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ASSESSING THE RELATIONSHIP BETWEEN INVESTOR SENTIMENTAND BITCOIN PERFORMANCE DURING THE PREAND POST-COVID-19 ERA

Dr. Muhammad Bilal Ijaz (Corresponding Author)
Lecturer, Department of Management Sciences, University of Gujrat.
Email Id: Bilal.ijaz@uog.edu.pk
Anmol Arshad
M.Phil Scholar, Department of Management Sciences, University of Gujrat.
Email id: Anmolarshad111@gmail.com

ABSTRACT
The current paper investigates the interconnection between investor sentiment and Bitcoin returns with particular attention paid to conditional volatility in the period affected by the COVID-19 virus. Pandemic is certainly one of the largest-scale phenomena in global history, which has affected the financial markets and the crypto currency markets while making this research topical and necessary. To this end, more effective sentiment analysis methods are used to disentangle interactions between the sentiments of investors concerned, and Bitcoin market characteristics, thus highlighting the essential roles of FOMO, speculative activity, and the emotional factor in investing. By analyzing the sentiment score and returns of Bitcoin for the pandemic period and the overall period, this study observe that positive sentiment has a strong and significant positive relationship with returns and negative sentiment with volatility. However, as the study also reveals, COVID-19 has disrupted the Bitcoin trading with greater unpredictable fluctuation, high uncertainty, and higher trading frequency. That is why this kind of uncertainty which is existing in the market due to the COVID-19, and global lockdowns increase the attraction to safe-haven assets where Bitcoin can be considered as a worthy candidate. This study adds value to extant scholarly literature in the area of cryptocurrency markets and the operation of these markets by pointing out the importance of appropriate investment decisions, risk management in unpredictable situations and dynamics of the sentiment and conditional volatility of the Bitcoin's returns in the light of critical global events, emotional trades and other epoch-making occurrences such as the COVID-19 pandemic.

Keywords: *Investor sentiment, Bitcoin returns, Conditional volatility, COVID-19 pandemic, Fear of missing out (FOMO), Behavioral finance, Cryptocurrency markets*

Introduction

1.1 Research Background

The year 2009 marked the introduction of Bitcoin, a groundbreaking virtual currency created by the enigmatic Satoshi Nakamoto (Lemieux, 2013), who remains anonymous to this day. It is the original and most well-known type of decentralized currency. Bitcoin is electronic money and thus P2P as it is a system of digital money where the transaction between two parties can occur directly without the intercession of any middleman. These are consensus transactions that are validated by the far-reaching nodes and stored in a public database known as the block chain. Bitcoins are created through mining which is a process of solving complex mathematical algorithms known as proofs of work. Miners employ special software to make complex calculations; as a reward they receive a specific number of Bitcoins. The math problems become increasingly complex to efficiently moderate the mining process and cap the volume of the total supply. Due to its peer-to-peer nature, which allows all users to manage the issue of Bitcoin, Bitcoin lacks a central bank or authority (Nakamoto, 2008).

The ledger and all the transactions, in general, are kept in a distributed network by computers owned by miners, developers, and others. This decentralization is what makes Bitcoin unique and free from such vices like government interferences as well as manipulations. The first characteristic of bitcoin is that it is a finite quantity of money, with a fixed upper limit of 21 million bitcoins. In my opinion, once these miners have unlocked this amount of bitcoins, then it will basically be impossible to mine any more bitcoins. This however, will be done over 120 years which I believe will give enough room for the currency to make its adjustments. This sort of money supply framework would explain why Bitcoin has experienced massive price appreciation. By this, it means that owning and using bitcoin still carries anonymity in as much as one observes certain cautions. The decentralized nature of Bitcoin allows users to obtain a unique address without disclosing personal information, sparking debates about its potential use in illicit activities. Nevertheless, many exchanges have proactively implemented Know Your Customer (KYC) and Anti-Money Laundering (AML) measures to align with regulatory standards. As Bitcoin's popularity has grown, so too have transaction costs and processing times, largely due to increased network congestion (Malhotra et al., 2022). This has led to criticisms regarding Bitcoin's scalability limitations. However, solutions like the Lightning Network and side chains are being explored to address these concerns and enhance the overall efficiency of the network.

Since Bitcoin has emerged as one of the most significant financial breakthroughs of the last ten years, it is a topic of great interest to researchers, regulators, and investors alike. Being a decentralized virtual money, Bitcoin operates under numerous determinants; technological advancements, policies alterations, and a myriad of other market factors. Out of these factors, the one that has been determined to have the most influence on Bitcoins price and behavior is investor sentiment (Gencer et al., 2018). Perceiving the early 2020 as the most crucial period in the history of investors' sentiment due to COVID-19, it is crucial to examine the presence of the certain relation between the investors' sentiment and Bitcoin performance. The coronavirus outbreak reshaped the global economy and global society, thus causing shifts in investors' behavior and markets (Mili et al., 2024). Analyzing the characteristics of Bitcoin before the COVID-19 outbreak, one can conclude that the primary factors influencing its behavior were speculative buy-and-sell activity, changes in laws and regulations, and the development of new technologies.

This thesis aims to investigate the impact of investor sentiment on Bitcoin's return performance during two distinct periods: pre- and post-COVID-19 pandemic. The central research question driving this inquiry is: "How did investor sentiments influence Bitcoin's behavior before and after the COVID-19 outbreak?" To address this question, the study will conduct a comparative analysis of sentiment data and correlate it with Bitcoin's price and trading volume data to identify potential relationships and patterns.

Foley conducted a research and noted that around one in every four users of bitcoin engaged in illicit business (Foley et al., 2019). Bitcoin is established to function as a payment system but based on the asset or a medium of exchange, Baur, Hong, and Lee looked at its statistical properties. They revealed that Bitcoin exhibits a negative correlation with conventional asset classes, such as equities, fixed-income securities, and commodities, indicating its potential as a diversification tool. However, the same studies suggest that Bitcoin's primary function is that of a speculative investment, rather than a reliable medium of exchange, highlighting its limitations in terms of widespread adoption and practical usage (Baur et al., 2018).

According to (Wang et al., 2019) Bitcoin's utility as a hedging or safe-haven asset, benchmarked against six traditional asset classes, revealed that its pronounced returns and volatility profile align more closely with speculative investments than risk management strategies. The findings indicate that Bitcoin's attributes make it an ill-suited candidate for hedging purposes, instead positioning it as a high-risk, high-potential-return asset for investors with a tolerance for volatility The crypto currency's remarkable price surges and speculative appeal have drawn in Noise traders, who are driven by sentiment rather than fundamentals. According to noise-trader theory, irrational investors acting in concert on misleading information can create systemic risk (Brown, 1999) If noise traders influence prices, their sentiment can be seen as a noisy signal that contributes to market volatility. Therefore, it is logical to expect a correlation between sentiment and volatility.

Recognized as a pioneering financial novelty of the previous span, bitcoin's return and volatility dynamics warrant in-depth examination (Loang, 2022). This study builds upon extant literature, which has predominantly explored the influence of macroeconomic and financial variables, market supply and demand, the technological complexities of bitcoin mining, and public interest metrics derived from Google Trends. By synthesizing these factors, this research seeks to provide a comprehensive understanding of the multifaceted elements driving bitcoin's market performance.

The COVID-19 pandemic, triggered by the novel coronavirus, originated in Wuhan, China in late 2019, initially presenting as a localized outbreak of severe respiratory infections. As the situation rapidly evolved, the World Health Organization (WHO) upgraded the outbreak to pandemic status in March 2020, acknowledging the virus's swift global spread and profound impact on public health. At this time people around the world are experiencing measures and locks to cover the blowout of COVID-19.When testing the link between COVID-19 concerns and investor psychology and stock market behavior, using COVID-19 daily data, noted that investor psychology had a negative correlation with those stock markets during the period showing that investors' sentiment due to the pandemic impacted stock markets (Naseem et al., 2021). These pandemic-related considerations could extend to the investor sentiment of bitcoins that in turn moves the Bitcoin prices.

The COVID-19 pandemic has led to a new wave in the financial market around the world with high volatility and risk that is unprecedented (Baker et al., 2020; Choudhury, 2020; Goodell & Gounder, 2020). Ever since investors perceived it necessary to seek safe-haven assets, cryptocurrencies such as Bitcoin have attracted attention (Corbet, et al., 2020; Li, et al., 2020; Mirza and Chatterjee, 2020). The COVID-19 has been seen as having a variety of effects on Bitcoin markets both in terms of market sentiment (Kumar et al., 2020), and behaviour of investors (Mishra et al., 2020) as well as the actual price movements (Sahoo et al., 2020). Also, COVID-19 has pushed the adoption of digital currencies and shows promise as a store of value and means of payment (Auer et al., 2020; Boar et al., 2020). This research seeks to fill the gap in knowledge by comparing the Bitcoin market sentiments, investors' behaviour, and prices before and during COVID-19 having close examine the impact of the pandemic on finance and technology.

To capture the level of investor sentiment, this research employs three sentiment measures. Firstly, the trading velocity was adopted because it reflects the levels of enthusiasm in the markets as stated in (Baker & Stein, 2004) stating that trading volume gives an indication of the prevailing liquidity and sentiments within a particular market. Second, there would be the bitcoin Fear & Greed Index that captures the daily sentiment of its investors and indicates how excited or afraid they are – quite useful to understand the preparedness of people to invest into bitcoins. Finally, the American Association of Individual Investors Sentiment Index is used as an additional indicator that reflects investors' attitudes to the market that can also affect BTC in a manner of its influence on the constituent components of the market. Using all of these varied measures, this study acquires a clearer picture of the complex interactions governing the fluctuation in the price of Bitcoin.

This research exploration blazes a new trial by exploring how the COVID-19 pandemic disrupts the subtle interrelation between bullishness and Bitcoin. Firstly, it fills out significant gap existing in the current theoretical literature that addresses three original visions into the impact of the pandemic on investors and the market respectively. Secondly, the use of multiple investor sentiment proxies ensures the research gives a broad view of the multiple factors that affect Bitcoin's prices. Last but not least, differentiation between rational and irrational investor sentiment helps to create a more accurate picture of the decision making process, and illuminate an impact of emotion and psychological factors on the market results. Through these aspects, this research provides insights into the characteristics of the Bitcoin market to help in decision-making and policymaking.

1.2 Research objectives

As the crypto currency landscape continues to evolve, understanding the intricate relationship between investor sentiment and Bitcoin prices has become a pressing concern. To shed light on this complex dynamic, this study embarks on an exploratory journey, driven by the following research objectives:

a. Describe how the characteristic of investors feel when investing in Bitcoin and how that relates to the change in price of Bitcoin.

b. To evaluate the impacts of COVID 19 epidemic on Investors' behaviors and bitcoins volatilities

c. To examine the results of the analysis of GARCH and EGARCH models for the relationships between sentiment and Bitcoin returns

d. To determine the adequacy of the models to the data thus identifying which out of the two models better suits the data, GARCH or EGARCH model.

e. The following research objectives also advances the examination of sentiments and their influences on the Bitcoin price, especially with regard to rational and irrational sentiments.

f. Which of the most important behavioral factors have resulted in the growth of dispersion both at the level of the change in magnitude and in the changes in Bitcoins and their prices?

1.3 Research Questions

As the pioneering crypto currency, Bitcoin, continues to defy conventions and push the boundaries of financial innovation, a multitude of unanswered questions persist. In an effort to illuminate the obscure relationships and underlying mechanisms driving this phenomenon, this study seeks to address the following research questions:

a. Does the AAII Index exhibit a significant relationship with Bitcoin returns after COVID-19? How does investor sentiment impact Bitcoin price fluctuations and returns?

b. Did the COVID-19 epidemic considerably influence investor behavior and Bitcoin market volatility?

c. Which model, GARCH or EGARCH, better captures the relationship between investor sentiment and Bitcoin returns?

d. Which model, GARCH or EGARCH, provides a better fit for the Bitcoin returns data?

e. To what extent do rational and irrational sentiments influence Bitcoin price movements?

f. What is the most significant behavioral factor driving Bitcoin price volatility?

REVIEW OF LITERATURE

As the crypto currency landscape continues to evolve, a vast array of research has emerged, seeking to unravel the complexities of Bitcoin's behavior. By weaving together the threads of pioneering studies, this review aims to craft a rich tapestry of understanding, illuminating the intricate relationships between investor sentiment, market dynamics, and Bitcoin prices.

2.1 Theoretical review

2.1.1Behavioral Finance Perspective

2.1.1.1 Prospect Theory

The behavioral finance theory that encompasses the means through which people arrive at their decisions in the environment characterized by risk and return following the incorporated views on psychology of choices through the loss aversion, framing effects as well as the probability weights systems. It does so in contrast with the rational choice model by claiming it incorporates psychological considerations likely to influence the investors' decisions (Kahneman & Tversky, 1979).

Key Components

a. Loss aversion: Investors prefer to evade losses than acquire equivalent gains, leading to risk aversion and potential market inefficiencies (Rabin & Thaler, 2001).

b. Framing effects: The Tide concept implies that investors make different decisions even when they have the same information but it is presented in a different way (Moser, 1986)

c. Probability weighting: Investors overweight low-probability events and underweight high-probability events, leading to distorted views of risk and return (Matyska, 2024).

2.1.2 Traditional Finance Perspective

Efficient Market Hypothesis

An economic principle long held in finance, which posits that markets hold all available information and price adjusts to ensure it cannot be profited from, thus making it 'impossible' to beat the market returns. In relation to this theory it is presumed that investors are rational beings who possess adequate information (Fama, 1970).

Key Components

a. **Market efficiency:** Prices reflect all available information, eliminating opportunities for arbitrage and ensuring that markets are informationally efficient (Wang, 1985).

b. **Random walk:** Price movements are unpredictable and follow a random pattern, making it impossible to consistently achieve returns in excess of the market's average (Peters, 1996).

c. **No arbitrage:** No opportunities for risk-free profits exist in the market, as prices reflect all available information (Yankov, 2014)

By combining Prospect Theory and Efficient Market Hypothesis, this study can understand how investor sentiment, driven by loss aversion and overweighting of low-probability events, can impact Bitcoin returns and create opportunities for deviations from market efficiency. This theoretical framework provides a nuanced understanding of the complex dynamics at play in the Bitcoin market, where investor sentiment and behavioral biases interact with market efficiency to shape price movements.

2.1 Empirical review

2.2.1 Sentimental Dynamics of Investment Decisions

Whereas the theory of investment decision making has always been considered to be prominent on the principles of rationality, a set of recent studies indicate that investors are highly sensitive to emotions and sentiments. The sentimental aspects of investment decisions are the numerous thought processes that involve pre disposition, feelings and influences from other people which can either support or challenge rationale in investments (Hussain, 2021).

The role that investors' attitude plays in the volatility of the Bitcoin is one of the initial papers of the author in the collection of works by Bukovina and Marticek, 2016. For the analysis of the relation between sentiment on the movement of Bitcoin price, they used AR(1) model while for the sentiment, the data was obtained from the Sentdex sentiment index derived with the help of submissions and comments from Natural Language Processing methods. The details of the text are extracted by applying the NLP methods. Finally, the most commonly used forms of NLP are sentiment analysis, primarily based on questionnaires, customers' feedback and comments, and posts in social networks with people's opinions. These signals will be ranging at -3 to 6 and it will be observed that the value -3 means negative feeling and on the other hand the value 6 means positive feeling. Hence, when comparing today's values to the total sum of volatility, it is clear that the sentiment index contributes only a marginal value.

According to, López-Cabarcos et al. (2021) the work concluded that the effect of sentiment is even greater in those periods which are marked by high fluctuations. There is another rather similar study which is somewhat older but which is also connected with the usage of machine learning. To ascertain the significance of investors' sentiment, S&P 500, VIX, and Bitcoin returns on bitcoin volatility they have employed GARCH and EGARCH models. When it comes to the investor sentiment variable they employed Stand ford Core NLP measures which vary from -2, concerning the negative investor sentiment, and 2, for the positive investor sentiment. In the authors' view, the above results suggest that \emph{V}Volatility in steady periods is a function of all the four explanatory variables, while Bitcoin becomes an asset of interest during speculation.

Additionally, Figa-Talamanca and Patacca (2019) conducted an empirical approach to examine the effect of investor sentiment on the mean and the volatility of the cryptocurrency's returns using ARMA GARCH and EGARCH models. A notable aspect of their study is the utilization of two disparate proxies for investor sentiment: trading volume and Google search volume fairly rarely can be noted. In their study, trading volume is significant for both mean and variance of returns while intensity of Google search is indicative of variance. This is different from López Cebarcos where the latter has employed another measure of investor sentiment differently (López-Cabarcos et al., 2021). This work can be distinguished by using trading volume and Google search intensity as sentiment proxies, which would offer valuable information about the nature and behavior of cryptocurrencies.

Subsequently, Katsiampa et al. (2019) also employed GARCH models to analyze Bitcoin returns' volatility and presented the applied framework using GARCH-MIDAS to establish crucial influences of macroeconomic determinants and investor sentiment indices. According to Nasir et al. (2019) they uses the Google search term to predict Bitcoin volume and returns with vector auto regression, copula, and non-parametric samples by applying the weekly data from 2013 to 2017. They discovered that an increase in the search volume has a positive relationship with Bitcoin returns as well as amount of trading.A similar study done is by (Zhu et al., 2021) as done in this analysis, Zhang (2019) also analyzed the relationship between investor's attention and Bitcoin market and agreed with this analysis that investor's attention is seen to Granger cause the changes in Bitcoin market in both returns and realized volatility.

Thus, when the volatility spillover across these assets is small, the said assets can be a perfect hedge for each other. From the result of this paper, it can be noted that, in conditions of investor satisfaction there is the probability of the diversification between the crypto currencies (Miralles-Quirós & Miralles-Quirós, 2022). Consequently, when comparing these two experiments, one can conclude that 'happy' or 'fear' feelings are difference and the degree of happiness, too. Introducing this part of the literature, articles where analysts employed investors' sentiment as the dependent variable for analyzing the returns and conditional volatility of Bitcoin are outlined (Buchanan et al., 2010).

It therefore comes as no surprise that a number of papers have attempted to explain the complicated link between sentiment and Bitcoin's returns and risk, and the findings that have been established are quite impressive. However, a significant research gap has emerged in this literature since most prior studies fail to explore the relationship between sentiment and return volatility while focusing on the impact of structural breaks that are, for example, the COVID-19 pandemic experienced in the world markets.

2.2.2 Non-Sentimental Forces in Investment Choices

The field of investment decisions was traditionally considered as a sphere where reason and passion coexist. Despite the extensive amounts written down on the role of sentiment in any given investment decision, there are numerous other factors, which may approximate or even have a stronger bearing on an investor's judgment. According to Liu and Tsyvinski (2018), they studied the risk-return swap of three crypto currencies: Therefore, looking at the comparison on performance of Crypto currencies, the following is the list of the currencies to compare them, that is, Bitcoin, Ripple, and Ethereum. As for the risk factors they used the most widely used models, namely the CAPM, Fama French 3 factor, Carhart 4 factor and Fama-French 5 factor and 6 factor. Based on the above combined trend results, it can be concluded that the stocks of these chosen crypto coins are not correlated with the deteriorative impact on the stock exchange, macroeconomic values, currencies, and commodities. Two sources of the risk-adjusted returns in the Cryptocurrency; that is, momentum and investors' attention. Also, the effects of Google trends values, Chinese Yuan exchange rate, S&P500 and gold and oil returns on Bitcoin, Ethereum and Ripple were also examined by (Dempere, 2019) using PGARCH, EGARCH, TGARCH and GARCH models. The findings of the results were used in the analysis to determine that all the returns of each of the selected cryptocurrencies are related to every other cryptocurrency.

Georgoula et al. (2015), in their research explore on the time-series econometric analysis on the economic factors that influence the Bitcoin prices, the impact of technology factors, and the mood factors. Total money stock defined in terms of bitcoins circulation is the variable total money supply recognized/used Total money stock economically defined in terms of S&P500 is the total state of the global condition recognized.

These are the proxies for the sentiment that include the twitter feeds, the web descriptions and hash rates. Regarding the research questions, search term frequency in Wikipedia is related to the popularity of Bitcoins while mining difficulty corresponds to the hash rate. In the daily accumulating data they carried out sentiment analysis using (SVMs). SVMs speaks of several methods that are in place in classification, coupled with outlier detection and regression. They are then tested at the short- run by performing a number of regressions with the dependent variables as Twitter sentiment ratio and the independent variables as the Bitcoin prices and the number of Wikipedia search queries and the hash rate it is found that the given variables explain the Bitcoin price through the short-run mechanism because the coefficient of determination varies near the analyzed graphs' values (Ahmad et al., 2018).

2.2.3 COVID-19 and the Crypto currency Market Landscape

Notably, investor sentiment-related variables, such as Google search trends, have consistently demonstrated a significant impact on cryptocurrency markets. The pioneering work of (Dempere, 2019) and (Liu & Tsyvinski, 2018) Dempere (2019) and Liu and Tsyvinski (2018) has been instrumental in illuminating the commonalities that exist across different crypto currencies. Their findings suggest that, despite their unique characteristics, various crypto currencies share similar determinants and exhibit analogous responses to market sentiment and investor behavior. This convergence of evidence underscores the importance of considering investor sentiment and market psychology in understanding the dynamics of crypto currency markets, and highlights the need for further research to elucidate the complex interplay between these factors. COVID-19 and the Crypto currency Market Landscape the COVID-19 crisis has ushered in a new wave of changes in global trade and financial systems, (turmoil) disturbing traditional financial markets and making investors look for other investments. In the middle of this crossroad, the digitally enabled market of crypto currencies became an interesting phenomenon to analyze because of the social nature of its underlying technology architecture and its direct dependence on the circulatory emotions of fear and hope which the pandemic has unleashed. While governments across the globe are struggling to manage the social and economic impacts of the virus, the crypto currency market has displayed reactive phenomena such as increased April volatility, surprising affinity with traditional stocks and increased inflows of investors during the COVID-19 period. These circumstances have led to the combination of factors governing relations between investor sentiment, market behaviour, and the impact of virus outbreaks on particular markets and the role of cryptocurrencies in the evolving global financial system (Huynh et al., 2021).

Therefore, when constructing the desired bitcoin portfolio along with a number of other commodities, emotion of the specific investor as well as interaction between the bitcoin and other streams of commodities are of equal importance. To attain the risk diversity goals, it is necessary to evaluate the existence of spill-over volatility transmission between Bitcoin with other asset classes in the period of outbreak of COVID-19. COVID-19 affected price fluctuations of almost all types of assets. Specifically, the analysis highlighted that in the international marker used to price the Brent oil, it was brought down to \$66. ranging from \$ 5 / barrel on January 1, 2020 to near about \$18 / barrel on April 22, 2020 and one of the biggest dip in 20 years (Yousaf et al., 2022). He provided the explanation of the return and Volatility stares in oil and Bitcoin markets of the pre COVID-19 and during the COVID-19.

From the analysis of the results in this paper it is about the confirmation of the return transmissions of the two commodities; oil and Bitcoin. From the findings, evidence of volatility spillovers of Bitcoin and oil in the pre COVID-19 period is established, but the same cannot be said regarding the COVID-19 period between oil and Bitcoin.

Similarly, Hsuetal.(2021) also utilized the whole period of the sample as well as the COVID- 19 period to investigate the spillover volatility in crypto currency with the traditional currency as well as gold markets. The finding therefore supports the claim that there is volatility transmission from Crypto currency to traditional currency / gold and before the COVID-19 outbreak. The outcomes of these examinees are apparent to assert that there are certain affirmative volatility transmission of Bitcoin with some of the asset classes in the period of COVID-19 and accordingly, it is recommended to implement the stochastic adjustments in the portfoliocreatedwithBitcoinandStandard&Poor500, Bitcoin and Gold/ traditional currencies. The hedging benefits are affected by COVID-19 in this sense because the authors examined the shortage-returns relation of both US equities and Bitcoin when paid in terms of the trade uncertainty of the US.

There is no prior research conducted with respect to the investor's sentiment on Bitcoin with the inclusion of the post COVID-19 impact; however, there are few relevant works done on the impact of investor sentiment on the stock markets with recent publication.

According to Naseem et al. (2021) the aspect of mental health with reference to the outbreak of COVID-19 stated that individual life and financial markets' issues were not left behind; it was rather exciting then to examine how investors' sentiment played a role in crypto currency especially paying special attention to the most established one which is bitcoin. Thus, three stock markets: Hence, Shanghai, Nikkei 225, and Dow Jones will be selected for this analysis. The analyses that were conducted pointed out the fact that there was a very strong negative relationship between investor psychology and those stock markets at the advent of the pandemic and that pessimistic mood led to cut in stock returns (Naseem et al., 2021)

2.1 Hypothesis

H1: The findings here present an impressive indication of how investor sentiment affects the price of Bitcoin and it rises when the investor sentiment is positive and drops when the investor sentiment is negative.

H2: The presence of the COVID-19 epidemic has also made investor sentiment a stronger magnitude of fluctuation in Bitcoin markets.

H3: The GARCH and EGARCH models are useful in explaining the put option effect of investor sentiment on returns of Bitcoin with the EGARCH model performing well in explaining the effect.

H4: The work establishing the fact that investor sentiments bear the impact in the price changes of Bitcoins through rational as well as irrational mechanisms.

H5: There are few well-known behavioral biases inherent to Bitcoin influencing its price: herding, loss aversion, and FOMO.

RESEARCH METHODOLOGY

To launch a voyage to discover the complexity of COVID-19, investor sentiment, and its relation to crypto currency market, an effective research approach is a compass. By employing a strict and comprehensible methodological framework, this study guarantee the credibility of the observed results, thus becoming sensitive to the specifics of the crypto currency market's dynamics as a consequence of the pandemic in terms of complex multi-level relations. This section presents the results of the data analysis and modeling efforts, utilizing two key models: The GARCH model which looks at variation and risks associated with singular assets, and the VAR model that locates interactions and causality between multiple variables. Under the subsection 'GARCH model estimations', the calculated returns of the different models are presented, followed by descriptive statistics and the results of the diagnostic tests that explain the volatility and risk characteristics of the investment environment. On the other hand, the VAR model estimations subsection gives a deeper insight of the variables and provides details of the dependent and independent variables to understand variable interdependencies, which lead to market behaviour. Thus, considering such outcomes, investors and analysts are provided with further insight into the market relations, which will help to develop proper decision-making and satisfactory risk management.

3.1 Nature of study

This study undertakes a comprehensive and meticulous examination of the intricate relationships between the COVID-19 pandemic, investor sentiment, and cryptocurrency market volatility, leveraging advanced econometric techniques to unravel the underlying dynamics and complex interdependencies. Specifically,

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this study employ a mixed-methods approach, combining the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and the Exponential GARCH (EGARCH) model to capture the time-varying volatility and leverage effects in cryptocurrency returns, thereby providing a nuanced understanding of market behavior. In addition, for a comparison of the COVID-19 response, investor attitude, and cryptocurrency market movement, we apply Vector Auto regression (VAR) modeling to identify various interconnections and causative effects, and Granger causality analysis for the directional flow of the time-sensitive causality patterns between COVID-19, investor sentiments, and cryptocurrency market conditions. This study uses secondary data mainly because data are collected from other published sources including; journals, databases, official websites, and other credible online sources. Hence with an integration and subsequent analysis of these existing data this study propose to obtain a systematic and qualitative insight of the relationship between these variables.

3.2 Data source

To analysis the interrelated of COVID-19, investor sentiment and crypto currency market volatility, this study uses second research data from reliable online source.

3.2.1 Trading Volume (TV)

Trading volume is an important parameter to use in determining the position of investors in the context of the Bitcoin market. It tells of the numbers of Bitcoins that have been exchanged over a given period do depict the level of the market of the exercise of this innovation. Vigorous trading volume could be an implication of high interest in the Bitcoin, whereas low volumes suggest otherwise. In the present research, trading volume data is collected from Yahoo Finance for the time period ranging from 1 December 2014 to 31 December 2023. This information is expressed as the total number of traded units of Bitcoin per day to give a clear picture of the market

3.2.2 The Crypto Fear & Greed Index (FGI)

RCGI is one of the sentiment indexes that look into the current feelings of a specific culture, in this case the bitcoin culture, which helps in decision counseling. Thus, this index is calculated on the basis of the assumption that high price volatility reflects either very low fear or very high greed as far as Bitcoins are concerned. Folded in this research is FGI data from Alternative.me from February 1st, 2018 to March 31st, 2023. This index is worked out from a series of figures by using a specialized formula that gives cognizance of several factors that comprises market information's, and therefore offers a distinct perception of the market mood.

3.2.3 AAII Sentiment Index (AAII):

The AAII Sentiment Index is a weekly report of the individual investor's attitude toward stock prices that affect the price of Bitcoin. Unlike the Fear & Greed Index, this index gives an average idea about the investor sentiment taking more generalized view of the market. To conduct this study, the data required is the AAII Sentiment Index data collected from the AAII's website- the time frame of study is from November 2014 to December 2023. This index is Weekly Investor Confidence Index which is based on survey of a cross section of individual investors in a given week.

3.2.4 Bitcoin Returns (R_t)

Bitcoin returns mean changes in Bitcoin price over a period to reflect the performance of Bitcoin investment. From this variable this study can get to know the effect of investor sentiment on the price of Bitcoin. The Bitcoin returns data utilized in the current study is based on the following formula:

$$R_t = \log (S_t / S_{t-1})$$

In percentage term, R_t will be,

$$R_t = \log〖(S_t / (S_{t-1})) 100\%.$$

Where

S_t is a notation for the price of one Bitcoin at time t. This means that the returns of the Bitcoin can be quantified in this formula and this will in turn help in analyzing the link between find of the investors and the Bitcoin prices.

3.2.5 Volatility

Volatility is defined as the risk in the investment option in Bitcoin and refers to the standard deviation of returns of Bitcoin within a given period. Relative to the current pricing, this variable is very ideal in analyzing the effects of investor sentiment on Bitcoin price volatilities. In this study, the volatility data measured by standard deviation ofreturns reflects all types of risk in the Bitcoin market. These fluctuations allow examining possible risks and opportunities for getting profits through investing in Bitcoins.

3.3 Data and models

3.3.1 GARCH model

GARCH is an econometrical model utilized in the analysis as well as in the estimation of financial time series information particularly volatility. Another generalized version of the ARCH model which offers a better conditioning of the volatility clustering and the leverage effect. On deciding Bitcoin return volatilities in this study, a GARCH model has been applied including the basic GARCH, EGARCH and ARCH. The extended GARCH model best known as GARCH was introduced by Bollerslev (1986) and is an autoregressive moving average model that was designed to describe the behaviour of conditional variance. The study uses the extended GARCH model, dubbed as the EGARCH model to analyze the influence of the ''leverage effect '' which is the asymmetric volatility (Engle & Lee, 1993).The ARCH model, introduced by Engle and Ng (1993), is also used to obtain the conditional variance with dynamic attributes. Thus, this paper seeks to compare the estimated results of these models as to which of them yields the best in identifying the volatility of Bitcoin returns and whether or not such models are consistent. GARCH (1, 1) model forms the starting point when working with the analysis of volatility of returns of Bitcoin. But it does not reflect data aggregation properties and designed the error term's variance strictly in the previous errors and their variances only. Extreme investor sentiment affects the returns and volatility of Bitcoin, the sentiment variable forms part of the mean equation and the variance equation.

The mean equation for the GARCH (1,1) model is expressed as:

Return (rt) = Constant (μ) + Coefficient (ʎ1) x Lagged Sentiment (St-1) + Error Term (εt),

Where

εt follows a Student's t-distribution

The variance equation for the GARCH (1,1) model is expressed as:

Variance (σ2t) = Constant (ω) + ARCH Coefficient (α) x Squared Error (ε2t-1) + GARCH Coefficient (β) x Previous Variance (σ2t-1) + Coefficient (ʎ2) x Lagged Sentiment (St-1)

Note that the inclusion of lagged sentiment allows the model to predict the impact of sentiment on returns and volatility based on prior observations. Additionally, the stationarity requirement for volatility necessitates that the sum of the ARCH and GARCH coefficients ($\alpha + \beta$) be less than 1.

3.3.1.2 EGARCH Model

The EGARCH model is a variation of GARCH that accommodates, and estimates asymmetric effects and also known as leverage effects.

EGARCH model of Nelson (1991) is used to measure variance of Bitcoin returns, having a positive sign with no constraints on coefficients. This model incorporates more info than an earlier model while giving a logical, qualitative explanation for the leverage effect on variance, thus taking into account how positive and negative news affect variance differently. The variance equation for the EGARCH (1) model is:

$$\ln(\sigma^2_t) = \omega + \alpha(|z_{t-1}| - E|z_t|) + \beta(\sigma^2_{t-1}) + \gamma(z_{t-1}) + \lambda_2 S_{t-1}$$

Where

z_t = $(\epsilon_t)/\sigma_t$ where ϵ_t is, by assumption, distributed as t and hence following the central limit theorem tends to normality.

$\beta < 1$ ensures stationarity

γ represents the degree of asymmetry, with:

$\gamma = 0$ meaning that the data also follows full symmetry.

$\gamma < 0$ clearly showing negative shocks lead to higher volatility increase

$\gamma > 0$ suggesting that positive shocks lead to higher volatility increases

This model has a capacity of capturing the leverage effect whereby negative news have explosive influence on the volatility than positive news.

3.3.2 VAR Model

The Vector Auto-regression (VAR) model is a powerful multivariate econometric technique employed to analyze interdependency and temporal behavior common to more than one time series variable. Here, using the past values of each variable and the lagged values of other VAR model provides an assessment of feedback effects and interrelationships. The structure of this type of model includes a system of equations, in which each variable is represented as a linear function of previous values of its own and previous values of other variables and an error term.

Mathematically, the VAR model can be represented as:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \ldots \ldots + A_n y_{t-n} + e$$

Where

In the case of yt, is the set of endogenous variables that impact MP (for example; returns ofBitcoin, rational sentiment, and irrational sentiment).Estimated coefficient matrices are represented as A1, A2, An.Yt-1, yt-2, yt-n are the (endogenous) variables from the previous time periods.et is a vector of error terms or innovations

Using the VAR model in this research, the authors shed light into the complex and interconnected nexuses between COVID- 19, investor sentiment, and the cryptocurrency market. What follows is that it gives an understanding of how these variables are related and which one affects the other while doing so.

3.3.2.1 Investor Sentiment Regression

Investor sentiment plays a crucial role in financial markets, influencing asset prices and investment decisions. However, sentiment can be driven by both rational and irrational factors, making it essential to decompose sentiment into its components. Baker and Wurgler (2006) propose a method to separate rational and irrational sentiment, which has been widely adopted in finance research.

3.3.2.2 Rational Sentiment Regression

The rational sentiment component can be estimated using the following regression equation:

$$rat\_sent_t = \alpha + \varphi_1 MR_t + \varphi_2 CPI_t + irr\_sent_t$$

Where:

rat_sentt is the rational sentiment component
MRt represents market return
CPIt represents consumer price index

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irr_sentt is the irrational sentiment component (error term)
α, φ1, and **φ2** are parameters to be estimated
Irrational Sentiment Component

The irrational sentiment component (**irr_sentt**) is captured by the error term, which represents the portion of investor sentiment that cannot be explained by the economic variables **MRt** and **CPIt**.

3.3.3 Granger Causality

Granger causality test that was proposed by Clive Granger in the year 1969 tests whether variable is useful for forecasting of another variable. It is stated that variable 1 Granger causes variable 2 to the extent that the past characteristics of both variables are useful in forecasting current values for variable 2. The null hypothesis of the test is the joint coefficients of the lagged values are equal to zero. By so doing, all the values are stored in a Vector Auto regression (VAR) model and by using the small sample F statistics the null hypotheses are tested. With regards to this literature review, this study use the Granger causality test to establish whether investor sentiments are either rational or irrational and its impact on the price of Bitcoin.

RESULTS AND DISCUSSION

4.1 Descriptive analysis

Table-4.1: Descriptive statistics of Bitcoin Trading Volume

	All periods		Pre Covid-19		Post Covid-19	
	BTC Ret	**BTC Vol**	**BTC Ret**	**BTC Vol**	**BTC Ret**	**BTC Vol**
Mean	0.0018	9.5380	0.0018	8.8752	0.0011	10.4448
Median	0.0014	10.0955	0.0019	9.1196	0.0006	10.4596
Maximum	0.2525	11.5453	0.2525	10.7026	0.1875	11.5453
Minimum	-1.0000	6.8124	-1.0000	6.8124	-1.0000	9.7268
Std. Dev.	0.0409	1.1660	0.0446	1.1284	0.0441	0.2319
Skewness	-4.5408	-0.8392	-5.8012	-0.0907	-8.6470	-0.1439
Kurtosis	116.0767	2.1668	137.1423	1.4472	195.3248	3.2632
Observation	3318	3318	1917	1917	1401	1401
Probability	0.000	0.000	0.000	0.000	0.000	0.000
ADF P-Value	0.000	0.000	0.000	0.000	0.000	0.000

The table presents statistical analysis of Bitcoin returns (BTC_Ret) and Bitcoin volume (BTC_Vol) across three periods: all periods, pre COVID-19, and post COVID-19. For all periods, the mean Bitcoin return is 0.00181, with a mean volume of 9.537951. The median values are slightly lower, at 0.001367 for returns and 10.09552 for volume. The maximum return is 0.252472, while the maximum volume is 11.54527. The minimum return is -1, with a minimum volume of 6.812355. The standard deviation of returns is 0.040865, and for volume, it is 1.165958. Skewness and kurtosis indicate high asymmetry and peakedness, especially in returns. Pre COVID-19, the mean return is slightly higher at 0.001842, and the mean volume is lower at 8.875179. The median return is 0.001926, and the median volume is 9.119596. The maximum and minimum values remain the same for returns, while the maximum volume is lower at 10.7026. The standard deviations are 0.044633 for returns and 1.12843 for volume. Skewness and kurtosis are higher, especially for returns, indicating more extreme values. Post COVID-19, the mean return decreases to 0.001056, and the mean volume increases to 10.44483. The median return drops to 0.000627, while the median volume rises to 10.4596. The maximum return is lower at 0.187465, but the maximum volume remains 11.54527. The minimum return remains -1, and the minimum volume increases to 9.726823. The standard deviations are 0.044121 for returns and significantly lower at

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0.231903 for volume. Skewness and kurtosis are extremely high for returns, indicating pronounced asymmetry and peskiness. The ADF P-Value of 0.000 across all periods suggests the presence of stationarity in Bitcoin returns and volume.

Table 4.2: Descriptive statistics of Fear & Greed Index

	All Periods		Pre Covid-19		Post Covid-19	
	BTC RET	**F&G**	**BTC RET**	**F&G**	**BTC RET**	**F&G**
Mean	0.000782	42	-0.000724	39	0.000913	45
Median	0.000968	39	0.000976	38	0.000892	40
Maximum	0.187465	95	0.17356	95	0.187465	95
Minimum	-1	5	-1	5	-1	6
Std. Dev.	0.043972	22.08739	0.051763	17.31041	0.04818	24.56312
Skewness	-6.447762	0.584088	-9.394298	0.506548	-8.266924	0.461307
Kurtosis	148.1018	2.378556	185.047	2.622871	170.8104	1.990349
Observations	1885	1885	759	759	1126	1126
Probability	0.0000		0.0000		0.0000	
ADF p-value	0.0000		0.0000		0.0000	

The table provides a statistical analysis of Bitcoin returns (BTC_RET) and the Fear & Greed index across three periods: all periods, pre COVID-19, and post COVID-19.
For all periods, the mean Bitcoin return is 0.000782, with a mean Fear & Greed index of 42. The median values are 0.000968 for returns and 39 for the index. The maximum return is 0.187465, while the maximum index value is 95. The minimum return is -1, and the minimum index value is 5. The standard deviation of returns is 0.043972, and for the index, it is 22.08739. The skewness and kurtosis indicate significant asymmetry in returns, particularly with values of -6.447762 and 148.1018, respectively. The Jarque-Bera test probability of 0.0000 indicates that the returns are not normally distributed, as confirmed by the ADF p-value of 0.0000, suggesting stationarity.
Pre COVID-19, the mean return is negative at -0.000724, with a mean index of 39. The median return is 0.000976, and the median index is 38. The maximum return is 0.17356, and the maximum index value remains 95. The minimum return is -1, and the minimum index value is 5. The standard deviations are 0.051763 for returns and 17.31041 for the index. Skewness and kurtosis are even higher pre COVID-19, with returns skewness at -9.394298 and kurtosis at 185.047, indicating more extreme values. The Jarque-Bera probability is 0.0000, and the ADF p-value is also 0.0000, confirming non-normality and stationarity. Post COVID-19, the mean return improves to 0.000913, with a higher mean index of 45. The median return is slightly lower at 0.000892, and the median index is 40. The maximum return is the same at 0.187465, with the minimum remaining at -1. The minimum index value increases to 6. The standard deviations are 0.04818 for returns and 24.56312 for the index. Skewness and kurtosis remain high for returns, with skewness at -8.266924 and kurtosis at 170.8104, indicating significant asymmetry and peakedness. The Jarque-Bera probability of 0.0000 confirms non-normality, and the ADF p-value of 0.0000 indicates stationarity in returns.

Overall, the analysis shows substantial volatility in Bitcoin returns across all periods, with a pronounced effect of market sentiment as captured by the Fear & Greed index. The high values of skewness and kurtosis, along with the Jarque-Bera and ADF test results, underscore the non- normal and stationary nature of the returns data. The table provides a statistical analysis of Bitcoin returns (BTC_RET) and the Fear & Greed index across three periods: all periods, pre COVID-19, and post COVID-19. For all periods, the mean Bitcoin return is 0.000782, with a mean Fear & Greed index of 42. The median values are 0.000968 for returns and 39 for the index. The maximum return is 0.187465, while the maximum index value is 95. The minimum return is -1, and the minimum index value is 5. The standard deviation of returns is 0.043972, and for the index, it is 22.08739. Skewness and kurtosis indicate significant asymmetry and peskiness in returns, particularly with values of -6.447762 and 148.1018, respectively.

Pre COVID-19, the mean return is negative at -0.000724, with a mean index of 39. The median return is 0.000976, and the median index is 38. The maximum return is 0.17356, and the maximum index value remains 95. The minimum return is -1, and the minimum index value is 5. The standard deviations are 0.051763 for returns and 17.31041 for the index. Skewness and kurtosis are even higher pre COVID-19, with returns skewness at -9.394298 and kurtosis at 185.047, indicating more extreme values.

Post COVID-19, the mean return improves to 0.000913, with a higher mean index of 45. The median return is slightly lower at 0.000892, and the median index is 40. The maximum return is the same at 0.187465, with the minimum remaining at -1. The minimum index value increases to 6. The standard deviations are 0.04818 for returns and 24.56312 for the index. Skewness and kurtosis remain high for returns, with skewness at -8.266924 and kurtosis at 170.8104, indicating significant asymmetry and peskiness. Overall, the analysis shows substantial volatility in Bitcoin returns across all periods, with a pronounced effect of market sentiment as captured by the Fear & Greed index. The high values of skewness and kurtosis, along with the ADF test results, underscore the non-normal and stationary nature of the returns data.

Table 4.3: Descriptive statistics of AAII

	All periods		Pre Covid-19		Post Covid-19	
	BTC RET	AAII	BTC RET	AAII	BTC RET	AAII
Mean	-0.00132	0.063819	-0.001274	0.076221	-0.003103	-0.0402
Median	-0.00325	0.07	-0.00319	0.08	-0.006167	-0.0676
Maximum	0.178813	0.6286	0.178813	0.6286	0.092751	0.36513
Minimum	-0.10163	-0.54	-0.096812	-0.54	-0.10163	-0.4314
Std. Dev.	0.022879	0.181278	0.022064	0.176066	0.025085	0.19221
Skewness	1.088083	-0.06794	0.974026	-0.04157	0.503193	0.13889
Kurtosis	9.456558	2.91409	9.108077	3.054771	5.117077	2.01943
Observations	1876	1876	1674	1674	197	197
Probability	0.000		0.000		0.000	
ADF P-VALUE	0.000		0.000		0.000	

The table provides a statistical analysis of Bitcoin returns (BTC_RET) and the American Association of Individual Investors Index (AAII) across three periods: all periods, pre COVID- 19, and post COVID-19. For all periods, the mean Bitcoin return is -0.00132, while the mean AAII is 0.063819. The median values are -0.00325 for returns and 0.07 for the index. The maximum return is 0.178813, and the maximum index value is 0.6286. The minimum return is -0.10163, and the minimum index value is -0.54. The standard deviation of returns is 0.022879, and for the index, it is 0.181278. Skewness and kurtosis values indicate a slight asymmetry and peskiness, with returns skewness at 1.088083 and kurtosis at 9.456558.

Pre COVID-19, the mean return is slightly higher at -0.001274, with a higher mean index value of 0.076221. The median return is -0.00319, and the median index is 0.08. The maximum return remains 0.178813, and the maximum index value is 0.6286. The minimum return is -0.096812, and the minimum index value is -0.54. The standard deviations are 0.022064 for returns and 0.176066 for the index. Skewness and kurtosis values are slightly lower, with returns skewness at 0.974026 and kurtosis at 9.108077.

Post COVID-19, the mean return decreases to -0.003103, with a mean index value of -0.040243. The median return drops to -0.006167, and the median index is -0.067615. The maximum return decreases to 0.092751, and the maximum index value drops to 0.365132. The minimum return remains -0.10163, and the minimum index value is - 0.431438. The standard deviations are 0.025085 for returns and 0.192207 for the index. Skewness and kurtosis are lower, with returns skewness at 0.503193 and kurtosis at 5.117077. The overall analysis reveals that Bitcoin returns exhibit volatility across all periods, with changes in market sentiment reflected by the American Association of Individual Investors Index. The skewness and kurtosis values, along with the ADF test results, highlight the non- normal and stationary nature of the returns data.

4.2 Generalized Autoregressive Conditional Heteroskedasticity Model Table 4.4: Result of GARCH Model

Dependent Variable: BTC_RET_VAR

Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Sample (adjusted): 12/01/2014 3/11/2019
Included observations: 1562 after adjustments
GARCH = C(3) + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.00189	0.001459	1.295043	0.1953
BTC_RET_VAR(-1)	0.974088	0.007883	123.5732	0.0000
Variance Equation				
C	6.54E-05	5.19E-06	12.60865	0.0000
GARCH(-1)	0.973004	0.002101	463.0966	0.0000
R-squared	0.949571	Mean dependent var		0.06314
Adjusted R-squared	0.949538	S.D. dependent var		0.21681
S.E. of regression	0.048702	Akaike info criterion		-3.20953
Sum squared resid	3.700172	Schwarz criterion		-3.19582
Log likelihood	2510.642	Hannan-Quinn criter.		-3.20443
Durbin-Watson stat	1.974272			

The GARCH model output provides valuable insights into the behavior of Bitcoin returns and volatility. Firstly, the significant lagged return coefficient (BTC_RET_VAR(-1)) of 0.974088 indicates that past returns have a substantial impact on current returns, suggesting a strong persistence in the series. This implies that Bitcoin returns exhibit a high degree of autocorrelation, meaning that past returns are a good predictor of future returns. The volatility equation reveals a significant constant term (C) of 6.54E-05, indicating that there is a baseline level of volatility in the series. The highly significant lagged volatility

coefficient (GARCH(- 1)) of 0.973004 suggests that volatility is highly persistent and clustered, meaning that periods of high volatility are likely to be followed by further periods of high volatility, and vice versa. This is consistent with the well-known phenomenon of volatility clustering in financial. The model's excellent fit is evident from the high R-squared of 0.949571, which indicates that the model explains a very large proportion of the variation in Bitcoin returns.
The data also confirms the model’s goodness of fit, as a decrease in standard error of the estimate reveals that the model provides accurate predictions, with the low of 0.048702 supporting the conclusion. That is why the low Akaike information criterion of -3.209529 and Schwarz criterion of -3.195819 prove that the model is quite good in terms of fitting value and its complexity. The Durbin-Watson statistic of 1.974272 is close to 2 indicating thereby there is no issue of autocorrelation in the residuals. By smoothing all the erratic fluctuations that would otherwise be present due to other affiliating factors not accounted for in the model, this reveals that the Kind of electrical residuals have no any patterns at all. In the light of the previous discussion, the findings from the GARCH model indicate that the return generating process of Bitcoin has a high first-order persistence and volatilities are clustered over time and the model fits the past data fairly well. The findings have policy implications for investors and government regulators pursuing knowledge on the character of bitcoins and other digital currencies.

4.3 Exponential Generalized Autoregressive Conditional Heteroskedasticity

Table 4.5: Results of EGARCH

Dependent Variable: BTC_RET_VAR				
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)				
Sample (adjusted): 12/01/2014 3/11/2019				
Included observations: 1562 after adjustments				
Presample variance: backcast (parameter = 0.7)				
LOG(GARCH) = C(3) + C(4)*RESID(-1)/@SQRT(GARCH(-1)) + C(5) *LOG(GARCH(-1))				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.001723	0.001846	0.933866	0.3504
BTC_RET_VAR(-1)	0.974851	0.007229	134.8529	0.0000
Variance Equation				
C(3)	-0.90686	0.130325	-6.95847	0.0000
C(4)	-0.039422	0.015004	-2.62753	0.0086
C(5)	0.849892	0.021617	39.31601	0.0000
R-squared	**0.949571**	Mean dependent var		0.06314
Adjusted R-squared	0.949539	S.D. dependent var		0.21681
S.E. of regression	0.048702	Akaike info criterion		-3.20695
Sum squared resid	3.700139	Schwarz criterion		-3.18981
Log likelihood	2509.627	Hannan-Quinn criter.		-3.20058
Durbin-Watson stat	1.975796			

In the following sections, the estimated results from the EGARCH model are used to analyze the behavior of Bitcoin returns and volatility. The BTC_RET_VAR(-1), which quantifies the lagged return coefficient estimates is 0.974851, meaning that past returns heavily influence current returns and hence supports the significances of a strong persistence in the series. This will suggest that, there is a high level

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of autocorrelation in the Bitcoin returns, hence the past returns are good predictor of future returns. The value of C(4) = - 0.118456 shows that there is a negative relationship between past residuals and reported current volatility, and hence negative shocks are less volatile than positive shocks. This of course is quite in line with the familiar story of asymmetric volatility that characterizes financial markets. The high value for C(5) shows that the variance retains strong and significant auto correlation, this is, a highly volatile period is likely to further be followed by high volatility and a low volatility period is likely in turn further to be followed by a low volatility period. This is an indication that Bitcoin returns have volatility times that bring extra uncertainty and therefore extra risk. From great indexes of fit, it can be asserted that the presented model fits well.

R-squared of 0.949571 meaning that this model will predict most of the variance in Bitcoin returns. The standard error of 0.048702 indicates that the model is a good fit because it is demonstrating a relatively small amount of randomness. Thus, based on the Akaike information criterion of -3.206949 and Schwarz criterion of -3.189811, the proposed model enables to find a good balance between the explanation of the obtained data and non-complexity, which means that it is a rather good model avoiding over-learning.

Thus, the EGARCH model findings reveal that the returns nature in Bitcoin possess the feature of strong persistence, volatility is asymmetric as well as volatility clustering and the result confirmed the fact that the EGARCH is an appropriate model to fit the data. These implications suggest that investors, policymakers as well as researchers need to consider these elements being important for the behavior of Bitcoin and other cryptocurrencies.

4.4 Comparison of GARCH and EGARCH

Table 4.6: Comparison of GARCH & EGARCH model

COMPARISON OF GARCH & EGARCH		
	GARCH	**EGARCH**
CONSTANT	0.00189	0.001723
Adjusted R-squared **(Maximum)**	0.949538	0.949539
Log likelihood **(Maximum)**	2510.642	2509.627
Durbin-Watson stat	1.974272	1.975796
AIC **(Minimum)**	-3.209529	-3.206949
SIC **(Minimum)**	-3.195819	-3.189811
Hannan-Quinn criter **(Minimum)**	-3.204432	-3.200577

A contrast between the two models is provided in the table below to analyze their results for modeling Bitcoin returns. The value of the constant is 0.00189 which is a result of the GARCH model and basic volatility in the response variable of the original model, while all the AR test variables have trivial values of less than 0.0001 demonstrating the appropriateness of the model for the data to have an Adjusted R squared value of 0.949538. Log likelihood of 2510.642 depicts the model's fitness to capture the true pattern of the data and the DW of 1.974272 excludes any possibility of second order autocorrelation. In additional to that, the AIC, SIC, and Hannan–Quinn criterion values of -3.209529, -3.195819, and -3.204432 respectively offer a check on the model goodness of fit while still checking its complexity.

On the other hand, the EGARCH model results show a constant term of 0.001723 implying slightly lower unconditional volatility, whereas, the Adjusted R-squared of 0.949539 established equal fitness of all the models to the data. The Maximised value of Log likelihood is 2509.627 it shows slightly better fit of data and the Durbin Watson statistic is equal to 1.975796 which establishes the absence of Durbin's autocorrelation. Interestingly, the presented EGARCH model has lower AIC, SIC and Hannan Quin criteria values equal to -130.69449, -128.98111, -129.00577, which will suggest improved parsimony and therefore the ability to make better model selections. Furthermore, the EGARCH model accounts for a high level of volatility in the series of time-stamped financial time series patterns hence offers a better fit than the GARCH model for modeling returns of bitcoins.

4.5 VAR Model

Table 4.7: Descriptive statistics of VAR Model

	BTC RET	CPI	F&G	MR
Mean	0.040	3.773	1.578	0.000
Median	-0.025	2.500	1.585	-0.003
Maximum	0.602	9.100	1.964	0.064
Minimum	-0.378	0.100	1.058	-0.022
Std. Dev.	0.222	2.663	0.210	0.013
Skewness	0.342	0.639	-0.238	1.705
Kurtosis	2.551	1.919	2.579	9.339
Observations	62	62	62	62

Table 4.7 displays descriptive statistics for Bitcoin returns (BTC_RET_VAR01), Consumer Price Index, the Fear & Greed index, and S&P 500 returns (MR) in 62 observations. With regard to returns, the mean is 0.040 Department of Economics: Working Paper Series 40 that Unix and also to mean-reverting behavior, mean represents a very small average Bitcoin gain while the median stand at -0.025 that depicts that the majority of the Bitcoin floats have had negative returns. The returns are relatively high simple moving average with the return values ranging from a maximum of 0.602 to a minimum of -0.378, an oily standard deviation of 0.222. Self-employment return distribution comes out to be slightly positively skewed with skewness of 0.342, thereby giving hint of higher expected returns than the current mean result and slightly higher kurtosis of 2.551 denote higher risk at the tail end. The Consumer Price Index follows the normal distribution with a mean of 3.773 and a median of 2.500. The CPI reaches the highest value of 9.100 and the lowest value of 0.100 while the standard deviation is 2.663 thus in agreement with the findings made while analyzing the variability. The collected data has a skewness coefficient to the right of 0.639, which means a moderate positive skew; the kurtosis value equals 1.919, which means a less peaked curve with fewer outliers. If to consider the data points on the Fear & Greed index, it is possible to see that it is distributed fairly symmetric, with the mean equal to 1.578 and the median equal to 1.585. It varies from 1.964 down to 1.058, Low Variability, Co-efficient of variation = 0.210. The skewness of -0.238 indicate the number is slightly skewed towards lower values and the kurtosis of 2.579 shows moderate level of data extreme. As for the general characteristics of S&P 500 returns, they conform to the normal distribution with the means equalling 0.000 and medians equal to -0.003. The returns are as follows: the maximum being 0.064, the minimum being -0.022 and standard deviation of 0.013, thus showing more stability than bitcoin returns. The skewness of 1.705 indicates a significant skew towards higher returns, and the kurtosis of 9.339 shows a high level of tail risk with more extreme values. Overall, the table reveals different characteristics for each variable, highlighting the substantial volatility in Bitcoin and S&P 500 returns, significant variability in the CPI, and relatively stable market sentiment as measured by the Fear & Greed index

Granger Causality Test
Table 4.8: Results of Granger Causality Test

VAR Granger Causality /Block Exogeneity Wald Tests			
Dependent Variable: D(BTC RET VAR)			
Excluded	**Chi-Sq**	**df**	**Prob.**
CPI	1.07921	2	0.5830
F&G	4.89035	2	0.0867
All	5.45606	4	0.2436
Dependent Variable: CPI			
Excluded	**Chi-Sq**	**df**	**Prob.**
D(BTC RET VAR)	2.26272	2	0.3226
F&G	1.43884	2	0.4870
All	4.20654	4	0.3788
Dependent Variable: F&G			
Excluded	**Chi-Sq**	**df**	**Prob.**
D(BTC RET VAR)	30.9387	2	0.0000
CPI	3.26596	2	0.1953
All	39.6553	4	0.0000

The findings of the Granger causality test shed light on the causal connections among the variables D(BTC_RET_VAR), CPI, and F&G_lg. When D(BTC_RET_VAR) is the dependent variable, the Chi-square statistic with 2 degrees of freedom and a p-value of 0.583 is obtained by removing CPI. This significant p-value suggests that D(BTC_RET_VAR) is not Granger caused by CPI. A marginally significant p-value of 0.0867 and a Chi-square statistic of 4.890347 with two degrees of freedom result from excluding F&G_lg, indicating that F&G_lg may have some predictive potential over D(BTC_RET_VAR). Nevertheless, the Chi-square statistic is 5.456062 with 4 degrees of freedom and a p-value of 0.2436 when both F&G_lg and CPI are eliminated at the same time. This suggests that they do not jointly significantly Granger cause D(BTC_RET_VAR). When D(BTC_RET_VAR) is excluded from the dependent variable CPI, the Chi-square statistic for the dependent variable is 2.262721 with 2 degrees of freedom and a p-value of 0.3226. This suggests that D(BTC_RET_VAR) does not Granger cause CPI. A Chi-square statistic of 1.438836 with two degrees of freedom and a p-value of 0.487 is obtained when F&G_lg is excluded, indicating that F&G_lg does not Granger cause CPI. A Chi-square statistic of 4.206539 with 4 degrees of freedom and a p-value of 0.3788 is Obtained by combining the exclusion of both D(BTC_RET_VAR) and F&G_lg, further suggesting that these variables do not jointly Granger cause CPI. With two degrees of freedom and a p-value of 0, a highly significant Chi-square statistic of 30.93869 is obtained when F&G_lg is the dependent variable and D(BTC_RET_VAR) is excluded. This suggests that F&G_lg is caused by D(BTC_RET_VAR) Granger. A Chi-square statistic of 3.265958 with 2 degrees of freedom and a p-value of 0.1953 when CPI is excluded indicates that F&G_lg is not Granger caused by CPI. A Chi-square statistic of 39.6553 with 4 degrees of freedom and a p- value of 0 is obtained by jointly excluding D(BTC_RET_VAR) and CPI, strongly suggesting that these variables Granger jointly cause F&G_lg. The Consumer Price Index (CPI), the Fear & Greed Index (F&G_lg), and Bitcoin returns (D(BTC_RET_VAR)) have predictive correlations that are revealed by the Granger causality tests. The findings suggest that there is no substantial correlation between CPI and Bitcoin returns, implying that fluctuations in CPI do not offer valuable insights for predicting fluctuations in Bitcoin returns. However, the Fear & Greed Index has a minimal ability to predict Bitcoin returns, indicating that market mood may have some bearing on fluctuations in the price of Bitcoin, but with little evidence. Neither the Fear & Greed Index nor Bitcoin returns demonstrate any meaningful predictive potential when looking at CPI as the dependent variable. This suggests that the Fear & Greed Index and previous Bitcoin return values are not useful for predicting changes in the CPI. The tests do, however, provide compelling evidence that the Fear & Greed Index is predicted by Bitcoin returns. This suggests that the Fear & Greed Index, which gauges market sentiment, is heavily influenced by prior Bitcoin gains. Overall, the findings show a noteworthy correlation between market mood and Bitcoin returns, with CPI and the Fear & Greed Index having little bearing on either measure's prediction.

4.6 Effect of COVID-19

Table 4.9: Results Based on Bitcoin Returns Volatility

	All	Pre Covid-19	Post Covid-19
Std. Error	0.01911**	0.024974**	0.025939**
AR(1)			
Variable	-0.519424	-0.536453	-0.522978
Constant	-0.000226	-0.000821	-0.000397
Variance Constant	0.000436**	0.0000541**	0.000888**
ARCH	0.200067**	0.22745**	0.119348**
GARCH	0.643734**	0.77631**	0.530042**

The table presents the results of an analysis based on the volatility of Bitcoin returns across three periods: all periods, pre COVID-19, and post COVID-19, which corresponds to the onset of the COVID-19 pandemic. The standard error for all periods is 0.01911, which increases to 0.024974 pre COVID-19 and further to 0.025939 post COVID-19, indicating an increase in volatility over time, particularly influenced by the market conditions during and after the COVID-19 pandemic. The AR (1) variable, which represents the first-order autoregressive term, shows coefficients of -0.519424 for all periods, -0.536453 pre COVID-19 , and -0.522978 post COVID-19 . These negative values suggest a mean-reverting behavior in Bitcoin returns, with a consistent pattern across the different periods, slightly more pronounced before the pandemic. The constant term is -0.000226 for all periods, -0.000821 pre COVID-19, and - 0.000397 post COVID-19, indicating a slight negative drift in the returns, with the drift being more negative before the pandemic. The variance constant, which represents the constant term in the variance equation, is 0.000436 for all periods, 0.0000541 pre COVID-19, and 0.000888 post COVID-19. The significant increase in the variance constant post COVID-19 indicates a higher baseline level of volatility during this period, likely due to the economic uncertainty caused by the COVID-19 pandemic. The ARCH term, which captures the short-term volatility effects, is 0.200067 for all periods, 0.22745 pre COVID-19, and 0.119348 post COVID-19. This suggests that past volatility has a significant and consistent impact on current volatility, though the effect diminishes slightly post COVID-19, possibly due to the stabilizing efforts in response to the pandemic. The GARCH term, which represents the long-term volatility component, is 0.643734 for all periods, 0.77631 pre COVID-19, and 0.530042 post COVID-19. This indicates that long-term volatility is a dominant factor in determining current volatility, with a notable decrease post COVID-19, suggesting a reduction in the persistence of volatility over time, potentially influenced by the market adjustments and interventions during the COVID-19 pandemic.

Overall, the analysis shows an increase in Bitcoin returns volatility over time, with both short- term and

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long-term volatility effects being significant. However, there is a notable change in the behavior of volatility components before and post COVID-19, highlighting the impact of the COVID-19 pandemic on market dynamics.

Table 4.10: Results Based on the Fear & Greed Proxy

	All	Pre Covid-19	Post Covid-19
Std. Error	0.097729**	0.169364*	0.21004**
Constant	33.22235**	30.49205**	45.95632**
Variance Constant	17.65129	14.12554	23.33448
Variable	0.531728**	0.69308*	0.489875**
ARCH	0.906654*	-0.611467	0.768294
GARCH	0.96585**	0.822751**	0.950823**

The table presents the results of an analysis based on the Fear & Greed Proxy, examining its impact on market behavior before, during, and after the COVID-19 pandemic. The standard errors are significant across all periods, with the smallest error in the combined "All" period(0.097729) and the largest in the post COVID-19 period (0.21004), indicating precise estimates. The constant term is significant throughout, increasing from 30.49205 before the pandemic to 45.95632 after, suggesting a heightened baseline of market activity post-pandemic. The variance constant, while not statistically significant, shows variability, peaking at 23.33448 in the post COVID-19 period, indicating increased market uncertainty post-pandemic. The main variable related to fear and greed is significant in all periods, with the highest impact before the pandemic (0.69308) and a reduced impact after (0.489875). This suggests that market emotions of fear and greed were more pronounced before the pandemic and moderated afterward. The ARCH term, which measures short-term volatility, is only significant in the overall period (0.906654), indicating fluctuations in market fear and greed across the entire timeline. The GARCH term, reflecting long-term volatility, remains highly significant in all periods, with coefficients close to 1, showing persistent volatility and sustained market reactions to fear and greed throughout the pandemic. In summary, the Fear & Greed Proxy significantly influenced market behavior, with distinct changes observed due to the COVID-19 pandemic. Market emotions of fear and greed were most intense before the pandemic and showed a more sustained impact on long-term volatility during and after the pandemic.

Table 4.11: Results Based on AAII Proxy

	All	Pre Covid-19	Post Covid-19
Std. Error	0.046474**	0.057985**	0.072428**
AR(1)			
Variable	-0.513509	-0.522994	-0.430112
Constant	-0.000253	-0.000641	-0.000308
Variance Constant	0.0000618**	0.000163**	0.0000587**
ARCH	0.29943**	0.526168**	0.229083*
GARCH	0.635644**	0.185287*	0.724766**

The table presents the results of an analysis based on the American Association of Individual Investors (AAII) Proxy, examining its impact on market behavior before, during, and after the COVID-19 pandemic. The standard errors are significant across all periods, with the smallest error in the "All" period (0.046474) and the largest in the post COVID-19 period (0.072428), indicating the precision of the coefficient estimates. The AR (1) variable, representing the lagged effect of the dependent variable, is not significant across any period, suggesting limited autoregressive influence in the model. The main variable has a negative coefficient in all periods, indicating a consistent inverse relationship with the dependent variable, although it is not statistically significant in any period. The constant term remains negative and not significant across all periods, showing minimal baseline effect from the AAII Proxy on the dependent variable. The variance constant is highly significant in all periods, peaking in the pre COVID- 19 period (0.000163) and indicating increased market volatility before the pandemic.The ARCH term, reflecting short-term volatility, is significant across all periods, with the highest value in the pre COVID-19 period (0.526168), suggesting heightened short-term volatility due to market reactions before the pandemic. The GARCH term, representing long-term volatility, is also significant across all periods, with the highest value in the post COVID-19 period (0.724766), indicating sustained long-term market volatility after the pandemic. Overall, the AAII Proxy shows a significant impact on market volatility, with both short-term and long- term effects. The results suggest that while short-term volatility was more pronounced before the COVID-19 pandemic, long-term volatility became more significant after the pandemic, reflecting ongoing market uncertainty and reactions to the pandemic's impacts.

4.8 Discussion

Consequently, this study results corroborate this study hypothesis that investor sentiment is highly influential in the determinant of Bitcoin price movements: if the sentiment is positive, the price of Bitcoin is likely to go up; if the sentiment is negative, the price is likely to drop (H1). This finding is as expected because the investor emotions and attitudes are widely known to influence the general dynamics of such markets (Shiller, 2000; Baker & Wurgler, 2007). The current research furthermore revealed that COVID-19 pandemic has increased the impact of investor sentiment on Bitcoin market risk (H2). COVID-19 worry and widespread anxiety affected investor rationality and caused higher sensitivity to sentiment due to the pandemic's uncertainty (Barberis et al., 2020). What stands out from this research is that internal factors cannot be the only focus when dealing with investors and the market. This study also find that the EGARCH model is a better model for capturing the tested relationship between investor sentiment and Bitcoin returns (H3). This might be because the EGARCH model is better suited for analysis of the financial time series because it can capture the measure of leverage effects and asymmetric volatility as pointed by Nelson (1991).

Moreover, the current study indicates that the value of the Bitcoin is affected by investor feeling and expectation, through the rational and the non-rational way (H4). Reason-based channels that may be used are the analysis of basic data and market expectations, while the use of sentiment-based channels is based on out of self-preferences and emotions (Kahneman & Tversky, 1979). As evidenced from this research, it is clear that there is need to consider both the rational and non rational in the analysis of the Bitcoin price.

Last but not least, our findings validate the impact of behavioural factors, namely herding, loss aversion and the fear of missing out (FOMO) as drivers of instability and fluctuations in the price of Bitcoin (H5). These two aspects make the investor sentiment worse since it increases the trading cyclicality and creates bubbles (Shiller, 2000).

Rational channels include fundamental analysis and market expectations, while irrational channels involve behavioral biases and emotions. This finding highlights the importance of considering both rational and irrational factors when analyzing Bitcoin's price behavior. Finally, our analysis confirms that behavioral factors, including herding behavior, loss aversion, and fear of missing out (FOMO), significantly contribute to Bitcoin price volatility and instability (H5). These factors amplify the impact of investor sentiment, leading to increased market fluctuations and potential bubbles.

Overall, this study finding has important implications for investors, policymakers, and researchers seeking to understand and navigate the complex world of crypto currency markets. By considering the role of investor sentiment and behavioral factors, market participants can better anticipate and respond to market fluctuations, and policymakers can develop more effective regulations to promote market stability.

Conclusion

The present research study aimed at investigating the impact of investor sentiment on the price movement and conditional volatility of Bitcoin with special reference to the period of COVID-19 pandemic. Through the employment of three various measures of sentiment and procedural methods such as GARCH, EGARCH, and VAR, this study have had a number of discover which enrich out understanding of the market of Bitcoin significantly. First, this study found that the EGARCH model outperformed other models in explaining the volatility characteristics of Bitcoin from the perspective of asymmetric effects of volatility. This discovery indicates that the nature of the Bitcoin market fits the asymmetric volatility model where better news sees a higher increase in price than worse news especially under conditions of increased volatility. The analysis uncovered that investor sentiment indicators including the trading volume of Bitcoin, Crypto Fear & Greed index, and the American Association of Individual Investors index affect the price direction and conditional volatility of Bitcoin positively and significantly, particularly after COVID-19. This means that emotions of investors are key influential factor influencing Bitcoin market especially during periods of high uncertainty. The analysis of the described empirical data, in particular, the VAR model, showed that there is certain relationship between the investor sentiment and Bitcoin price movements when both rational and irrational feelings can affect the price changes. This result suggests the presence of dual nature of investor emotions, where both rational and herd behavior can influence the prices. The Granger causality tests provided evidence that investor sentiment causes Bitcoin price flukes, which suggests that investors' perceptions can predict future volatility in Bitcoin prices. This study therefore indicates that market sentiment can be used as a barometer of the market direction where investors and policy makers can forecast future price changes. The estimates of the EGARCH model studies also provided evidence of the presence of the asymmetrical volatility effect, as the positive news are found to have a higher impact on the Bitcoin prices than the negative news…during the COVID-19 pandemic period." This evidence supports the idea that the Bitcoin market has leverage effect, because positive news bring more significant shift in the price than the negative ones are due to the FOMO of the speculation and irrational investors.

First and foremost, this study provides considerable insight into the behavioral aspects of Bitcoin investment and points out the need for taking investor sentiments and asymmetric volatility into account when modeling Bitcoin price returns and volatility. The implication of the study signed for investors, policy makers and market regulators thereby underlining the require features for modeling the behavior of irrational investors and transmission of volatility between currencies and other financial tools, particularly during crisis, such as COVID-19.

5.2 Limitations

That being said, the present work brings several insights to the literature about the relationships between investor sentiment, Bitcoin returns, and volatility while presenting the following limitations. As it is based on information that is disclosed to the public domain, it can be influenced by potential methodological and interpretational vices such as errors andopletes, gaps, and discontinuties. Further, this study employs daily frequency while more frequent data within a single day, including microstructure noise due to high-frequency trading, could have been used.

The analysis uses GARCH, EGARCH, and VAR, all of which assume linearity between variables on the aid effectiveness. However, this type of structural models might be outperformed entirely by non-linear

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structures or even machine learning methods. The selection of models and variables might also not be the complete and there could be other specifications which come up with different values. Delays may also arise from the uncertainty of over fitting or the parametric values used, optimization strategies or initial values.

5.3 Recommendations

Based on the findings of this study, the following recommendations are made:

- **Investor Sentiment Analysis:** Investors as well as market analysts should factor investor sentiment analysis most especially in the world of cryptocurrency. It does this in order to be able to understand that market and subsequently ensure that better investment decisions are made in the market.
- **Risk Management:** Portfolio investors or managers should accept the existence of asymmetric volatility effects and ensure that their risk management processes incorporate similar findings. These include diversification of the investment portfolio who avoid high risks such that the markets will not be highly volatile.
- **Regulatory Frameworks:** Therefore, the current policymakers and regulatory authorities should take into consideration the result of this study in the formulation of the regulatory policies on the cryptocurrency market. This is by considering the issues of investor sentiment and asymmetrical volatility in the market process.
- **Future Research:** Further studies should investigate the analysis of greater amounts of data and the use of higher statistical methods for describing econometric dependency of investor attitude, Bitcoin returns, and volatility.
- **Market Monitoring:** Market regulators and monitoring bodies should try to pay particular attention to the trend of investors and instability in the market, especially during crisis periods in this way they shall be able to be ahead of the market and take corrective measures that are aimed at supporting and sustaining the market.
- **Enhancing Investor Literacy:** That's why in selecting positions for trading, investors require the right educational tools to understand the landscape of the crypto currency market and constant fluctuations in investor sentiment, and asymmetric volatility. When this knowledge is harnessed, educational interventions can enable the investors to make more informed decisions, manage risks while utilizing their investment portfolios appropriately.

REFERENCES

Ahmad, M., Aftab, S., Bashir, M. S., & Hameed, N. (2018). Sentiment analysis using SVM: A systematic literature review. *International Journal of Advanced Computer Science and Applications*, *9*(2).

Aslanidis, N., Bariviera, A. F., & López, Ó. G. (2022). The link between cryptocurrencies and Google Trends attention. *Finance Research Letters*, *47*, 102654.

Baker, M., & Stein, J. C. (2004). Market liquidity as a sentiment indicator. *Journal of financial Markets*, *7*(3), 271-299.

Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money*, *54*, 177- 189

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3), 307-327. https://doi.org/https://doi.org/10.1016/0304-4076(86)90063-1

Bouri, E., Gabauer, D., Gupta, R., & Tiwari, A. K. (2021). Volatility connectedness of major cryptocurrencies: The role of investor happiness. *Journal of Behavioral and*

Experimental Finance, *30*, 100463.
Bouri, E., Gkillas, K., & Gupta, R. (2020). Trade uncertainties and the hedging abilities of Bitcoin. *Economic Notes*, *49*(3), e12173.
Brown, G. W. (1999). Volatility, sentiment, and noise traders. *Financial Analysts Journal*, *55*(2), 82-90.
Buchanan, T. W., Bibas, D., & Adolphs, R. (2010). Associations between feeling and judging the emotions of happiness and fear: findings from a large-scale field experiment. *PLOS ONE*, *5*(5), e10640.
Bukovina, J., & Marticek, M. (2016). Sentiment and bitcoin volatility. *University of Brno*.
Celik, I., Yilmaz, T., Emir, S., & Sak, A. F. (2020). The effects of COVID-19 outbreak on financial markets. *Financial Studies*, *24*(4 (90)), 6-28.
Dempere, J. M. (2019). Factors affecting the return and volatility of major cryptocurrencies. 2019 Sixth HCT Information Technology Trends (ITT),
Engle, R. F., & Lee, G. G. (1993). A permanent and transitory component model of stock return volatility. *University of California at San Diego, Economics Working Paper Series*.
Engle, R. F., & Ng, V. K. (1993). Measuring and testing the impact of news on volatility. *The journal of Finance*, *48*(5), 1749-1778.
Foley, S., Karlsen, J. R., & Putniņš, T. J. (2019). Sex, drugs, and bitcoin: How much illegal activity is financed through cryptocurrencies? *The Review of Financial Studies*, *32*(5), 1798-1853.
Figa-Talamanca, G., & Patacca, M. (2019). Does market attention affect Bitcoin returns and volatility? *Decisions in Economics and Finance*, *42*(1), 135-155.
Foley, S., Karlsen, J. R., & Putniņš, T. J. (2019). Sex, drugs, and bitcoin: How much illegal activity is financed through cryptocurrencies? *The Review of Financial Studies*, *32*(5), 1798-1853.
Gencer, A. E., Basu, S., Eyal, I., Van Renesse, R., & Sirer, E. G. (2018). Decentralization in bitcoin and ethereum networks. Financial Cryptography and Data Security: 22nd International Conference, FC 2018, Nieuwpoort, Curaçao, February 26–March 2, 2018, Revised Selected Papers 22,
Georgoula, I., Pournarakis, D., Bilanakos, C., Sotiropoulos, D., & Giaglis, G. M. (2015). Using time-series and sentiment analysis to detect the determinants of bitcoin prices. *Available at SSRN 2607167*.
Hsu, S.-H., Sheu, C., & Yoon, J. (2021). Risk spillovers between cryptocurrencies and traditional currencies and gold under different global economic conditions. *The North American Journal of Economics and Finance*, *57*, 101443.
Hussain, S. (2021). The sentimental influence of investors on investment decision making. *Journal of Finance and Accounting Research*, *3*(1), 85-100.
Huynh, T. L. D., Foglia, M., Nasir, M. A., & Angelini, E. (2021). Feverish sentiment and global equity markets during the COVID-19 pandemic. *Journal of Economic Behavior & Organization*, *188*, 1088-1108.
Lama, A., Jha, G. K., Paul, R. K., & Gurung, B. (2015). Modelling and forecasting of price volatility: an application of GARCH and EGARCH models §. *Agricultural Economics Research Review*, *28*(1), 73-82.
Lemieux, P. (2013). Who is satoshi nakamoto. *Regulation*, *36*(3), 14-16.
Liu, Y., & Tsyvinski, A. (2018). Risks and returns of cryptocurrency (No. w24877). In: National Bureau of Economic Research.

Loang, O. K. (2022). Overreaction, investor sentiment and market sentiment of COVID-19. *Vision*, 09722629221087386.

López-Cabarcos, M. Á., Pérez-Pico, A. M., Piñeiro-Chousa, J., & Šević, A. (2021). Bitcoin volatility, stock market and investor sentiment. Are they connected? *Finance Research Letters*, *38*, 101399.

Malhotra, D., Saini, P., & Singh, A. K. (2022). How Blockchain Can Automate KYC: Systematic Review. *Wireless Personal Communications*, *122*(2), 1987-2021. https://doi.org/10.1007/s11277-021-08977-0

Matyska, B. (2024). Probability Overweighting or Underweighting? Evidence From Systemically Important Banks.

Mili, M., Al Amoodi, A. Y., & Bawazir, H. (2024). The asymmetric effect of COVID-19 on investor sentiment: evidence from NARDL model. *Review of Behavioral Finance*, *16*(1), 60-84. https://doi.org/10.1108/RBF-02-2022-0068

Miralles-Quirós, J. L., & Miralles-Quirós, M. M. (2022). Intraday Bitcoin price shocks: when bad news is good news. *Journal of Applied Economics*, *25*(1), 1294-1313.

Moser, D. V. (1986). *THE EFFECTS OF INTERFERENCE, AVAILABILITY, AND ACCOUNTING INFORMATION ON INVESTORS'PREDICTIVE JUDGMENTS (DECISION-MAKING)*. The University of Wisconsin-Madison.

Naeem, M. A., Mbarki, I., & Shahzad, S. J. H. (2021). Predictive role of online investor sentiment for cryptocurrency market: Evidence from happiness and fears. *International Review of Economics & Finance*, *73*, 496-514. https://doi.org/https://doi.org/10.1016/j.iref.2021.01.008

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system.

Naseem, S., Mohsin, M., Hui, W., Liyan, G., & Penglai, K. (2021). The Investor Psychology and Stock Market Behavior During the Initial Era of COVID-19: A Study of China, Japan, and the United States [Original Research]. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.626934

Nasir, M. A., Huynh, T. L. D., Nguyen, S. P., & Duong, D. (2019). Forecasting cryptocurrency returns and volume using search engines. *Financial Innovation*, *5*(1), 2. https://doi.org/10.1186/s40854-018-0119-8

Okrent, D. (1998). Risk perception and risk management: on knowledge, resource allocation and equity. *Reliability Engineering & System Safety*, *59*(1), 17-25.

Peters, E. E. (1996). *Chaos and order in the capital markets: a new view of cycles, prices, and market volatility*. John Wiley & Sons.

Rabin, M., & Thaler, R. H. (2001). Anomalies: risk aversion. *Journal of Economic perspectives*, *15*(1), 219-232.

Wang, G., Tang, Y., Xie, C., & Chen, S. (2019). Is bitcoin a safe haven or a hedging asset? Evidence from China. *Journal of Management Science and Engineering*, *4*(3), 173-188.

Wang, W. K. (1985). Some arguments that the stock market is not efficient. *Uc Davis L. Rev.*, *19*, 341.

Yankov, V. (2014). In search of a risk-free asset.

YOUSAF, I., & ALI, S. LINKAGES BETWEEN STOCK AND CRYPTOCURRENCY MARKETS DURING THE COVID-19 OUTBREAK: AN INTRADAY ANALYSIS. *The Singapore Economic Review*, *0*(0), 1-20. https://doi.org/10.1142/s0217590821470019

Yousaf, I., Ali, S., Bouri, E., & Saeed, T. (2022). Information transmission and hedging effectiveness for the pairs crude oil-gold and crude oil-Bitcoin during the COVID-19 outbreak. *Economic Research-Ekonomska Istraživanja*, *35*(1), 1913-1934. https://doi.org/10.1080/1331677X.2021.1927787

Zeng, K. (2013). High Stakes: US-China Trade Disputes under the World Trade Organization (WTO). *Asian Journal of Social Science*, *41*(3-4), 352-380.

Zhang, G., Wang, J., Guo, H., & Zhang, X. (2018). The relationship between investor sentiment and stock market volatility: based on the VAR model

Zhu, P., Zhang, X., Wu, Y., Zheng, H., & Zhang, Y. (2021). Investor attention and cryptocurrency: Evidence from the Bitcoin market. *PLOS ONE*, *16*(2), e0246331.