized identity-based blockchain solution for privacy-preserving licensing of individual-controlled data to prevent unauthorized secondary data usage. *Ledger*, *6*, 126–151. https://doi.org/10.5195/LEDGER.2021.239

Kufo, A., Gjeci, A., & Pilkati, A. (2024). Unveiling the Influencing Factors of Cryptocurrency Return Volatility. *Journal of Risk and Financial Management*, *17*(1). https://doi.org/10.3390/jrfm17010012

Li, X., Liu, Y., Liu, Z., & Zhu, S. (n.d.-a). *Cryptocurrency return prediction: A machine learning analysis*. https://ssrn.com/abstract=4703167

Li, X., Liu, Y., Liu, Z., & Zhu, S. (n.d.-b). *Cryptocurrency return prediction: A machine learning analysis*. https://ssrn.com/abstract=4703167

Lucey, B. M., Vigne, S. A., Yarovaya, L., & Wang, Y. (2022). The cryptocurrency uncertainty index. *Finance Research Letters*, *45*. https://doi.org/10.1016/j.frl.2021.102147

Paper, S., Cai, Z., Liu, F., Lim, E. T. K., Tan, C.-W., & Zheng, Z. (2018). *Unraveling the Effects of Google Search on Volatility of Cryptocurrencies*. http://gs.statcounter.com/search-engine-

Sah, A., & Patra, B. (2023). Dynamic Linkages Among Cryptocurrencies: The Role of COVID-19. *Asian Economics Letters*, *4*(2). https://doi.org/10.46557/001c.70289

Schletz, M., Constant, A., Hsu, A., Schillebeeckx, S., Beck, R., & Wainstein, M. (2023). Blockchain and regenerative finance: charting a path toward regeneration. *Frontiers in Blockchain*, *6*. https://doi.org/10.3389/fbloc.2023.1165133

List of appendices

	Variable names	Symbol	Variable Definition
Dependent variable	Cryptocurrency returns	CMKR	$Log\ (\frac{p_t}{p_{t-1}})$
Independent variable	Google SVI	GSVI	Abnormal google search volume Index
	Market Uncertainty	UCRY	$Log(UCRY)$
	Investor Sentiment	SENT	$Log(SENT)$
	Covid-19 pandemic	COVR	We use dummy Variables, for periods when COVID-19 is in effect, post covid period is denoted by 1, pre covid-19 period is denoted by 0.
Control variables	Cryptocurrency Market	CMKT	difference between the cryptocurrency market index return and the risk-free rate measured as the one-month Treasury bill rate
	Size	CSMB	market capitalization, price, maximum price, and age
	Momentum	CMOM	One-week momentum