KARADENIZ TECHNICAL UNIVERSITY* INSTITUTE OF SOCIAL SCIENCES

DEPARTMENT OF BUSINESS ADMINISTRATION

Ph.D. PROGRAM IN BUSINESS ADMINISTRATION

THE DYNAMICS OF CRYPTOCURRENCY MARKET FROM BEHAVIORAL FINANCE PERSPECTIVE

Ph.D. DISSERTATION

Basma ALMISSHAL

NOVEMBER-2023

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Thesis Advisor: Prof. Dr. Halil İbrahim BULUT

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APPROVAL

Upon the submission of the dissertation, Basma ALMISSHAL has defended the study 'The Dynamics of Cryptocurrency Market from Behavioral Finance Perspective' in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration at Karadeniz Technical University, and the study has been found fully adequate in scope and quality as a thesis by unanimous vote on January 3, 2024.

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ABSTRACT

The years 2008-2009 witnessed a series of major events and developments in the financial realm. Starting from the global financial crisis and its disastrous consequences to the revolution of financial technology and the emergence of a cryptocurrency phenomenon. These accelerating events have drawn significant interest from scholars, financial analysts, and investors who seek to understand the cryptocurrency ecosystem and its implications on the modern financial landscape. Fourteen years have passed since the advent of the first cryptocurrency of its kind, Bitcoin, followed by thousands more, and yet, the intricate dynamics of the cryptocurrency market still reveal a limited understanding of its complexities. Despite the market's continued growth over the past few years, the high volatility and uncertainty of cryptocurrency values are a cause for concern among stakeholders that may lead to irrational investment choices and fear of missing out.

From a behavioral finance perspective, investors are driven by social and psychological factors in their investment decisions. Emotions such as fear and greed may play an important role in investors' choices. By contrast, traditional approaches ignore sentiment and view the investor as a rational entity. However, this may cause a gap between market reactions and the outcomes predicted solely through fundamental analysis, particularly during market anomalies and financial crashes.

By employing weekly data from March 2018 to July 2023, this study aims to explore the dynamics of the cryptocurrency market in three main aspects. Firstly, generating a novel sentiment index using six proxies: (1) Crypto Fear & Greed Index, (2) AAII Investors Sentiment Survey, (3) Google Trends, (4) Tweet Volume, (5) Crypto Trading Volume Trend and (6) CBOE Volatility Index (VIX). Secondly, distinguishing crypto investor sentiment into rational and irrational components through an Automatic Regression of Lag (ARDL) model, utilizing exchange rates of EUR/USD, S&P 500 returns, S&P Goldman Sachs Commodity Index, Cryptocurrency Volatility Index, Crude Oil WTI Futures prices, and S&P Cryptocurrency Broad Digital Market Index. Next, assessing the relationship between cryptocurrency investor sentiment and the returns and volatility of the Royalton CRIX Crypto Index using a Vector Auto Regressive (VAR) model. Finally, the Impact Response Analysis presents the findings, highlighting distinct dynamics in CRIX returns and volatility triggered by shocks in rational and irrational investor sentiment. Therefore, the research problem revolves around understanding how behavioral finance impacts cryptocurrency market dynamics.

Keywords: Behavioral Finance, Investor Sentiment, Cryptocurrency, Autoregressive Distributed Lag Models (ARDL), Vector Auto Regressive Models (VAR), Financial Markets.

ÖZET

2008-2009 yılları, finans alanında önemli olayların ve gelişmelerin yaşandığı bir dönem olmuştur. Küresel finansal kriz ve beraberindeki yıkıcı sonuçlarla başlayan süreç, finansal teknoloji devrimi ve kripto para olgusunun ortaya çıkmasıyla devam etmiştir. Bu hızlı gelişmeler, kripto para ekosistemi ve modern finans alanındaki etkilerini anlamaya çalışan akademisyenler, finansal analistler ve yatırımcılar tarafından büyük ilgi çekmiştir. Bununla birlikte, ilk kripto para olan Bitcoin'in ve bunu takip eden binlerce yeni kripto paranın ortaya çıkışından 14 yıldan fazla bir süre geçmesine rağmen, kripto para piyasasının karmaşık dinamikleri hala tam olarak anlaşılamamıştır. Son yıllarda, piyasanın sürekli büyümesine rağmen, kripto para fiyatlarının yüksek volatilitesi ve belirsizliği, paydaşlar arasında endişelere yol açmaktadır. Bu durum irrasyonel yatırım kararlarına ve yatırım fırsatlarını kaçırma korkusuna yol açabilmektedir.

Davranışsal finans açısından bakıldığında, yatırımcıların yatırım kararları sosyal ve psikolojik faktörlerden etkilenmektedir. Korku ve açgözlülük gibi duygular, yatırımcıların tercihlerinde önemli bir rol oynayabilmektedir. Buna karşın geleneksel yaklaşımlar, duygusal faktörleri göz ardı etmekte ve yatırımcıyı rasyonel bir varlık olarak değerlendirmektedir. Ancak bu durum, özellikle piyasa anomalileri ve finansal çöküşler sırasında piyasa tepkileri ile sadece temel analize dayalı tahminler arasında bir boşluğa neden olabilmektedir.

Bu çalışma, Mart 2018 - Temmuz 2023 arasındaki haftalık veriler kullanılarak kripto para piyasasının dinamiklerini üç ana yönüyle incelemeyi amaçlamaktadır. İlk olarak, (1) Crypto Fear & Greed Index, (2) AAII Yatırımcı Duygu Anketi, (3) Google Trends, (4) Tweet Hacmi, (5) Kripto İşlem Hacmi Eğilimi ve (6) CBOE Volatilite İndeksi (VIX) gibi altı araç (proxy) kullanılarak yeni bir duygu endeksi oluşturulmuştur. İkinci olarak, EUR/USD döviz kuru, S&P 500 getirileri, S&P Goldman Sachs Emtia Endeksi, Kripto Para Volatilite Endeksi, Ham Petrol WTI Vadeli İşlemleri fiyatları ve S&P Kripto Para Geniş Dijital Piyasa Endeksi gibi değişkenler kullanılarak kripto para yatırımcı duygusu rasyonel ve irrasyonel bileşenlere ayrıştırılmış ve ardından, Vektör Otoregresif (VAR) modelleri kullanılarak kripto para yatırımcı duygusu ile Royalton CRIX Kripto Endeksi getirileri ve volatilitesi arasındaki ilişki değerlendirilmiştir. Son olarak da, Etki Tepki Analizi, rasyonel ve irrasyonel yatırımcı duygusunun tetiklediği CRIX getirilerindeki ve volatilitesindeki farklı dinamikler görsel olarak sunulmuştur. Böylece araştırma davranışsal finansın kripto para piyasası dinamiklerini nasıl etkilediğini ortaya koymaktadır.

Anahtar Kelimeler: Davranışsal Finans, Yatırımcı Duygusu, Kripto Para, Otoregresif Dağıtılmış Gecikme modelleri (ARDL), Vektör Otoregresif modelleri (VAR), Finansal Piyasalar.

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LIST OF ABBREVIATIONS

ADF	: Augmented Dickey–Fuller Test
AIC	: Akaike Information Criterion
ARDL	: Autoregressive Distributed Lag
ATM	: Automated Teller Machine
BIC	: Bayesian Information Criterion
CFT	: Combating the Financing of Terrorism
CRIX	: Royalton CRIX Crypto Index
DAX	: German Stock Index (Deutscher Aktienindex)
DeFi	: Decentralized Finance
DJI	: Dow Jones Industrial Average
EMH	: Efficient Market Hypothesis
ETFs	: Exchange-Traded Funds
Fintech	: Financial Technology
FTSE	: FTSE 100 Index in London Stock Exchange
KYC	: Know Your Customer
NFT	: Non-Fungible Token
OECD	: Organisation for Economic Co-operation and Development
RALS	: Residual Augmented Least Squares
S&P 500	: The Standard and Poor's 500
USEPUINDXM	: United States Economic Policy Uncertainty Index
VAR	: Vector Autoregression

INTRODUCTION

In the context of behavioral finance, the impact of investor sentiment on cryptocurrency market dynamics is of significant interest, particularly in light of consecutive financial crashes and the loss of confidence in traditional financial systems. These concerns have brought alternative decentralized financial systems to the forefront of attention alongside the integration of Financial Technology (Fintech) in financial ecosystems (Harvey et al., 2021: 10). Amidst these challenges, behavioral finance has emerged as an approach that considers the human dimension in psychological and social aspects when making investment decisions (Barberis et al., 1998: 315; Montier, 2007: 189). As a result, the debate between behavioral finance and traditional finance theories has gained traction among researchers worldwide due to the limitations in traditional theories in explaining various market behaviors and anomalies, as well as the necessity to keep abreast of massive developments in the financial landscape (Tseng, 2006; Birău, 2012; Ramiah et al., 2015).

Currently, Fintech innovations drive financial markets worldwide (CFTC, 2017). Fintech encompasses various technologies emerging in the modern financial ecosystem such as; machine learning, artificial intelligence, cloud computing, algorithmic trading, blockchain, network cartography, and many others. Through the integration of Fintech and its applications the centralized financial markets and the economy as a whole encounter potential transformations and developments (Harvey et al., 2021: 11). There is no doubt that the rise of digital assets such as cryptocurrencies is one of the most recent and interesting market developments (Tapscott & Tapscott, 2016; KPMG, 2020: 24).

In the midst of the financial markets' rational dilemma generated in face of traditional theories, the question arises of whether cryptocurrency markets are rational (Grobys & Junttila, 2021: 8). The cryptocurrency market, in particular, provides a lens through which to explore the interplay between investor sentiment and market dynamics in the context of behavioral finance. By delving into the underlying motivations and emotions that drive investors to participate in cryptocurrency markets with a social and psychological conscience, researchers can shed light on how behavioral factors contribute to the ever-changing landscape of digital assets. Understanding these dynamics may provide valuable insights for both investors and market analysts attempting to decipher the complex workings of the cryptocurrency arena in the face of global challenges.

Behavioral finance considers psychological theories to explain observed outcomes and anomalies in financial markets. In contrast, traditional finance theories presented the Efficient Market

Hypothesis (EMH), which rests on two key assumptions: that investors act rationally and that the market functions efficiently. Nobel laureate in economics, Eugene F. Fama, referred to it as the 'Fair Game' model (Fama, 1970: 384). Financial bubbles, crises, and market crashes are among the many controversial issues that both classic financial theories and behavioral finance theory strive to provide explanations for. While behavioral finance argues that investors are not always rational individuals and may be emotionally biased when making investment decisions, the efficient market hypothesis is built on the fundamental assumption that investors act rationally based on fairly distributed information. However, Fama concluded in his paper to defend EMH that the "long-term return anomalies are economically or statistically marginal... and this does not suggest that market efficiency should be abandoned" (Fama, 1998: 304). Overall, defenders of the EMH argue that market efficiency can persist even if numerous investors make systematic errors, as long as overall market prices remain rational (Thaler, 1999: 12).

Nevertheless, several studies have concluded that investors do not always act rationally (Bakar & Yi, 2016; Kabir, 2018) as stated in traditional finance theories, and they are influenced by emotional and psychological factors. One interesting illustration of this can be seen in the Global Financial Crisis (GFC) of 2007-2008. The GFC demonstrated that markets can be prone to irrational behavior and speculative bubbles. The crisis revealed that investors' behavior was influenced by herd mentality, overconfidence, and a lack of consideration for the systemic risks associated with the complexity of Mortgage-Backed Securities, eventually leading to a massive financial meltdown. This failure of the efficient market hypothesis (Subramanian, 2010) to predict and explain the severity of the crash exposed the limitations of the theory in capturing the impact of human emotions and irrational decision-making on financial markets, thus increasing the interest in the domain of behavioral finance.

In fact, behavioral finance theory has played a crucial role in filling the gaps left by traditional economic theory, particularly in understanding the decision-making processes of investors who exhibit irrational choices amid market anomalies such as price bubbles, crashes, and herding behavior. The roots of behavioral finance can be traced back to the 1980s when psychologists Daniel Kahneman and Amos Tversky (Budhiraja et al., 2018), in collaboration with economist Robert J. Shiller, conducted pioneering research examining the profound impact of deeply ingrained cognitive biases and heuristics on individuals' financial decision-making. Their groundbreaking endeavors revolutionized the academic understanding of the complex dynamics underlying the financial decision-making processes of investors, leading to significant advancements in this field of knowledge. It is evident that multiple biases can affect investors' decision-making, which is not necessarily rational (Bakar & Yi, 2016). In fact, behavioral finance is derived from Prospect Theory, developed by (Kahneman and Tversky, 1979), which indicates that investors value gains and losses differently. The presence of anomalies in financial markets has led to the emergence of behavioral finance (Budhiraja et al., 2018). Indeed, significant changes in financial markets and investors'

behavior can be observed during periods of crisis. In the past two decades alone, the world has witnessed two massive market crashes: the GFC and the COVID-19 pandemic.

The cryptocurrency market emerged with the creation of Bitcoin in 2009. Specifically, on January 3, 2009, the first block of the Bitcoin blockchain, also known as the 'genesis block', was mined by the pseudonymous person called Satoshi Nakamoto (CoinDesk.com, 2023; Investopedia, 2023a). This event marked the birth of the cryptocurrency market, as Bitcoin became the first decentralized digital currency based on blockchain technology. Following the creation of Bitcoin, other cryptocurrencies began to emerge, and the cryptocurrency market gradually started to develop and expand. Over the years, the market has seen significant growth, attracting both investors and enthusiasts from around the world. Unlike traditional financial markets, which typically operate during specific hours on business days, the cryptocurrency market operates without any breaks. This continuous trading activity is one of the defining features that allows investors and traders from different time zones to participate at any time. This round-the-clock trading contributes to the high liquidity and rapid price movements seen in the cryptocurrency market. The absence of centralized exchanges and regulatory bodies overseeing trading hours means that cryptocurrencies can be bought and sold at any time of the day, enabling investors to react quickly to market developments and news. As of August 2023, there are 9752 cryptocurrencies in existence, with a global market cap of $1.16 trillion. The top 20 cryptocurrencies make up nearly 90% of the total market, with Bitcoin, in particular, dominating approximately 49% of the cryptocurrency market (CoinMarketCap.com, 2023). Overall, the cryptocurrency market, with its unique features, has become a significant player in the global financial landscape.

Due to its unique and decentralized nature, the cryptocurrency market exhibits characteristics and behaviors that are consistent with some aspects of traditional financial theories, but it also demonstrates unique traits that challenge certain assumptions in traditional finance. For example, in the cryptocurrency market, the EMH is often challenged, as cryptocurrencies are known for their extreme price volatility and the potential for significant price discrepancies across different exchanges. These factors have led to instances of arbitrage opportunities and price inefficiencies that may not align with the principles of the EMH. In the cryptocurrency market, there is evidence of both rational and irrational behavior (Almeida & Gonçalves, 2023). While some investors may conduct thorough research and analysis before making decisions, others may be influenced by fear of missing out or speculative trends. On the other hand, the principles of behavioral finance are highly relevant in the cryptocurrency market. Emotional biases, such as fear, greed, and herd mentality, can lead to dramatic price swings and asset bubbles (Ballis & Verousis, 2022). The frequent boom-and-bust cycles of cryptocurrencies are often attributed to the impact of investor sentiment and emotional decision-making.

As per the U.S. Commodity Exchange Act (CEA), virtual currencies like Bitcoin are classified as commodities rather than securities (CFTC, 2015: 3). Commodities, including grains, gold, oil, and natural gas, are known for their high volatility due to their susceptibility to natural disasters and geopolitical influences. Interestingly, Bitcoin has demonstrated even higher volatility than other commodities, such as gold. Consequently, the World Gold Council has suggested that portfolios with greater allocations to cryptocurrencies might benefit from increasing allocations to gold, which has a recognized role in hedging against risk (World Gold Council, 2021: 6).

The nature of cryptocurrency volatility has been extensively examined in literature (Cankaya et al., 2019; Rognone et al., 2020; Gunay et al., 2022). Researchers indicate that cryptocurrency volatility surpasses that of gold and other traditional currencies (Koutmos & Booth, 2019). This heightened volatility can be attributed to factors such as the absence of regulation, the lack of a central authority, and limited market depth. Several factors are responsible for this volatility, with studies pointing to indicators like the Consumer Confidence Index (CCI), the Standard and Poor's 500 index, and social media platforms such as Twitter, as well as online search engines like Google Trends. Additionally, financial regulations and country-specific restrictions play pivotal roles in shaping cryptocurrency market dynamics. Behavioral finance, as an interdisciplinary field that encompasses both psychology and finance, offers a unique perspective on the dynamics of the cryptocurrency market promising to interpret market behaviors and trends driven by the complex interplay of human emotions, cognitive biases, and financial decision-making processes.

This research has been presented in five chapters. In the first chapter, the study begins by introducing the scope and the conceptual dimension of the cryptocurrency market and its dynamics. Following that, the second chapter focuses on sentiment analysis in the context of cryptocurrency markets. The third chapter presents a detailed literature review. In the fourth chapter, the attention shifts to constructing a cryptocurrency investor sentiment index CIST and analyzing its impact on cryptocurrency market dynamics. This section also addresses the formatting of the CIST index, the statistics used in model estimation, and the criteria for model selection. Lastly, the fifth chapter discusses the results and conclusion on the findings, as well as the study implications, limitations and suggestions for future research. Accordingly, the problem statement of this research is to understanding how behavioral finance impacts cryptocurrency market dynamics.

CHAPTER ONE

1. CRYPTOCURRENCIES AND THEIR MARKET DYNAMICS

1.1. Digital Currency

The 20th and 21st centuries have become synonymous with an era of ultra modernization and advanced technology. This Information Age (or digital age) has normalized computerization in industries, communication, and human interaction on a global scale. As a result, the need for secure and instant online-based financial transactions has led to the creation of an electronic equivalent to cash called digital currency, E-cash or cyber-cash. Digital currency is a medium of exchange existing solely in electronic form over the internet without any physical representation like banknotes and coins (Clemons et al., 1996: 6). Unlike credit card transactions, in which both the payer and recipient can be easily identified, digital currency facilitates instantaneous, near-zero fees, and borderless global transactions (Katsiampa, 2019: 333).

Digital money can be categorized as either centralized or decentralized with the former meaning there is a central authority controlling the money supply, such as a central bank digital currency, where central banks initiate a digital form of a country's fiat currency, directly regulated by the central bank rather than commercial banks (Federal Reserve Board, 2023). In the decentralized model, the control over the money supply is predetermined or agreed upon including virtual currency and cryptocurrency.

The first digital currency can be attributed to an American computer scientist named David Chaum. He pioneered cryptography in his study 'Blind Signatures for Untraceable Payments', which outlined the concept of anonymous digital money (Chaum, 1983). In 1989, Chaum invented 'DigiCash', putting his research concepts into practice. In 1996, E-gold was introduced as the first widely used private electronic currency by Douglas Jackson and Barry K. Downey, allowing instant transfer of gold or other precious metals between members using modern technology, with over 2.5 million account holders performing daily transactions in 2005. However, E-Gold faced legal troubles and was shut down by U.S. courts due to money laundering and illegal money transmitting charges (U.S. Dep. of Justice, 2007).

After the launch of Bitcoin in 2009, cryptocurrencies established themselves as decentralized blockchain-based digital currencies, operating without a central server or tangible assets held in

reserve. Their decentralized nature rendered them resistant to government regulation. The recent surge in interest in cryptocurrencies has revitalized the interest in digital currencies, with Bitcoin emerging as the most widely used and accepted form of digital currency.

1.2. Blockchain Technology

Blockchain technology, as defined by Nakamoto (2008), is a decentralized digital ledger that registers transactions throughout a network of computers. Originally implemented as the foundation for the cryptocurrency Bitcoin, it has since been applied to a variety of fields, including supply chain management, digital identity (Verma & Jain, 2019), and smart contracts (Harvey et al., 2021). The potential of blockchain technology to revolutionize the financial sector is noteworthy. Its decentralized, immutable, and secure nature makes it a valuable tool for a range of financial applications, encompassing digital payments, remittances, and asset management.

The decentralization aspect of blockchain technology, elucidated by Swan (2015), eliminates the need for a central authority to verify transactions, resulting in enhanced security and efficiency within the network. Transactions are verified by network nodes through complex algorithms, and once verified, are added to the digital ledger, known as the blockchain (Tapscott & Tapscott, 2016). This structure ensures that once a transaction is recorded on the blockchain, it remains unalterable or deletable, a property referred to as immutability.

Transparency is another pivotal aspect of blockchain technology, underscored by the World Economic Forum (WEF, 2016). It fosters the open participation of any individual in the network, thus boosting accountability and transparency in various industries. The WEF (2016) also emphasizes the potential of blockchain technology to revolutionize industries and reshape the way we live and work, reducing transaction costs and risks while enhancing the security and privacy of digital identity.

- Advantages of Blockchain Technology

One of the most significant advantages of blockchain technology in the financial sector is its ability to increase the speed and efficiency of transactions. Traditional financial transactions, such as wire transfers and check clearing, can take several days to complete due to the need for intermediaries to verify and clear the transactions. Blockchain technology, on the other hand, can facilitate near-instant transactions through its distributed ledger system. As a result, it has the potential to reduce costs and increase the speed of financial transactions (Narayanan et al., 2016). Another potential benefit of blockchain technology in the financial sector is its ability to increase the security of transactions. The decentralized nature of blockchain technology makes it resistant to tampering and

hacking, as there is no single point of failure in the system. This makes it a valuable tool for protecting sensitive financial information and reducing the risk of fraud (Narayanan et al., 2016). In addition to these benefits, blockchain technology also has the potential to democratize the financial sector by enabling the inclusion of underbanked and unbanked populations. For example, blockchain-based digital wallets can provide individuals without access to traditional banking services with a secure and accessible way to store and transfer funds (Tapscott & Tapscott, 2016).

- Disadvantages of Blockchain Technology

However, alongside these potential benefits, there are challenges associated with using blockchain technology in the financial sector. One of the primary challenges is regulatory uncertainty, as governments and financial institutions grapple with how to properly regulate and integrate blockchain-based systems into existing financial infrastructure. This hurdle can impede adoption and constrain blockchain technology's potential in the financial sector (Tapscott & Tapscott, 2016). Another challenge is scalability, given that current blockchain systems struggle to handle the high transaction volumes required for mainstream financial sector adoption. This is a field of active research, with solutions such as off-chain scaling and sharding being proposed (Buterin, 2014). The disadvantages of blockchain technology, as listed by (Namasudra & Akkaya, 2023: 17), are as follows:

- *Energy Consumption:* The blockchain mining process requires high power usage because the addition of a new node to the network demands communication with all other nodes simultaneously. Additionally, maintaining a real-time ledger significantly contributes to this power usage.
- *Time Consumption:* Adding a new block to the blockchain network involves complex computations that are highly time-consuming.
- *Emerging Stage:* Blockchain technology is still in its early stages, which presents certain obstacles to investing in this technology due to a lack of widespread knowledge and maturity.
- *Legal Regulations*: Due to the emerging stage of blockchain technology, specific regulatory standards have yet to be established.
- *51% Attacks*: A 51% attack is an attack on a cryptocurrency blockchain carried out by a group of miners who control over 50% of the network's mining hash rate.
- *Difficulty of development and Network Robustness:* Blockchain applications feature a fixed and unalterable business logic that cannot be modified after the network's development.
- *Scalability:* Scalability is a significant constraint in blockchain technology, primarily due to the fixed block size in blockchain networks. For example, if a specific blockchain

network has a 1 MB block size, it can only accommodate a limited volume of transaction data within each block.

- *Storage:* Within a blockchain network, each block or transaction is appended to the chain, leading to an expanding database size and subsequent growth in ledger dimensions over time.

1.3. Introduction of Cryptocurrency

Cryptocurrency is a form of digital or virtual currency that uses encryption techniques to regulate the generation of units and verify transactions (Nakamoto, 2008). It is decentralized, meaning that it is not controlled by any central authority, such as a government or financial institution. The idea of cryptocurrency dates back to the 1980s, but it was not exposed until the invention of Bitcoin in 2008 that the concept gained widespread attention. Therefore, Cryptocurrency is better explained by the birth of Bitcoin, the oldest and best-known form of its kind.

Bitcoin, the currency for which blockchain technology was invented, was developed by pseudonymous founder named Satoshi Nakamoto[1] who released the currency's Whitepaper in 2008 titled 'Bitcoin: A Peer-to-Peer Electronic Cash System'. The paper described a decentralized digital currency that could be used for online transactions without the need for a central authority (Nakamoto, 2008). The first Bitcoin transaction took place in January 2009 when Nakamoto sent 10 Bitcoins to a programmer named Hal Finney (Popper, 2015). Hence, on January 3, 2009 Bitcoin was launched as the first decentralized cryptocurrency after Genesis Block was mined. The Genesis Block is the opening of the Bitcoin blockchain also known as 'block 0', where 21 million Bitcoin (BTC) have spawned, also representing the limited available supply of Bitcoin (CoinDesk.com, 2023; Investopedia, 2023a).

In the early years, Bitcoin found its main user base among technology enthusiasts and early adopters. However, in 2010, the value of Bitcoin began to rise as more people became interested in the technology. In May 2010, a programmer named Laszlo Hanyecz made the first recorded purchase using Bitcoin, buying two pizzas for 10,000 Bitcoins (Popper, 2015). At the time, the value of Bitcoin was just a few cents, but by the end of the year, it had risen to over $1 (Popper, 2015; Polasik, et al., 2015: 13).

[1] Satoshi Nakamoto, the creator of Bitcoin, published a seminal white paper in 2008 titled "Bitcoin: A Peer-to-Peer Electronic Cash System," which laid the groundwork for Bitcoin's intended purpose and Nakamoto's vision for its future. Nakamoto's paper challenges the current methods of handling payment transactions, highlighting the vulnerabilities of trust-based systems, such as high transaction costs and the potential for reversibility. Instead, Nakamoto proposed a technology based on proof of work, enabling peer-to-peer transactions through blockchain or distributed ledger technology. By adopting a peer-to-peer transaction model, the reliance on a central authority or financial institution to record transactions, establish identity, and prevent fraud could be significantly reduced. Blockchain technology, driven by mathematics and consensus among a network of nodes, can independently accomplish these tasks, diminishing the need for excessive trust in a central authority.

The next few years saw the emergence of other cryptocurrencies, such as Litecoin and Ripple. In 2013, the value of Bitcoin skyrocketed, reaching an all-time high of over $1,100 in November of that year. However, the value then dropped dramatically, with Bitcoin trading at around $200 in early 2015 (Popper, 2015).

Despite this volatility, the popularity of cryptocurrency continued to grow. In 2017, the value of Bitcoin once again surged, reaching a peak of nearly $20,000 in December of that year. This sparked a wave of interest in cryptocurrency, with many new investors entering the market. In Table 1 below the yearly average prices of Bitcoin in ten years is listed.

Table 1: Bitcoin Prices Over the Past Ten Years

Year	Bitcoin Average Price*
2013	314
2014	503
2015	277
2016	591
2017	4,343
2018	7,188
2019	7,344
2020	12,320
2021	47,042
2022	27,795
2023**	27,096

* Currency denominated in US Dollars.

**Prices in 2023 cover the average up to September 30, 2023.

Source: CoinMarketCap.com. Retrieved on October 6, 2023.

Cryptocurrencies have often been regarded as a hedge against excessive money printing and are considered significant risk-on assets. As a result, they tend to perform exceptionally well when monetary policy is loosened, while experiencing downturns when monetary policy is tightened. The year 2022 witnessed a period of tightening monetary policy which contributed to the crash in cryptocurrencies.

With an increasing market capitalization and proliferation of various cryptocurrencies, such as Bitcoin and Ethereum, these digital assets have presented a novel and complex set of challenges and opportunities for the financial industry (Bouri et al., 2017). Despite the growing popularity of cryptocurrencies, concerns have been raised about their long-term potential as an asset class,

particularly given their volatility and lack of regulatory oversight. The market was also plagued by scams and fraud, as well as concerns about the lack of regulation and security in the industry.

In addition, many people began to question the underlying value of cryptocurrency, arguing that it was a speculative bubble rather than a legitimate form of currency. For example, the case of BitConnect, an open-source cryptocurrency platform that operated from 2016 to 2018 and promised high-return investments. However, it was revealed to be a Ponzi scheme (SEC, 2021: 3) that fraudulently obtained $2.4 billion from investors, resulting in substantial financial losses (U.S. Dep. of Justice, 2022). This case underscored the risks associated with the lack of regulatory oversight in the cryptocurrency space and the potential for fraudulent activities.

After fourteen years, cryptocurrencies are proliferating and show substantial increase in popularity and spread. With the overall cryptocurrency market capitalization having reached USD 1.17 trillion as of August 2023, and boasting over 420 million users globally[2], the projection is for the global cryptocurrency market to attain a value of USD 32.4 trillion by 2027, accompanied by a user count surpassing 994 million within the same timeframe (Yahoo Finance, 2022a; CoinMarketCap.com, 2023; Statista, 2023a). The following Figure 1 exhibits the total market cap of 10,434 cryptocurrencies tracked across 895 exchanges from 2014 up to October, 2023.

Figure 1: Overall Cryptocurrency Market Capitalization

Source: CoinGecko website. 2023.

[2] Refer to Figure 3 for the Total Number of Global Crypto Owners.

Cryptocurrencies have notable popularity, particularly in developing economies, especially where countries are susceptible to exchange rates fluctuations. For example, in Turkey, the adoption of cryptocurrencies has experienced remarkable growth. Turkey witnessed a surge of 27.1% in one year followed by Argentina, Philippines and Thailand with 27.1%, 23.5%, and 23.4% respectively (GWI research, 2023). Furthermore, in June 2021 El Salvador became the first country to among to recognize Bitcoin as legal tender, followed by the Central African Republic in April 2022 (Reuters, 2021, 2022).

The well-known and influential investor Warren Buffett has expressed a cautious stance towards cryptocurrencies, particularly Bitcoin. Known for his value investing philosophy, Buffett has voiced skepticism about the digital currency market. During the Berkshire Hathaway Annual Shareholders Meeting in 2018, he referred to Bitcoin as “rat poison squared” characterizing it as a non-productive asset that attracts speculative behavior (CNBC.com, 2018). Buffett argues that investing in cryptocurrencies primarily involves speculating on price movements rather than investing in productive assets. His reservations stem from the lack of intrinsic value and underlying assets or cash flows supporting cryptocurrencies (CNBC.com, 2022).

In contrast, Elon Musk, another influential figure and one of the world's wealthiest individuals, has emerged as a significant force in the cryptocurrency market. With a vast Twitter following exceeding 160 million, Musk actively engages with his audience on various topics, including cryptocurrencies such as Bitcoin and Dogecoin. Through his tweets and comments, Musk has demonstrated the capacity to impact market dynamics and exert considerable influence, particularly in relation to Bitcoin and Dogecoin. For instance, in May 2021, Musk's tweet announcing Tesla's decision to discontinue accepting Bitcoin as payment due to environmental concerns resulted in a substantial decline in Bitcoin's value (CNBC.com, 2021a). Bitcoin experienced a notable drop from $54,819 to $45,700, reaching its lowest level since March 1, 2021. Additionally, Musk's endorsement of Dogecoin through social media and media appearances has led to significant price fluctuations within the cryptocurrency (CNBC.com, 2021b).

However, the cryptocurrency market has continued to exhibit volatility, as the values of Bitcoin and other cryptocurrencies experience significant fluctuations. Nevertheless, there are also indications of increasing mainstream adoption, as major companies like Tesla and PayPal embrace Bitcoin as a valid payment method (Tangem, 2023).

1.4. Characteristics of Cryptocurrency

The development of cryptography and blockchain technology has positioned cryptocurrency as an alternative medium of exchange. Since its launch in 2009, the presence of cryptocurrency has been progressively acknowledged on a global scale. Its unique attributes have attracted substantial

attention, due to its distinctive characteristics that make it revolutionary. Herein below are the main key characteristics of cryptocurrency (Medium, 2020):

- *Decentralization*: Unlike traditional fiat currencies, which are controlled by central authorities and banks, transactions involving cryptocurrencies can be conducted directly between two parties in a peer-to-peer manner. These transactions are validated by a distributed and open network that is neither owned nor authorized by any specific party or government, eliminating the need for intermediary institutions such as banks or payment platforms like PayPal (Amsyar et al., 2020: 155). The decentralized nature of cryptocurrency networks eliminates the reliance on singular entities or third parties for trust, as every participant holds a copy of the blockchain (accessible distributed ledger).

- *Anonymity*: Due to the absence of a central authority, individuals are not forced to reveal their identities while conducting transactions using cryptocurrency. When a transaction is initiated, the decentralized network assesses and authenticates the transaction, subsequently documenting it on the blockchain. Cryptocurrencies, such as Bitcoin, utilize a private key and public key mechanism to validate these transactions. This approach empowers users to generate incognito digital identities and digital wallets for engaging in transactions within the decentralized framework, all while maintaining secure transaction authentication.

- *Immutability and Irreversibility*: One of the main features of cryptocurrency exchange is that it is impossible for anyone other than the owner of the respective private key to move or transfer crypto assets, and once recorded on the blockchain, transactions cannot be modified. Consequently, transaction records are made publicly accessible and unchangeable. While changing the transaction ledger is not impossible, cryptographic security makes it highly difficult, as it requires the compromise of the entire network of cryptocurrency users (Cankaya et al., 2019).

- *Scarcity and Limitation*: Fiat currencies possess unlimited supply due to the central bank's currency issuance policies, which contribute to the inflationary nature of fiat currencies as they decrease in value over time. Conversely, most cryptocurrencies feature a predetermined supply coded into its underlying algorithm during creation. In cryptocurrency market, no individual or consortium can influence the currency’s supply or exert substantial control over it without majority approval. Notably, prominent cryptocurrencies like Bitcoin, Ripple and Litecoin have a maximum supply of 21 million, 100 billion, and 84 million respectively, making them deflationary by nature. Any increase

in cryptocurrency demand or adoption will cause a corresponding price increase (Harvey et al., 2021: 11).

Some researchers and market specialists[3] in addition to mainstream financial media platforms[4], tend to label Bitcoin as the 'new gold', suggesting that cryptocurrency is in the process of 'digitizing' gold. They support their point of view by highlighting the shared characteristics of cryptocurrency and gold. Both assets exhibit a predominantly decentralized nature, possess limited availability, and are acquired through mining. This mining process fosters competition that impacts their pricing and performance. Additionally, both are utilized as stores of value in hedging strategies, and their demand is influenced by the anticipation of value appreciation (IMF, 2018: 19).

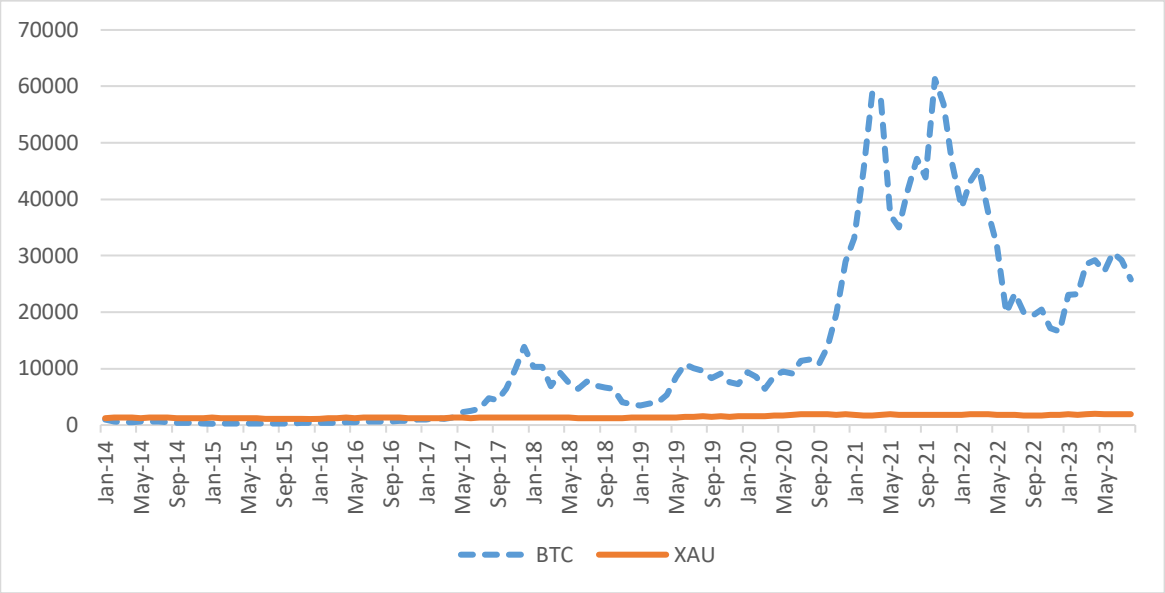
However, significant differences exist between cryptocurrencies and gold, casting doubt on the notion of Bitcoin directly replacing gold. These differences encompass the fundamental nature of the assets, the methods of storage employed, the regulatory landscapes they operate within, their levels of volatility, and their respective purposes of use. Given these distinctions, considering Bitcoin as a 'new gold' lacks a meaningful basis. Figure 2 shows the impressive increase of Bitcoin (BTC) compared to ounce gold (XAU) over the past years.

In January 2013, the price of BTC was $20, while an ounce of gold was priced at $1,663. Moving forward to January 2023, the price of BTC surged to $23,125, while an ounce of gold was valued at $1,928 (Investing.com, 2023; CoinMarketCap.com, 2023). The BTC increase percentage is approximately 113,000 %, reflecting substantial growth from its 2013 price while the increase percentage for gold stands at 16%, signifying a more moderate price change over the same period. In other words, cryptocurrencies do not hold value like gold does (Polizu, et al., 2023).

[3] Researchers and market specialists such as; Andreas M. Antonopoulos, a well-known Bitcoin educator and advocate, he has discussed the idea of Bitcoin as *digital gold* in various talks, interviews, and in his book "Mastering Bitcoin" published in 2017, and Saifedean Ammous, and economist and author. In his book "The Bitcoin Standard" published in 2018, Ammous explores the parallels between Bitcoin and gold, discussing how Bitcoin shares characteristics with gold as a store of value and medium of exchange.

[4] Financial media platforms such as; Bloomberg, CNBC, and others have covered the comparison between Bitcoin and gold, featuring discussions by market experts, economists, and investors on whether Bitcoin can be considered a new form of *digital gold*.

Figure 2: Bitcoin Price vs Ounce Gold Price



Source: Prepared by the author form data retrieved from investing.com and CoinMarketCap websites.

1.5. Types of Cryptocurrencies

In April 2013, CoinMarketCap only listed a modest number of seven legitimate cryptocurrencies. Recently, resources indicate that more than 23,000 different cryptocurrencies have emerged and followed in the footsteps of Bitcoin, mainly due to the ease of creation. However, not all cryptocurrencies are active or hold value. As of August 2023, the net number of tradable cryptocurrencies, after eliminating the vanished ones, stands at 9,722 (CoinMarketCap.com, 2023). Among these, Bitcoin continues to occupy the apex position within the cryptocurrency ecosystem, boasting a market share of nearly half of the overall market capitalization. Other cryptocurrencies apart from Bitcoin are commonly referred to as ‘Altcoins’, encompassing digital assets like Ether, Tether, and Dogecoin. The number of altcoins available on cryptocurrency exchanges is rapidly increasing, and they are known for their high volatility. The following Table 2 shows the most valuable cryptocurrencies in the market.

Table 2: Top 10 Cryptocurrencies in Terms of Market Capitalization

Rank	Cryptocurrency	Symbol	Volume*	Market Cap*	Market Share
1	Bitcoin	BTC	13,661,242,680	567,835,736,376	48.95%
2	Ethereum	ETH	5,873,901,838	220,080,689,116	18.97%
3	Tether USDt	USDT	24,081,925,709	83,485,040,674	7.20%
4	Binance Coin	BNB	431,438,835	37,253,426,248	3.21%
5	Ripple	XRP	1,423,739,809	37,253,924,659	3.21%
6	USD Coin	USDC	2,917,907,448	26,145,621,458	2.25%
7	Dogecoin	DOGE	344,040,076	10,325,246,202	0.89%
8	Cardano	ADA	264,581,524	10,204,540,314	0.88%
9	Solana	SOL	356,022,050	9,402,275,053	0.81%
10	TRON	TRX	176,131,720	6,871,515,537	0.59%

*Currency denominated in US Dollars
Source: Coinmarketcap.com, 8 August, 2023.

1.5.1. Bitcoin (BTC)

Bitcoin is known as the inaugural cryptocurrency boasting the largest market capitalization. Amongst cryptocurrency ownership 52% is for BTC users. In November 2021, Bitcoin achieved a milestone by reaching its all-time highest price of USD 68,789.63, driven by the launch of a Bitcoin ETF in the United States (Statista, 2023a). However, shortly after, BTC prices experienced a significant drop to USD 16,442 in November of the following year. This marked a fall of 65% in its market value over the course of a single year. This decline was attributed to a series of unfortunate events, including the bankruptcy of FTX, one of the world's largest cryptocurrency exchanges. In October 2023, the price of BTC stands at USD 29,700, with crypto experts predicting a price surge up to USD 33,000 by the end of 2023. (Crypto.com, 2023; CoinMarketCap.com, 2023).

1.5.2. Ethereum (ETH)

The second most widely traded cryptocurrency globally is Ethereum. ETH was created by programmer Vitalik Buterin in 2013, and was released to the public on July 30, 2015, as an open-source decentralized finance system (DeFi). ETH is operated with smart contract functionality and powered by cryptocurrency ether (ETH), along with various decentralized applications including non-fungible tokens (NFTs). Unlike Bitcoin which has a limited tradable supply at 21 million coins, ETH does not have such limitations. There is no set limit on the number of ETH coins that can be created. As of October 2023, the circulating supply of Ethereum is 120.16 million, representing nearly 20% of the overall cryptocurrency market volume (Ethereum.org, 2023; Blockworks.co, 2023; CoinMarketCap.com, 2023).

1.5.3. Tether (USDt)

Tether is a stablecoin cryptocurrency pegged to the US dollar as one of the first cryptocurrencies to peg its market value to a fiat currency[5]. Unlike most cryptocurrencies, which can experience significant price volatility, stablecoins such as USDt are designed to minimize price fluctuations and maintain a stable value. USDt has preserved its value at USD 1.00. As of 2023, it is ranked as one of the three largest cryptocurrencies after Bitcoin and Ethereum, with a total market share exceeding 7%. Furthermore, USDt is the largest stablecoin with a market capitalization that exceeds USD 83 billion (CoinDesk, 2023).

1.5.4. Binance Coin (BNB)

Binance cryptocurrency was established in 2017 by Binance Exchange, the largest cryptocurrency exchange in the world. Despite its recent entry into the market, BNB occupies the fourth place with a market share of 3.2%. BNB has been heavily traded since 2021 and its prices have increased significantly. One of the most important reasons for this is the support of altcoin investments and crypto transactions.

1.5.5. Ripple (XRP)

The Ripple (XRP) cryptocurrency was developed by US-based technology company Ripple Labs in 2012. XRP has experienced notable growth in 2023 as a leader in the top five cryptocurrencies in terms of market share. Unlike other cryptocurrencies, Ripple is not built on a traditional blockchain architecture. Instead, it utilizes a distinct technology known as the XRP Ledger to enable fast and efficient cross-border transactions for financial institutions. XRP's decentralized technology assets its ability to conduct financial transactions fast and green, with settling transactions in 3-5 seconds (Ripple, 2023).

1.5.6. Other Altcoins

The cryptocurrency marketplace is experiencing rapid expansion with thousands of digital currencies continuously appearing on crypto exchanges across the globe. Alongside the round-the-clock operation of crypto exchanges, it contributes to ever-changing rankings. Among the altcoins with relatively lower market share are USD Coin, Dogecoin, Cardano, Solana, TRON, Polygon, Litecoin, Polkado, Shiba Inu, Dai, Wrapped Bitcoin, Bitcoin Cash, Avalanche, Toncoin and Chinlink. This ranking is based on their respective market capitalizations as reported by CoinMarketCap.com in 2023. It is important to note that this ranking is subject to constant change

[5] Others currencies include USD Coin, Dai and Binance USD.

due to changes in cryptocurrency market dynamics. Appendix 1 provides an up-to-date list of the top 100 cryptocurrencies available for trading, ranked by their coin market capitalization as of August 2023.

1.6. Cryptocurrency Market Participants

The concept of market participants is mainly defined in financial markets as the legal individuals or entities (e.g. investors, regulators, financial intermediaries and financial service companies) that are involved in trading financial assets and securities. They play a crucial role in the functioning of markets by providing liquidity, price discovery, and overall market efficiency.

In the context of cryptocurrency ecosystems, the major components can be categorized into three groups; miners, traders and exchanges.

1.6.1. Miners

Cryptocurrency mining is the process of creation of new cryptocurrency tokens, validating transactions, and adding them to the shared blockchain database. Miners perform these tasks by solving complex mathematical equations, which ensures the integrity and security of the network. In order to increase their chances of successfully mining a block and receiving rewards, miners often prefer joining mining pools rather than solo mining. In mining pools, groups of miners combine their computational resources to collectively solve problems and earn rewards together. When a pool successfully mines a block, the rewards are distributed among the participants based on their contributed resources. The mining process contributes to the security of the network by preventing double-spending and it ensures the immutability and consensus of the blockchain ledger across all participants.

Mining requires specialized hardware, a significant amount of computational power, and access to a stable internet connection to effectively participate in the competitive process of solving complex mathematical problems and validating transactions on the blockchain network. However, this creates a serious environmental impact due to the high energy consumption associated with cryptocurrency mining, particularly in regions where the electricity used is generated from non-renewable sources such as gas and coal-fired power plants. For instance, the energy consumption of Bitcoin’s mining has escalated significantly to a degree that requires more energy than most countries consume. (Dilek & Furuncu, 2018: 99).

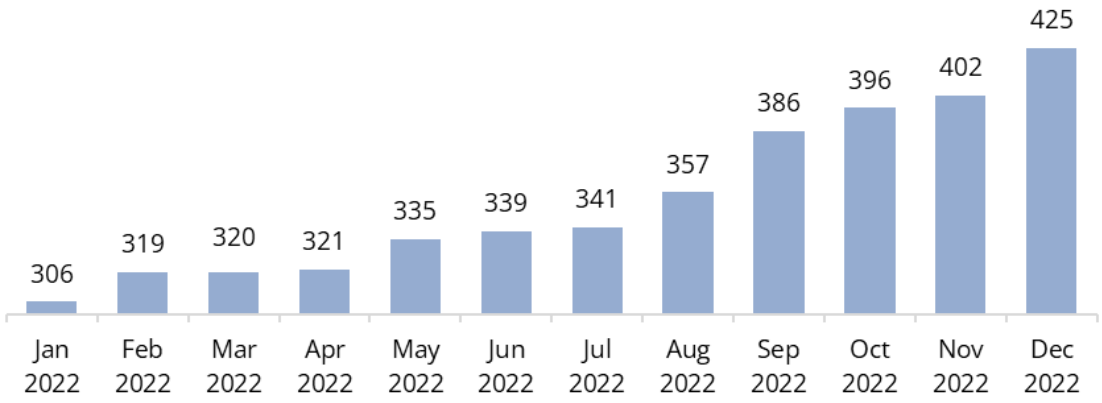
According to statistics, the Cambridge Centre for Alternative Finance estimated that as of September 2021, Bitcoin's annual energy consumption was around 95.68 terawatt-hours (TWh). By December 2022, it reached a peak of 204.5 terawatt-hours for Bitcoin alone (Statista, 2023b). This

consumption surpassed the energy usage of numerous countries, including Argentina and the Netherlands. Additionally, the energy consumption per transaction on the Bitcoin network was approximately 707 kilowatt-hours (kWh), equivalent to the energy consumption of an average US household for about 24 days. Meanwhile, the global market for cryptocurrency mining demonstrated a size of USD 1.92 billion in 2022 and is anticipated to achieve approximately USD 7 billion by 2032 (Precedence Research, 2023).

1.6.2. Traders

Cryptocurrency traders are individuals who buy and sell digital assets like Bitcoin, Ethereum, and other altcoins on different online platforms with the goal of profiting from price fluctuations in the volatile and rapidly evolving world of digital currencies. Since the inception of Bitcoin over a decade ago, the total number of cryptocurrency owners has witnessed a remarkable increase. In 2022 the number of verified users surged by 39%, rising from 306 million in January to 425 million by the end of the year. This growth occurred despite the global challenging macroeconomic conditions, including; escalated inflation rates, ramifications of the COVID-19 pandemic, disruptions in supply chains, and the Russia-Ukraine conflict in Europe. The following Figure 3 shows the increase in global crypto ownership as of January 2023. Further understanding of cryptocurrency ownership based on population statistics for the top 100 countries are provided in Appendix 2 as of May 2023.

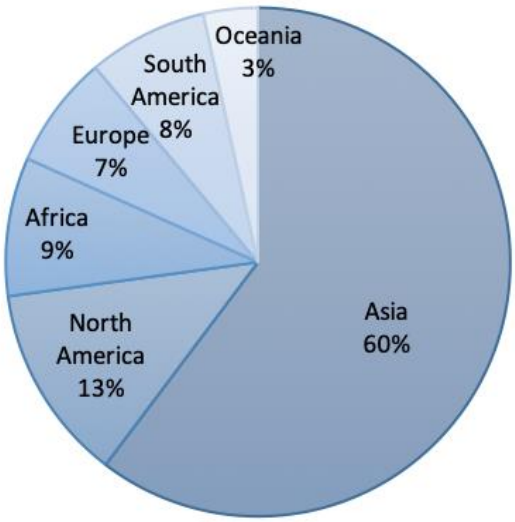
Figure 3: Total Number of Global Crypto Owners (in Millions)



Source: Crypto.com Research, 2023.

Furthermore, statistics show that almost 72% of crypto traders are under 34 years of age and from different geographical regions. Figure 4 below shows the distribution of owners based on their continent.

Figure 4: The Distribution of Crypto Owners Worldwide



Continent	Crypto Owners (in million)
Asia	260
North America	54
Africa	38
South America	33
Europe	31
Oceania	15

Source: Triple-A, 2023.

1.6.3. Cryptocurrency Exchanges

Cryptocurrency exchanges are online platforms serving as the primary venue to facilitate buying, selling, and trading of various cryptocurrencies. (Aspris, et al., 2021). They act as intermediaries allowing traders to exchange different cryptocurrencies for traditional fiat currencies (like US Dollars, Euros, etc.) for fees charged trading, which can include maker fees (for providing liquidity to the market) and taker fees (for executing market orders). Cryptocurrency exchanges play a central role in the cryptocurrency ecosystem by providing a marketplace for users to engage in trading activities, with around 500 exchanges (CoinMarketCap, 2023). These platforms offer a wide range of services and features, catering to both novice and experienced traders. Users can typically create accounts, deposit funds, and start trading various cryptocurrencies within minutes. Additionally, some exchanges offer advanced trading tools, margin trading, lending and borrowing services, and even futures and options contracts, expanding the scope of financial instruments available for trading (Binance Academy, 2023; CoinTelegraph, 2023).

However, the huge number of exchanges has led to varying levels of reliability, security, and regulatory compliance. It is crucial for users to conduct thorough research before choosing an exchange, considering factors such as reputation, trading fees, available trading pairs, security measures, and adherence to legal and regulatory standards. Many countries require cryptocurrency exchanges to obtain licenses or register with relevant financial regulatory authorities. These licenses ensure that the exchange operates within legal frameworks and follows specific guidelines. Furthermore, several financial websites provide ranking for the best exchanges done based on several criteria such as (volume, fees, confidence and decentralized exchange). The following Table 2 shows

a list of the best 10 crypto exchanges of 2023 (CoinMarketCap.com, 2023). Binance is the largest and most well-known cryptocurrency exchanges globally, offering a wide range of cryptocurrencies for trading. It has a high score, reflecting its popularity and trading volume. The remaining exchanges featured in Table 3 also enjoy reputable standing in the industry, operating within diverse geographical regions and serving a heterogeneous international clientele. Each of these exchanges has attained its position in the rankings through a steadfast commitment to providing secure and efficient cryptocurrency trading services, collectively contributing to the vibrant and dynamic landscape of the cryptocurrency market.

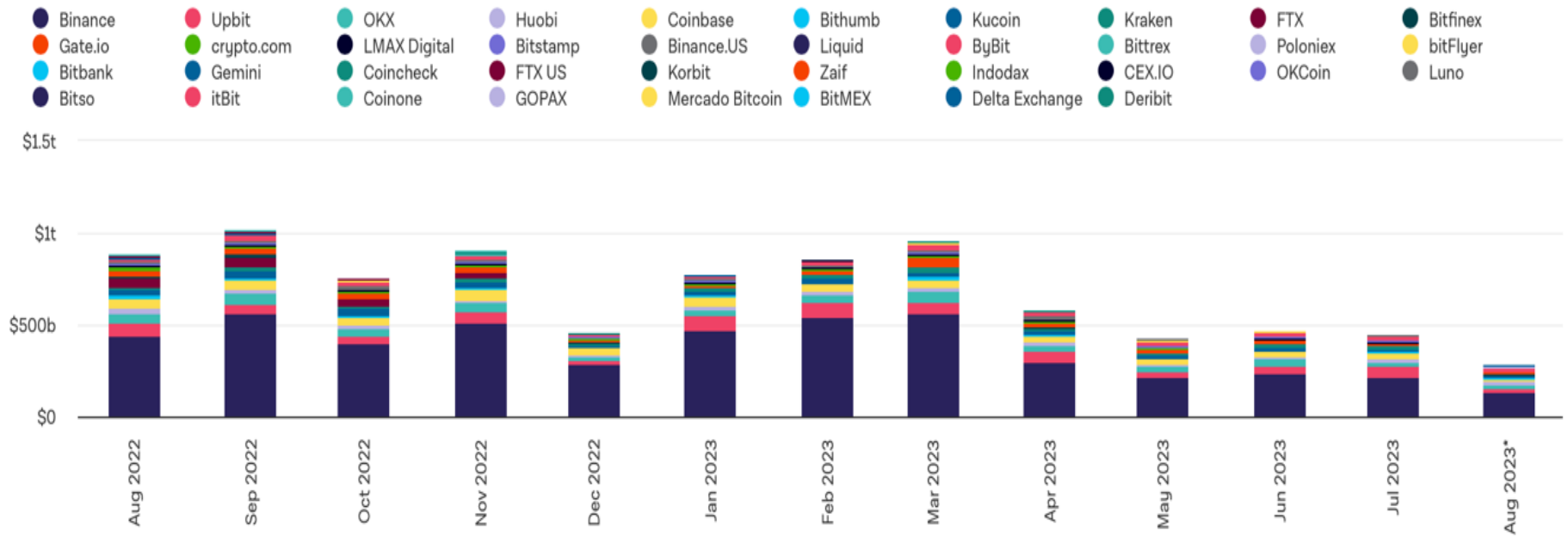
Table 3: Top 10 Cryptocurrency Spot Exchanges

Crypto Exchange	Score*	Number of Coins
Binance	9.9	388
Coinbase Exchange	8.6	246
Kraken	8.2	231
Bybit	7.5	422
KuCoin	7.3	764
OKX	7.3	339
Bitstamp	7	74
Gate.io	6.9	1,736
Bitfinex	6.9	178
Gemini	6.8	117

* CoinMarketCap ranks and scores exchanges based on traffic, liquidity, trading volumes, and confidence in the legitimacy of trading volumes reported as a score ranging from 0-10 (CoinMarketCap, 2023).

In the following Figure 5, the monthly spot market volumes across cryptocurrency exchanges for the past year are being illustrated. The data shows that Binance exchange dominates with almost 50% compared to the other exchanges.

Figure 5: Cryptocurrency Monthly Exchange Volume



Source: The Block.co website, August 2023a.

1.7. Country Regulations on Cryptocurrency Trade

The global adoption of cryptocurrencies is growing with a range of countries acknowledging their potential to reshape financial landscapes. India, for instance, tops the list of cryptocurrency users, its vast population positions it as a significant player in the global crypto adoption scene. India has more than 93 million users. However, forward-thinking approaches to crypto are evident with major cryptocurrency exchanges and government support for blockchain technology (Analytics Insight, 2023).

China, once one of the largest cryptocurrency markets, tightened its grip on the industry in 2021, declaring all cryptocurrency-related transactions illegal (Statista, 2023c). The People's Bank of China cites the ban as a measure to combat financial crime and avert economic instability. However, this move coincides with apprehensions that cryptocurrencies are enabling capital flight, circumventing established restrictions. The ban is emblematic of a broader trend in Chinese economic policy toward increased state intervention, exemplified by the ‘common prosperity’ campaign (World Economic Forum, 2022). Therefore, this puts cryptocurrency trade in China in absolute ban along with Saudi Arabia and Qatar (PwC, 2022: 8).

During the early 2010s, China emerged as a dominant player in the cryptocurrency market due to factors like affordable energy, governmental endorsement, and blockchain support. However, as the industry expanded, concerns about energy consumption and capital movement prompted regulatory intervention from Beijing. Initially supportive, the government later viewed the sector as contradictory to its decarbonization and capital control objectives. It has been indicated that China's cryptocurrency ban is a calculated move to safeguard economic stability, protect the Yuan's value, counter cybercrime risks, and position itself favorably in the global cryptocurrency landscape (Cheng, 2019: 43). This culminated in a ban on crypto trading and mining in May 2021, with reinforced enforcement. Nonetheless, an underground crypto mining industry persists today, with miners using remote areas and alternative energy sources such as hydro dams and solar power. Employing tactics such as overseas pools and VPNs, miners adeptly navigated the challenges of evasion. Remarkably, around 20% of global mining persisted in China post-ban, showcasing the industry's resilience in the face of regulatory barriers.

Turkey's cryptocurrency regulatory strategy combines caution, innovation, and safeguarding consumers, recognizing both the advantages and risks linked to blockchain technology and cryptocurrencies. In April 2021, the Central Bank of the Republic of Turkey (CBRT) prohibited non-fiat crypto-assets for payments, followed by regulations compelling crypto exchanges to register with the Financial Crimes Investigation Board (MASAK), aligning with anti-money laundering (AML) measures and counter-terrorism financing regulations. This obliges crypto service providers to adhere to AML legislation, including Know Your Customer (KYC) processes and reporting

suspicious transactions. Despite the ban, crypto adoption is surging in Turkey, with 5.6 million users (6.5% of the population) in 2023, driven by a desire to hedge against Turkish lira depreciation. Given the growing interest, regulatory authorities may introduce relevant measures in the near future (Ante, et al., 2023; PwC, 2022).

In the United States, digital currencies have generated increasing attention from regulators and financial authorities due to their growing prominence and potential impact on various aspects of the economy and financial system as whole. As a result, the U.S. has adopted an approach marked by a combination of encouraging innovation and implementing regulatory oversight. While the U.S. recognized the potential of blockchain and digital assets, it also worked to find a balance between promoting innovation and safeguarding consumers and investors. Furthermore, The U.S. hosts the largest network of crypto ATMs by more than 26,000 spread across the states (CoinATMRadar, 2023), underscoring its presence in this domain.

Initially, cryptocurrencies like Bitcoin were traded with less regulations due to their novelty. As the industry expanded, U.S. cryptocurrency ownership has increased to nearly 15% of population making it in the third place worldwide. However, numerous concerns arose regarding investor protection, money laundering, and market manipulation. The U.S. government and regulatory bodies, notably the Securities and Exchange Commission (SEC) and the Commodity Futures Trading Commission (CFTC), gradually introduced a set of regulatory guidelines, clarifications and enforcement actions. The U.S. Treasury classified Bitcoin as a convertible decentralized virtual currency in 2013, and in September 2015 the CFTC, classified Bitcoin as a commodity. According to the Internal Revenue Service (IRS), Bitcoin is taxed as property. Cryptocurrency exchanges, serving as vital infrastructure, are subject to regulatory requirements, with the focus on anti-money laundering (AML) and Counter-Terrorist Financing (CTF). The Anti-Money Laundering Act of 2020 codified prior guidance from the Financial Crimes Enforcement Network (FinCEN), making all transactions involving ‘value that substitutes for currency’ subject to reporting and money transmitter registration, including digital currencies (Bloomberg Law, 2022; Global Legal Insights, 2023).

Japan and Switzerland are considered pioneering countries in cryptocurrency adoption. Japan took an early and comprehensive approach to embracing digital currencies, officially recognizing Bitcoin as legal tender in 2017. In Japan, the pioneering and most prominent Bitcoin exchange was Mt. Gox, headquartered in the Tokyo, which abruptly ceased operations following a hacking incident. The collapse of Mt. Gox led the Japanese government to introduce protective measures for consumers while maintaining a substantial presence in the global cryptocurrency market. In 2022, the government acknowledged the achievements of seven mayors by gifting them NFTs, thus enhancing the formal acknowledgment of this technology and promoting its broader adoption. Nowadays, Japan continues to lead with crypto-friendly policies and a well-established crypto community (CoinTelegraph, 2023).

Similarly, Switzerland has emerged as a global frontrunner in crypto adoption. It hosts 'Crypto Valley', a hub for advanced exchanges and innovative blockchain projects, setting a benchmark for financial innovation. Switzerland solidified one of the most mature regulatory frameworks for digital assets in 2020, providing market participants with clarity on the legal and regulatory aspects of their projects and intended activities (PwC, 2022: 61).

Cryptocurrency is generally legal throughout most of the European Union (EU). Notably, the EU's Fifth and Sixth Anti-Money Laundering Directives (AML) have recently been enacted, imposing stricter KYC/CFT obligations and standardized reporting requirements. In September 2020, the European Commission introduced the Markets in Crypto-Assets Regulation (MiCA), a comprehensive framework that enhances consumer protections, establishes clear standards for the crypto industry, and introduces new licensing requirements. This framework was provisionally agreed upon in 2022. In April 2023, Parliament approved measures to enable legislation that mandates certain crypto service providers to obtain an operating license. The primary purpose of this legislation is to empower regulators with the necessary tools to monitor cryptocurrency usage for potential money laundering and terrorism financing activities (Investopedia, 2023b).

Other notable examples of cryptocurrency adoption include the United Arab Emirates, where Dubai authorities are establishing the world's first authority solely dedicated to virtual assets: the Virtual Assets Regulatory Authority (VARA). In the United Arab Emirates, Abu Dhabi Global Market (ADGM) introduced virtual asset regulation as early as 2018.

Additionally, South Korea boasts a robust crypto economy with strict exchange regulations and a thriving Bitcoin trading market, maintaining its leadership in crypto adoption with a 64.2% share of crypto holdings in 2018. As of 2023, approximately 3.9% of South Korea's total population currently owns cryptocurrency. Moreover, the laws governing South Korean cryptocurrency exchanges are stringent, encompassing government registration and other procedures supervised by the Financial Supervisory Service of South Korea (FSS) to enhance investor protection. In 2017, the South Korean government has imposed restrictions on the use of anonymous accounts in cryptocurrency trading and introduced mandatory anti-money laundering and counter-terrorist financing obligations (PwC, 2022; Triple-A, 2023; Bloomberg, 2023).

Singapore, at the forefront of cryptocurrency adoption in the Asia-Pacific region and known for its tech-savviness, aims to enhance its status as a global financial hub by leveraging digital innovation and advancing Fintech development in the country. The government's regulatory framework skillfully navigates between safeguarding investor interests and fostering innovation. The people of Singapore therefore perceive Bitcoin as an investment asset and a store of value.

Similar to the United States, the United Kingdom proceeds cautiously in adopting cryptocurrencies, focusing on regulating exchanges and fostering numerous blockchain startups, thereby making strides in innovative solutions. In Germany, a significant crypto player in Europe, exchange regulations and the promotion of digital assets for everyday transactions contribute to its reputation as a crypto-friendly nation.

Despite slower adoption, Russia demonstrates potential with its tech-friendly culture and steps toward legalizing cryptocurrencies, reflecting a positive attitude toward crypto and blockchain technology. Lastly, Canada stands among the world's crypto-friendly countries, regulating exchanges and facilitating everyday transactions through digital assets (PwC, 2022: 30). With a broad regulatory framework that fosters innovation, the Canadian Securities Administrators (CSA) are actively encouraging Fintech startups to introduce their products to the Canadian market, provided that appropriate safeguards are established. Numerous cryptocurrency trading platforms and ETFs have been launched in the country. Both the CSA and the Investment Industry Regulatory Organization of Canada (IIROC) oversee the securities legislation as it pertains to crypto asset trading platforms, ensuring registration through the Regulatory Sandbox. This has effectively narrowed the gap between regulated and unregulated platforms operating in Canada. However, the regulatory framework and approval for cryptocurrency as a form of payment are still undergoing processing (PwC, 2022: 7).

1.8. Macroeconomic Implications

While cryptocurrency prices may seem less affected by traditional macroeconomic drivers compared to traditional financial assets like stocks (Polizu, et al., 2023; Naeem, et al., 2021), they are not completely immune to macroeconomic changes. The factors influencing cryptocurrency prices include market confidence, adoption, technology, and liquidity conditions, in addition to macroeconomic indicators. It is important to emphasize that the cryptocurrency market is relatively young and still evolving, and its interactions with macroeconomic factors may change over time. As more institutional investors enter the cryptocurrency space, the market's sensitivity to macroeconomic indicators could potentially increase, making it more aligned with the behavior of traditional financial assets. As the crypto market matures, the evolving implications of macroeconomic factors on the crypto market highlight the need for continuous research. Understanding these macroeconomic influences is crucial for investors, policymakers, and researchers. Regulatory changes and global events can significantly impact cryptocurrency dynamics. However, the real effect is still under discussion due to the early emergence of cryptocurrencies compared to other financial assets in the market.

The inherent volatility and speculative nature of cryptocurrency markets have historically led to rapid price fluctuations driven by sentiment, news, and technological advancements. While

macroeconomic factors may not have been the primary driver in the past, their potential impact on overall market sentiment and investor behavior should not be underestimated. Notably, as Bitcoin increasingly becomes deeply integrated into global economic patterns, it is poised to establish new and intricate interactions with various macroeconomic events (Polizu, et al., 2023). As it gains more widespread acceptance for general economic activities, Bitcoin's valuation and usage could be influenced by factors such as its role in payment systems, its potential as an inflation hedge, its status as a safe-haven asset during periods of economic uncertainty, regulatory developments, and its involvement in cross-border transactions and remittances. Additionally, the evolving landscape of central bank digital currencies (CBDCs) and their potential interactions with cryptocurrencies introduce further dimensions to this complex relationship. In essence, while cryptocurrency markets may have historically shown relatively less sensitivity to macroeconomic drivers compared to traditional financial assets, the increasing integration of Bitcoin into broader economic frameworks is likely to reshape its interactions with macro-level forces, potentially leading to a more intricate and intertwined relationship between cryptocurrency dynamics and macroeconomic events (Polizu, et al., 2023).

The relationship between macroeconomic indicators and cryptocurrency returns is multifaceted. While there is no direct causal link, changes in unemployment can influence investor sentiment and overall market dynamics, potentially affecting cryptocurrency returns. During periods of economic uncertainty marked by high unemployment, investors might seek cryptocurrencies as an alternative investment or safe-haven asset, potentially leading to increased demand and higher returns (Almeida & Gonçalves, 2023). Conversely, low unemployment and economic growth might divert investor attention to traditional assets, possibly impacting cryptocurrency demand and returns. Factors like market confidence, risk appetite, and global economic conditions further contribute to this intricate relationship. Lately in 2022, Bitcoin recorded gains by 2% right after the US unemployment rate announced a rise to 3.7% (Yahoo Finance, 2022b).

CHAPTER TWO

2. BEHAVIORAL FINANCE AND INVESTOR SENTIMENT ANALYSIS

2.1. Introduction to Behavioral Finance

As a subfield of behavioral economics, behavioral finance has emerged in the business world as a contrast to neoclassical economic theory (Bikas et al., 2013: 871), particularly the efficient market hypothesis (Fama, 1970). The EMH (efficient market hypothesis) is based on several assumptions: that all individuals are rational, their choices are guided by their risk appetite and preferences, and they update their beliefs and thoughts based on new information. Essentially, the EMH suggests that individuals in an ideal market are capable of making optimal decisions by evaluating all available opportunities through rational cost-benefit analysis. They are unaffected by external factors or emotions in their decision-making. Therefore, attempts to outperform the market are essentially viewed as "a game of chance rather than one of skill" (Fama, 1970). In contrast, behavioral economics argues that psychological, emotional, cognitive, cultural, and social factors can influence individuals' decisions (Angner and Loewenstein, 2007). Specifically, it suggests that psychological aspects such as greed and fear can impact investors' behavior (Birău, 2012). behavioral economics emphasizes the importance of individual financial behavior among capital market investors, acknowledging that they do not strictly adhere to classical financial theory. Behavioral finance serves as a reminder that at our core, we are fundamentally human.

The roots of behavioral finance can be traced back to the 1980s when psychologists Daniel Kahneman and Amos Tversky, in collaboration with economist Robert J. Shiller, conducted pioneering research examining the profound impact of deeply ingrained cognitive biases and heuristics on individuals' financial decision-making. Their groundbreaking endeavors revolutionized the academic understanding of the complex dynamics underlying the financial decision-making processes of investors, leading to significant advancements in this field of knowledge. It is evident that multiple biases can affect investors' decision-making, which is not necessarily rational. In fact, behavioral finance is derived from Prospect Theory, developed by (Kahneman and Tversky, 1979), indicating that investors value gains and losses differently. Budhiraja et al. (2018) argued that the presence of anomalies in financial markets has led to the emergence of behavioral finance.

Behavioral finance disrupts conventional financial theory by recognizing the significance of human behavior and emotions in investment choices. It highlights that investors should not be treated

as purely rational entities and raises questions about the efficiency of information. The theory suggests that stock prices display unpredictability due to people's varied responses to new information. It also acknowledges the influence of past actions and experiences on decision-making. Behavioral finance emerges as a compelling alternative to the conservative EMH, challenging its assumptions and providing a successful theoretical framework (EkanshiGupta et al., 2014). Moreover, behavioral finance theory has played a crucial role in filling the gaps left by traditional economic theory, particularly in understanding the decision-making processes of investors who exhibit irrational choices amid market anomalies such as price bubbles, crashes, and herding behavior. Investor profiles are shaped by behavioral factors such as life stage, personality, and source of wealth, significantly influencing the way individuals' approach and make their investment decisions.

The debate between behavioral finance and traditional finance theories has led academics and economists to explore their impact on financial markets (Tseng, 2006; Birău, 2012; Ramiah et al., 2015). This ongoing controversy arises from the differing assumptions, methodologies, and implications associated with these two approaches in understanding market behavior and decision-making processes. While behavioral finance, including narrative economics, emphasizes the role of psychological biases and narratives in shaping investor behavior, traditional finance theories rooted in EMH emphasize rational decision-making and market efficiency. The limitations of traditional economic models in explaining the various anomalies observed in financial markets have prompted researchers to conduct further studies to provide explanations for these deviations from established theoretical models. Specifically, the failure of the EMH in elucidating investors' irrational choices during periods of extreme market stress has sparked significant theoretical criticisms of this hypothesis (Subramanian, 2010), leading to the emergence of narrative economics and behavioral finance as subjects of growing scholarly interest. Indeed, significant changes in financial markets and investors' behavior can be observed during crisis periods. In the past two decades alone, the world has witnessed two massive market crashes: the Global Financial Crisis (GFC) of 2007-2008 and the COVID-19 epidemic.

2.1.1. Definition of Behavioral Finance

The concept of behavioral finance has evolved through the contributions of several researchers over time. Among the pioneering figures who have significantly shaped the field and outlined its early definitions are Daniel Kahneman and Amos Tversky (Kahneman & Tversky, 1979; Kahneman & Tversky, 1984). Their groundbreaking work on cognitive biases and heuristics revealed that individuals frequently make decisions departing from the predictions of rational choice theory due to systematic cognitive biases. Their studies highlighted concepts like 'loss aversion', where losses are felt more intensely than gains, and the 'prospect theory', which explains how people assess potential outcomes relative to reference points rather than absolute values al-Mansour (2020).

Richard Thaler, on the other hand, has delved into understanding how behavioral inclinations can lead to deviations from rational economic decision-making (Thaler, 1980; Thaler, 1991). Coining the term ‘mental accounting’, Thaler explored how individuals categorize and treat money differently based on its source or purpose, while also introducing concepts like the ‘endowment effect’, wherein owned items are given higher value than equivalent non-owned items. Focusing on the behavioral dimensions of asset prices and market dynamics, Robert Shiller introduced the concept of ‘irrational exuberance’ to describe instances where market prices significantly deviate from intrinsic values due to investor psychology and emotions (Shiller, 1981; Shiller, 2000a). Shiller also emphasized the role of collective psychology and narratives in driving market trends and speculative bubbles. Additionally, Hersh Shefrin's contributions encompass the development of ‘behavioral portfolio theory’, which integrates investor behaviors and biases into portfolio construction (Shefrin & Statman, 1985; Shefrin, 2000). He introduced the concept of ‘mental biases’, cognitive errors that influence investment decision-making. Shefrin's work underscores the significance of comprehending investor psychology in explaining market anomalies.

On the whole, to provide a general definition of behavioral finance; behavioral finance is a field of study that explores the psychological and emotional factors influencing financial decision-making and market outcomes. Behavioral finance recognizes that humans are not always logical and rational when it comes to managing their finances; instead, their behaviors are often driven by biases, emotions, and cognitive limitations. By integrating concepts from psychology, economics, and finance, behavioral finance seeks to understand how these irrational behaviors impact investment choices, asset pricing, and overall market efficiency. It provides valuable insights into phenomena such as herding behavior, overconfidence, loss aversion, and other biases that can lead to market anomalies and suboptimal investment decisions (al-Mansour, 2020; Budhiraja et al., 2018). Through a deeper understanding of human behavior, behavioral finance aims to improve financial decision-making and enhance our understanding of how markets function in the real world.

Consequently, the failure of traditional economic models to elucidate anomalies within financial markets, along with the overlook of the role of narrative factors, has contributed to the ascendancy of behavioral finance as an increasingly prominent discipline of research. Considering the heightened economic volatility witnessed in recent times and the emergence of decentralized financial instruments, the study of irrational behavior and the pervasive influence of cognitive biases in investors' decision making has assumed a paramount position in the academic landscape. Behavioral finance offers a more robust and holistic understanding of the decision-making propensities exhibited by investors in financial markets.

2.1.2. Behavioral Biases

In 1974, Daniel Kahneman and Amos Tversky introduced the term ‘cognitive bias’ to describe the consistent yet potentially flawed patterns of responses people exhibit in judgment and decision problems. Their groundbreaking research uncovered several key biases that have since gained widespread recognition in the field of behavioral economics. These biases include loss aversion, anchoring and adjustment, availability heuristic, representativeness heuristic, confirmation bias, framing effect, and overconfidence bias. The work of Kahneman and Tversky laid the foundation for understanding the systematic deviations from rationality in human decision-making (Tversky & Kahneman, 1974).

Prominent researchers and scholars, such as Richard Thaler, Dan Ariely, Robert Cialdini, Cass R. Sunstein, Robert Shiller, and George Akerlof, have made significant contributions to the exploration of behavioral biases. Thaler expanded on Kahneman and Tversky's work, introducing the concept of ‘nudges’ in decision-making. Ariely focused on irrational behavior and the social and psychological factors influencing economic choices. Cialdini explored principles of influence and persuasion, shedding light on biases like social proof and scarcity (Cialdini, 2007). Sunstein examined how behavioral biases can be addressed through policy and legal frameworks (Thaler & Sunstein, 2008; Kahneman, et al., 2021). Shiller delved into behavioral finance (Shiller, 1981), while Akerlof explored the effects of irrational behavior on economic outcomes (Akerlof & Yellen, 1987). These researchers have advanced our understanding of behavioral biases and their implications across various fields.

George Katona, a pioneer in behavioral economics and economic psychology, revolutionized the study of consumer confidence from the 1950s to the 1970s (Katona, 1974; Crockett, et al., 1974). His work challenged the assumption of rationality in economic decision-making and emphasized the significance of psychological factors in shaping consumer behavior. Katona's research, which emphasized the need to consider psychological factors and introduced consumer confidence indexes, paved the way for a comprehensive understanding of consumer behavior. His contributions remain influential in the intersection of economics and psychology (Curtin, 2016: 3).

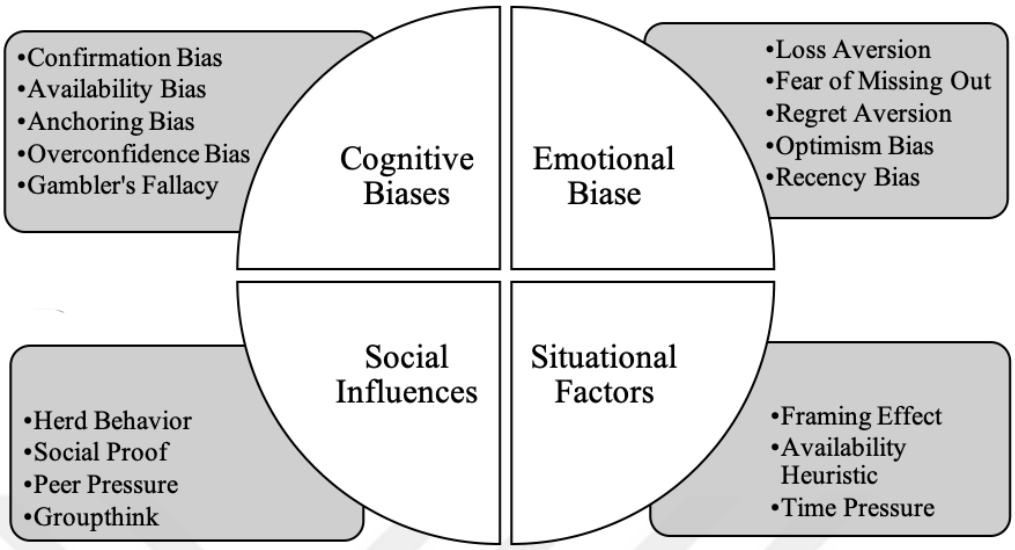
By examining the decision-making processes and cognitive biases of investors, behavioral finance can provide a deeper understanding of the underlying factors that drive the market's volatility and returns (Thaler, 2015). Behavioral finance challenges traditional assumptions of rational economic decision-making and market efficiency by studying the influence of human behavior and psychology on financial decisions and market outcomes. It recognizes that individuals often exhibit irrational behavior due to cognitive biases and emotions. By examining biases such as overconfidence, availability bias, anchoring, and loss aversion, behavioral finance seeks to understand why people make suboptimal investment choices (Budhiraja et al., 2018; Jlassi et al.,

2014). It also explores how social influences, such as herd behavior, impact decision-making and contribute to market trends. By incorporating overviews from behavioral finance, economists and financial professionals can improve their understanding of investor behavior and develop strategies to enhance decision-making processes for better financial outcomes.

Vasileiou (2021) revealed in his paper that when extreme conditions emerge, economic variables alone may not be sufficient to explain the markets' behavior. Accordingly, behavioral factors, such as fear, may be better indicators to explain investor decisions. However, the study showed that the US stock market, the world's largest stock market, did not react rationally as financial theory suggests, but fear drove the performance of the S&P 500 and negatively influenced the performance of the US stock market. Jlassi et al. (2014) examined the overconfidence effect on dynamic market volatility using the conditional volatility model EGARCH to measure the asymmetry effect of volatility. According to the results, the excessive and asymmetric volatility in financial markets can be attributed to the overconfidence bias, which generates aggressive trading volume and stock price fluctuations, as experienced during the GFC 2007-2008.

Moreover, overconfidence can also make investors overly optimistic, increasing their appetite for risk and leading to hasty, risky decisions, which can adversely affect post-crisis regulatory reforms and prolong economic recessions. An article by Clarke (2021) shed light on fear, uncertainty, and isolation during the COVID-19 pandemic as the largest drivers of human behavior experienced over the last two years due to country-wide quarantines and social distancing regulations. This puts pressure on financial services firms to make their clients feel understood and focused on what is best for them. Considering the benefits of technology that can help in constant connectivity rather than traditional face-to-face meetings and its importance in soothing clients' feelings of fear and isolation. Francisco (2020) mentioned that the value proposition to the customer is a main point of development for any Fintech platform. Therefore, it is necessary to include behavioral finance to enhance the customer experience, especially by understanding the impact of behavioral biases and preconceived opinions in the adoption of Fintech. The following Figure 6 illustrates the drivers of behavioral biases and their types.

Figure 6: Drivers of Behavioral Biases and their Types



Source: Prepared by the author based on the review of the relevant literature.

2.2. Investment Sentiment

Sentiment is a dynamic realm shaped by evolving technologies, new data sources, and advanced analytical tools. According to Barberis et al. (1998), sentiment encompasses the collective beliefs and expectations of investors, influencing their decision-making. The landscape is evolving with trends like the integration of artificial intelligence and machine learning for more accurate sentiment analysis, leveraging alternative data sources like social media for real-time insights, employing data visualization for sentiment pattern interpretation, and the emergence of sentiment trading platforms with specialized tools. These advancements aim to furnish investors with timely, actionable sentiment-based insights for well-informed choices.

Market sentiment, also known as investor attention, refers to prevailing investor outlooks on expected market price shifts. Influenced by factors like historical pricing, economic indicators, and global events, its significance is explored in Charoenrook's study ‘Does Sentiment Matter?’ (2005). It encapsulates the dominant mood and investor inclination towards trading. It is classified into bullish (positive outlook) and bearish (negative outlook) investing. Bullish sentiment indicates upward price expectations, often linked with price hikes. Conversely, bearish sentiment suggests downward movement anticipation. Market sentiment acts as a contrarian indicator and is harnessed for market shift predictions. Monitoring involves technical and statistical methods, along with sentiment analysis of news stories.

Challenging classical finance theory, Baker and Wurgler (2006) provide evidence of investor sentiment's impact on stock returns. Initial sentiment levels impact future stock returns conditionally. High sentiment leads to lower future returns for stocks favored by optimists but shunned by arbitrageurs. Conversely, low sentiment weakens or reverses these patterns. Investor sentiment's importance in comprehending stock returns is underlined, suggesting pricing models consider this role.

Market sentiment significantly influences individual stocks. The sentiment's manifestation is often described by a popular Wall Street phrase as ‘all boats float or sink with the tide’, akin to ‘the trend is your friend’. Professional investors are less prone to attention-driven purchases, while individual investors react to media and extreme returns (Barber and Odean, 2008). Renault (2017) provides empirical evidence supporting online investor sentiment's predictive power for intraday stock index returns.

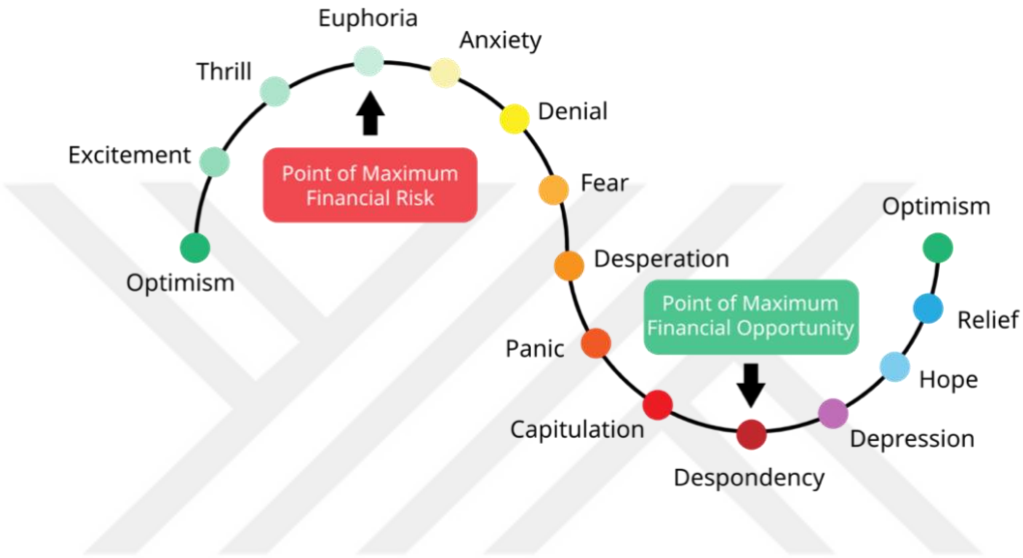
Investor sentiment encompasses a fusion of beliefs, emotions, and expectations shared by investors, which profoundly shapes their decisions within financial markets (Odean, 1998). This psychological construct serves as a gauge of the prevailing attitudes and perspectives investors hold towards market conditions, potential price shifts, and investment prospects. The composition of this sentiment is influenced by an array of factors, ranging from economic indicators and pivotal news events to prevailing societal trends and individual cognitive biases.

Research has significantly advanced the comprehension of investor sentiment and its nuanced dimensions. One notable contribution is the illumination of how psychological biases and sentiment sway individual investor behaviors, particularly in aspects such as overconfidence, trading patterns, and the disposition effect (Odean, 1998: 1776). Another important area of investigation involves market psychology and behavioral finance, which examines how trading influenced by sentiment can have a significant effect (Shleifer & Summers, 1990: 30). Insights into the dynamics of investor overreaction and underreaction have also emerged, indicating that markets tend to disproportionately react to immediate information while showing restrained responsiveness to more sustained trends (De Bondt & Thaler, 1985: 793). Moreover, research underscores that sentiment profoundly influences cross-sectional stock returns, thereby challenging conventional finance theories (Baker & Wurgler, 2006: 1645). These cumulative insights underscore the intricate interplay of psychological biases in shaping investor sentiment, with ramifications extending to market dynamics and asset valuation.

Psychological factors and emotions strongly shape investor sentiment, impacting decisions and market dynamics. Sentiment shifts through phases in response to market conditions. Optimism signifies positive sentiment, associated with bullishness and trend following. Euphoria involves extreme optimism, warranting caution and contrarian strategies. Pessimism marks negative

sentiment, prompting defensive strategies and value-focused investing. The despondent phase is marked by maximum negativity, yet offers opportunities for patient, contrarian investors before a potential recovery. The Cycle of Market Emotions Figure 7 portrays this journey, starting from optimism, escalating to euphoria, then anxiety and fear, before hitting deep despondency. Euphoria denotes peak risk, while despondency signifies peak opportunity.

Figure 7: The Cycle of Market Emotions



Source: PIXTAStock.com, 2023.

2.3. Investor Sentiment in Cryptocurrency Markets

The decentralized nature of the cryptocurrency market means that prices are subject to fluctuations based on factors like public sentiment, natural disasters within a country, global news events, geopolitical crises, and more. As a result, the absence of a central governing authority allows these variables to influence and impact cryptocurrency prices. The cryptocurrency market is commonly perceived as an immature market, where a mere 10% of the available information is effectively utilized, indicating a significant reliance on speculation (Kang et al., 2022). Consequently, this market is prone to inefficiencies, creating potential openings for investors to engage in arbitrage (Andrade et al., 2021; Tadi & Kortchemski, 2021).

2.3.1. Efficient Market Theory and Behavioral Realities of Cryptocurrency Market

The cryptocurrency market serves as an illustrative example to shed light on the controversy between behavioral finance, including narrative economics, and traditional finance theories grounded in the efficient market hypothesis. Cryptocurrencies, such as Bitcoin and Ethereum, have experienced

notable volatility and price fluctuations, making them a suitable context for studying investor behavior. Traditional finance theories would argue that the efficient market hypothesis (EMH) applies to cryptocurrencies, suggesting that prices reflect fundamental values and rational expectations. According to this perspective, any deviations from equilibrium are short-lived and driven by the arrival of new information.

In the cryptocurrency market domain, the efficient market hypothesis is a conceptual framework that suggests that the prices of cryptocurrencies in the market encompass all the relevant information available. The EMH, as applied to the cryptocurrency market, assumes that individuals participating in the market make rational decisions based on the information at their disposal. This implies that whenever new information emerges, such as news, events, or market data, it is promptly incorporated into cryptocurrency prices. Consequently, the EMH asserts that consistently surpassing the market by taking advantage of market inefficiencies or patterns is not feasible.

Nevertheless, it is crucial to acknowledge that the validity of the EMH in the cryptocurrency market is an ongoing subject of discussion and research. Researchers extensively explore the EMH within the context of the cryptocurrency market to evaluate its soundness. Recent studies conducted by (Yi et al., 2023) demonstrate that the Bitcoin market does not conform to EMH principles. Similarly, (Kang et al., 2022) find that the efficiency of the cryptocurrency market is influenced by factors such as scale and creation timing. Although the market exhibits some degree of efficiency, it remains considered immature due to significant underutilized information, indicative of its highly speculative nature. Souza & Carvalho (2023), in their recent study, analyzed the price movement of cryptocurrencies on various exchanges. Their findings indicated a weak EMH due to cross-information within the primary crypto platforms.

Furthermore, the application of long-term investment strategies based on efficient-market assumptions poses challenges. Consequently, applying financial theories developed for stock market efficiency, which rely on the EMH premise, is deemed inappropriate for the cryptocurrency market. Apopo & Phiri (2021) argue that cryptocurrencies lack sufficient market efficiency to function as formal exchange systems, emphasizing the need for increased regulatory intervention. Sahoo & Sethi (2022) confirm that trading volume fails to predict cryptocurrency returns, and the validity of EMH varies over time for certain currencies. Souza & Carvalho (2023) recommend a multivariate approach to assess the cryptocurrency market, promoting its maturation process and a comprehensive understanding of inherent risks. Additionally, Tran & Leirvik (2020) reveal that market efficiency in the five largest cryptocurrencies is highly time-varying, with improvements observed over time in terms of volume and volatility.

In contrast, behavioral finance emphasizes the role of psychological biases, narratives, and market inefficiencies in shaping cryptocurrency markets. Narratives surrounding cryptocurrencies,

such as narratives of technological or financial revolution, can significantly influence investor perceptions and drive market dynamics. Behavioral finance highlights the impact of cognitive biases, such as overconfidence, herding behavior, and the fear of missing out, which can lead to market inefficiencies and deviations from rational decision-making (Budhiraja et al., 2018; Jlassi et al., 2014: 129). Where investors' perception of events is influenced by their emotional and psychological swings, leading to heightened euphoria, optimism, and greed, it is crucial to acknowledge and control emotional influences when engaging in investments.

2.3.2. Factors Influence Sentiment on Cryptocurrency Market

Cryptocurrency prices are influenced by a variety of factors. One crucial aspect is the interplay between supply, demand, and mining difficulty, which can impact the overall value of cryptocurrencies. Additionally, market trends and macro-economic factors play a significant role in shaping cryptocurrency prices. The performance of established financial indices, such as the S&P 500, and the fluctuating USD/EUR exchange rate can also influence the cryptocurrency market. Political issues within a country, like the case of Venezuela, can have ripple effects on cryptocurrency prices. Furthermore, the sentiments expressed on social media platforms like Twitter can contribute to price fluctuations (Shen et al., 2019: 118). The introduction of new regulations by governments and the opinions of investors can also significantly impact cryptocurrency prices.

Investors in cryptocurrency markets perceive high volatility as an opportunity to achieve greater profits, contrasting with the perception in traditional financial markets where volatility is generally viewed negatively (Nadler & Guo, 2020). In addition, cryptocurrency investors demonstrate a tendency to engage in behavioral trading patterns by focusing on short-lived trends and conducting trades with high sentiment and volume at hourly and daily frequencies. This behavior serves as evidence of the prevalence of noisy trading within the crypto market (Karaa, et al., 2021).

The impact of investor sentiment on the cryptocurrency market is significant, as indicated by researches findings (Jo et al., 2020; Anamika et al., 2023). However, the extent of this impact varies depending on microeconomic and macroeconomic sentiments. Notably, microeconomic sentiment, which pertains to everyday concerns like job search and unemployment, exerts a more pronounced effect compared to macroeconomic sentiment (Burggraf et al., 2021). Moreover, in the Bitcoin market, a shift towards pessimistic investor sentiment leads to a decline in returns, while heightened sentiment tends to result in a more risk-averse behavior among investors (Burggraf et al., 2021). This highlights the crucial role played by investor sentiment in shaping the performance of the cryptocurrency market.

Furthermore, during periods of fear and bearish sentiment in equity markets, investors tend to gravitate towards the cryptocurrency market, causing an upsurge in cryptocurrency prices (Gaies, et

al., 2021). This suggests that investors seek refuge in cryptocurrencies during uncertain times (Anamika et al., 2023). In the short term, both optimistic and pessimistic Bitcoin investors tend to increase their trading volume when Bitcoin prices rise. However, in the event of a decline in Bitcoin price, pessimistic investors reduce their trading volume as they anticipate future losses, while optimistic investors continue to trade normally. In the long term, if Bitcoin prices continue to fall, even optimistic investors decrease their trading volume (Gaies, et al., 2021). Mnif et al. (2022) revealed in their study that behavioral biases triggered by the COVID-19 pandemic can account for cryptocurrency anomalies.

In their study, al-Mansour (2020) concluded that investors in the cryptocurrency market exhibit speculative behavior. The findings of the study highlight the significant impact of the herding theory, prospect theory, and heuristic theory on investors' decision-making within the cryptocurrency market. Consequently, this market inefficiency suggests that the prices of digital currencies do not consistently align with their intrinsic values, resulting in pronounced fluctuations or volatility in prices. The presence of a cryptocurrency market bubble can be attributed to the participation of noise traders, ultimately contributing to market inefficiencies. Therefore, the involvement of noise traders presents a compelling hypothesis for examining behavioral finance factors, such as theories of herding, prospect, and heuristics, as crucial elements in the study of the cryptocurrency market. Baker and Wurgler (2006) find that Bitcoin returns resemble those of high sentiment beta stocks, suggesting similarities between cryptocurrencies and stocks with strong growth potential (Jo et al., 2020).

An illustrative example of the factors shaping cryptocurrency investor sentiment and demonstrating the market's sensitivity is provided by the famous entrepreneur and influencer, Elon Musk. In support of Musk's impact on the cryptocurrency market, Ante conducted a comprehensive study examining the effects of Musk's Twitter activity on cryptocurrency markets (Ante, 2023). Through an analysis of 47 cryptocurrency-related Twitter events, the study identified a significant ‘Musk Effect’, characterized by noteworthy abnormal returns and increased trading volume subsequent to Musk's tweets. The study specifically observed substantial effects on Dogecoin but not on Bitcoin, as positive and negative news surrounding Bitcoin tended to offset each other. These findings highlight the influential role of high-profile individuals' social media activity in shaping cryptocurrency markets and raise pertinent concerns regarding the balance between freedom of expression, ethical considerations, and investor protection. These developments have sparked debates about Musk's influence and whether his actions amount to market manipulation in the cryptocurrency sphere. Rahman, a legal specialist in cryptocurrency-related fraud stated in his publication that “Musk’s latest series of tweets … could, from both a civil or criminal prospective, be perceived as market manipulation” (Rahman Ravelli, 2021).

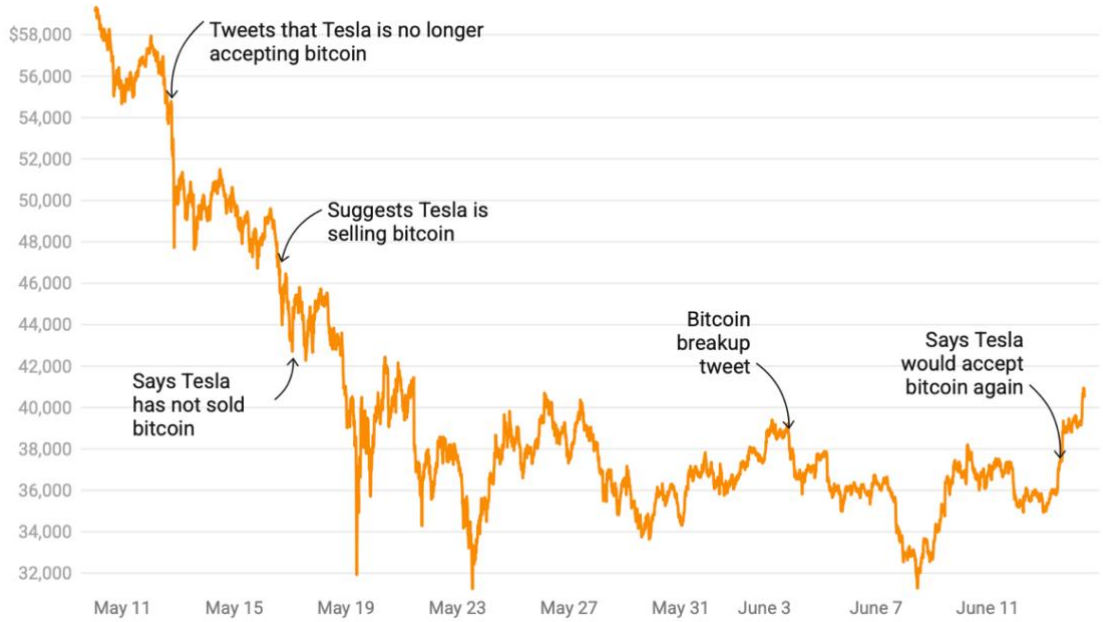
Moreover, According to Forbes magazine, Elon Musk and his electric car company, Tesla, are currently embroiled in a lawsuit filed by cryptocurrency investors seeking damages of $258 billion.

Musk and Tesla, both listed as defendants in the lawsuit, are accused of pursuing a "deliberate course of carnival barking, market manipulation, and insider trading," which allegedly defrauded investors, as stated in the filing. The early 2021 dogecoin rally, which coincided with the broader crypto market surge, was allegedly influenced by Musk, who frequently posted about the cryptocurrency on Twitter (Fobes, 2023).

Furthermore, evidence shows that there is a direct relationship between the sentiment expressed in consumer reviews, feedback, social media posts, or blog posts and the movements in market prices. A clear example of this can be seen when Elon Musk included the Bitcoin hashtag in his Twitter biography in January 2021 and sent out a cryptic tweet saying, "In retrospect, it was inevitable". This caused the price of Bitcoin to increase from $32,000 to $38,000 up to 18% increase within a matter of hours (Yahoo Finance, 2021; CNBC.com, 2021c).

Figure 8 illustrates five popular tweets posted by Musk and his impact on Bitcoin prices over one-month timeframe.

Figure 8: Elon Musk's Effect on Bitcoin Prices Based on Social Media Tweets



Source: CoinDesk.com, 2021.

Therefore, the impact of social media, particularly Twitter, on cryptocurrency market dynamics, and the resulting controversy generated by influencer tweets—measured by factors such as the number of search terms or hashtags used, along with retweets and shares, referred to as 'Tweet Volume' or 'Trend'—exerts significant influence. This phenomenon, as highlighted in studies like Critien, et al. (2022), exemplifies researchers' efforts in conducting a comparative analysis utilizing

various neural models. Their objective was to delve deeply into the intricate interplay between Twitter sentiment, data volume, and the prediction of Bitcoin's price dynamics. At the core of their investigation was the hypothesis that the amalgamation of sentiment and viewpoints expressed across social media platforms could serve as a dependable indicator for foreseeing price fluctuations in the cryptocurrency market. Similarly, in an exploration by Shen et al. (2019), the connection between investor attention and a range of factors, including Bitcoin returns, realized volatility, and trading volume, was investigated. The findings underscored that tweet counts on Twitter hold the potential to serve as a noteworthy signal for predicting future realized volatility and trading volume within the Bitcoin market. These insights collectively emphasize the pivotal role of social media in shaping cryptocurrency dynamics and the multifaceted interplay between online sentiment, market data, and price forecasts.

However, in the changing landscape of the cryptocurrency market, Elon Musk's formidable presence on social media and his palpable impact on market sentiment have captured widespread attention. His tweets and statements have notably influenced the prices and trends of various cryptocurrencies. Musk's influential role on Twitter, capable of sparking rapid market fluctuations, contrasts with Warren Buffett's emphasis on disciplined and well-researched investment decisions. Buffett, on the other hand, has expressed concerns about the lack of intrinsic value in cryptocurrencies and in his interview with CNBC's Squawk Box has likened them to gambling rather than investing (CNBC.com, 2023). He believes in investing in assets with clear value and predictable income streams, and he has stated that he does not consider cryptocurrencies as fitting within his investment philosophy. Buffett's cautious stance on cryptocurrencies acts as a reminder for investors to approach this asset class with caution. His investment philosophy's emphasis on the necessity of understanding the fundamentals and tangible attributes of an asset before investing aligns with a conservative and value-oriented approach.

2.3.3. Measures of Cryptocurrency Investor Sentiment

The techniques employed for measuring market sentiment are diverse, encompassing methods like surveys and polls (e.g., AAII Investor Sentiment Survey), market indices (e.g., CBOE Volatility Index or VIX, known as the ‘fear index’, and Bullish Percent Index or BPI), news and social media analysis (e.g., Twitter and Google Trends), and economic indicators (e.g., Consumer Confidence Index).

In the cryptocurrency markets, sentiment measurement tools share similarities with those used in traditional financial markets, as both are influenced by analogous drivers. However, due to the inherent volatility and speculative nature of cryptocurrencies, grasping the emotions and attitudes of market participants poses a unique challenge. Most common techniques within the cryptocurrency market context include:

- News and Social Media: Evaluating news and social media sentiment is a prevalent method for assessing cryptocurrency investor emotions. Active cryptocurrency communities on platforms like Twitter, Reddit, and Telegram provide rich data sources. Using sentiment analysis algorithms, these tools investigating social media posts, comments, and discussions linked to specific cryptocurrencies. These analyses provide insights into positive or negative market sentiment, thanks to their broad reach at lower cost.

- Google Trends: Monitoring the popularity of cryptocurrency-related searches on Google yields insights into public interest that might correlate with market sentiment. Google Trends allows simultaneous search for up to five terms within specified timeframes, regions, categories, and search types (e.g., Image, news, Google shopping, or YouTube search).

- Cryptocurrency Oriented Indices: Specific platforms[6] offer sentiment analysis tools tailored to the cryptocurrency market. These tools assess news articles, social media posts, and discussions related to cryptocurrencies, thereby gauging overall sentiment.

- Crypto Fear and Greed Index: This index quantifies cryptocurrency market sentiment on a scale of 0 to 100. Ratings of 0 indicate 'Extreme Fear', while 100 signifies 'Extreme Greed'. The index employs data points like volatility, market momentum, social media engagement, surveys, coin dominance, and Google Trends to evaluate sentiment and discern whether investors lean towards fear or greed. The index updates daily, affording a comprehensive view of cryptocurrency market sentiment.

- Trading Volume Trend: Trading volume reflects the number of shares or coins traded within specific timeframes. Notably, significant trading volume surges can signal heightened market interest and sentiment.

6 Platforms offering sentiment analysis tools tailored to the cryptocurrency market include The TIE, CryptoCompare, and alternative.me.

CHAPTER THREE

3. LITERATURE REVIEW

Since its inception in 2009, the field of cryptocurrency has undergone remarkable growth and continues to be a realm full of surprises (White, 2015). This growth is attributed to rapid technological advancements, regulatory shifts, market fluctuations, and the allure of decentralized financial systems. However, the existing literature on cryptocurrency research falls short of capturing the dynamic nature of this field. While the field of cryptocurrencies and blockchain technology has been one of the most researched topics in recent years, there is a consensus that further research is still needed to fully understand and address the various aspects of this rapidly evolving domain. A deeper and more comprehensive research endeavor is needed to unveil the intricate workings of cryptocurrencies and their wide impacts on finance, technology, economics, and society as a whole.

While the ongoing debate continues over whether cryptocurrency represents a form of gambling or simply a speculative bubble, Price Waterhouse Coopers in its global cryptocurrency regulation report (PwC, 2022) highlights countries such as Germany, Switzerland, the United Kingdom, and Japan that have legalized cryptocurrencies and recognized them as official means of payment. Conversely, countries like China, Saudi Arabia, and Qatar have imposed complete bans on crypto trading, while the USA and Canada view cryptocurrencies as valuable for investment and tax purposes despite the lack of regulation. In Turkey, the Central Bank of the Republic of Turkey (CBRT) has introduced diverse restrictions on cryptocurrency usage through the 'Regulation on the Non-Use of Crypto Assets in Payments'. These ongoing developments have spurred researchers to seek empirical evidence regarding the economic impact of cryptocurrency adoption in these countries. For instance, Yen et al. (2023) conducted a comparative study on the influence of economic policy uncertainty on Bitcoin returns in cryptocurrency-friendly and unfriendly countries. Likewise, matters such as anti-money laundering regulations within the European Union and Switzerland, explored by Frick (2019), alongside cryptocurrency adoption in financial literacy surveys in Japan, as investigated by Fujiki (2020), have attracted scholarly attention. Additionally, the influence of regulations on cryptocurrency adoption in the United States had been investigated by Middlebrook & Hughes (2013), Corbet et al. (2014), and Nabilou & Prum (2019), while Ante et al. (2023) undertook a study profiling Turkish cryptocurrency owners.

In this literature review chapter, an exhaustive overview of previous studies within the domain of cryptocurrency market dynamics and behavioral finance, with a specific emphasis on sentiment

analysis within financial markets is provided. This review explores the recent research into various dimensions of sentiment, methodologies for its measurement, and its consequential effects on cryptocurrency markets. Studies examining rational and irrational sentiments, as well as sentiment within the cryptocurrency market, are summarized in Table 4 and subsequently discussed further.

Table 4: Summary of Study's Literature Review

Research	Methodology	Time Series Data	Sentiment Indicator(s)
Anamika et al. (2023)	Regression and Impulse response analysis	BTC	Sentix database, Baker-Wurgler sentiment Index and VIX Index
Basak et al. (2023)	ARDL Models	FTSE 100 Index and GBP against EUR and USD	Loughran word-based lexicon and Bayesian learning Media sentiments
Kyriazis, et al. (2023)	Granger causality	BTC, ETH, BNB, ADA, XRP, DOGE, BCH, LTC, ETC, XLM[7]	Twitter-based sentiment
Van Eyden et al. (2023)	A panel data-based regression model	Stock market indices of the G7 countries	Business Confidence and Consumer Confidence indicators
Caferra (2022)	Transfer Entropy and VAR models	S&P500 and BTC	U.S. Economic sentiments and Global Online News Coverage Dataset
Gunay et al. (2022)	MS-VAR Model	NFT markets	Google Trend, Fear and Greed Index, Volatility Index
Hamraoui & Boubaker (2022)	VAR Model	Tunindex 22	Twitter volume and sentiment
Atri et al. (2021)	ARDL Models	West Texas Intermediate oil prices and Gold prices	COVID-19 Panic index, media coverage index, worldwide confirmed new cases and deaths, VIX and USEPUINDXM

[7] List of Cryptocurrencies and abbreviations available in Appendix 1.

Table 4 (continued)

Research	Methodology	Time Series Data	Sentiment Indicator(s)
Demirel (2021)	ARDL Models	BIST 100 index	Consumer Confidence Index
Naeem, et al. (2021)	OLS and (QR) methodology	BTC, LTC, XRP, DASH, XMR, ETH	FEARS index and Twitter Happiness sentiment
Kraaijeveld & De Smedt, (2020)	Lexicon-based analysis approach	BTC, ETH, XRP, BCH, EOS, LTC, ADA, XLM, TRX	Twitter sentiment
Oad Rajput et al. (2020)	ARDL Models	BTC and USD	Google Trends
Rognone et al. (2020)	VAR-X Model	BTC, AUD, CAD, CHF, EUR, GBP, JPY[8]	News sentiment using Ravenpack News Analytics 4.0
Chen, & Hafner, (2019)	STAR Model	CRIX index	StockTwits sentiment
Smuts, (2019)	LSTMs Long Short-Term Memory	BTC and ETH	Google Trends and Telegram messaging platform
Abraham et al. (2018)	VADER Sentiment Analysis	BTC and ETH	Twitter and Google Trends
Dash and Maitra (2018)	Nonparametric nonlinear causality	The National Stock Exchange of India indices	Put-Call, Adv-Dec, Turnover, India IV, FII Inflow.
Dhaoui & Bacha (2017)	Non-linear ARDL approach	S&P500 stock exchange	American Association of Individual Investor (AAII)
Lamon et al. (2017)	Logistic Regression	BTC, LTC, ETH	Twitter text-based sentiment classification

[8] GBP (British Pound), EUR (Euro), USD (United States Dollar), AUD (Australian Dollar), CAD (Canadian Dollar), CHF (Swiss Franc), JPY (Japanese Yen).

Table 4 (continued)

Research	Methodology	Time Series Data	Sentiment Indicator(s)
Perez-Liston et al. (2016)	GARCH and VAR Models	DJ Islamic equity indices	Investors Intelligence survey (II) or the American Association for Individual Investors (AAII)
Colianni et al. (2015)	Naive Bayes and Logistic regression	BTC	Twitter sentiment
Ranco et al. (2015)	Event study methodology	DJIA index	Twitter volume and sentiment
Uygur & Taş (2013)	EGARCH model	Market index of U.S., Japan, Hong Kong, U.K., France, Germany, and Turkey	Market indices' trading volumes
Lux, 2011	VAR Model	DAX	German animusX-Investors sentiment survey
Zhang et al. (2010)	(S)VAR Model	Chinese stock markets	American Association of Individual investors (AAII)
Canbaş & Kandır (2009)	VAR Model	Istanbul Stock Exchange	Closed-end discount, fund flows, odd-lot ratio, repo holdings.
Schmeling, (2009)	Cross-sectional Analysis	18 countries U.S., Japan, Australia, New Zealand and 14 European countries	Consumer Confidence Index
Verma & Soydemir (2009)	VAR Model	DJIA and S&P500 index	American Association of Individual Investor (AAII)
Baker and Wurgler (2006)	Sentiment-driven waves in stock prices	CRSP/Compustat Merged Database	Closed-end fund discount, NYSE share turnover, IPOs' first-day returns, equity share in new issues, dividend premium.

3.1. Financial Markets from a Behavioral Finance Perspective

Behavioral finance theory emphasizes the significant impact of investor sentiment on investment choices, asset prices, and risk management. Sentiment can drive short-term stock price movements, including volatility and market jumps. Several studies explored the impact of sentiment in financial market dynamics. Kearney & Liu (2014) investigated textual sentiment in behavioral and traditional finance, analyzing announcement effects, the connection between qualitative and quantitative data, and enhancing linguistic analysis methods. They concluded that textual sentiment influences stock returns and trading volumes, highlighting the dynamic relationship between textual sentiment and investor behavior.

Investor sentiment stands as a focal point within the behavioral finance domain, understanding the interplay between psychological factors and financial market dynamics. Rooted in the seminal research of Kahneman and Tversky during the 1970s, investor sentiment challenges conventional economic models by determining the influence of emotions and cognitive biases on decision-making. Early contributions by Kahneman and Tversky (1979) laid the foundation for understanding cognitive biases and emotional factors in decision-making. Subsequent studies by Shefrin and Statman (1985) and DeLong et al. (1990) further demonstrated the role of irrational investor sentiment in shaping market behavior and asset prices.

Empirical evidence by Baker and Wurgler (2006) demonstrated the emergence of sentiment-driven waves in stock prices, highlighting sentiment's impact on market returns and trends. Robert Shiller’s (2000b) study expanded on investor sentiment, emphasizing its role in market anomalies, bubbles, and crashes. Shiller's work highlighted sentiment's capacity to drive deviations from the efficient market hypothesis.

Tseng's study (2006) offers a comprehensive overview of economic and financial theories, encompassing the efficient market hypothesis, bounded rationality, behavioral finance, neuro-finance, and the adaptive market hypothesis (AMH). It emphasizes deviations from efficient market assumptions and contributions from psychologists like Herbert Simon and Daniel Kahneman in the realm of bounded rationality and behavioral theories. The study concluded with noteworthy findings concerning autocorrelations and volatility, challenging the efficient market hypothesis. Furthermore, the study proposed advancements through the utilization of neural/medical finance and the examination of drug effects, aiming to enhance our understanding of investor decisions and further deepen insights into investor behavior and market dynamics.

Basak et al. (2023) studied Brexit's impact on British stock prices, returns, and currency using machine learning-based sentiment model. They find short and long-term effects, linking Brexit to currency fluctuations. This has policy implications, backing behavioral theories on media sentiment's

asset price influence. They suggest that officials and regulators should take potential economic risks from sudden sentiment shifts into consideration.

Lux's (2011) study examined the impact of sentiment on the German stock market using VAR models. In contrast to similar studies on the U.S. and Shanghai markets, the findings indicate that the relationship between sentiment and returns is either exogenous or defines a simultaneous system with mutual causation, contingent on the VAR model specification. Medium-run sentiment captures the market mood, reacting to fundamentals and psychology. Short-run sentiment exhibits wild swings but weaker feedback. However, the causal link weakened during the 2008 crisis, potentially due to market adaptation or model limitations.

Perez-Liston et al. (2016), in their study concerning the influence of investor sentiment on returns and volatility of Islamic equities, concluded that the traditional finance perspective, rooted in rational expectations is inadequate in explaining the fluctuations in Shari'ah-compliant equity returns and volatility. As a result, it is recommended that investors extend their evaluations beyond conventional factors and incorporate investor sentiment into their decision-making process.

Van Eyden et al. (2023) conducted a study that explored how investor sentiment, proxied by business confidence and consumer confidence indicators, shapes equity market bubbles within G7 countries. The research uncovers synchronized boom-bust cycles across these markets. Through regression analysis, the study reveals that sentiment impacts positive bubbles and mitigates negative ones, particularly in medium to long-term contexts. This challenges the efficient market hypothesis, indicating that market dynamics stem from behavioral choices rather than rational expectations.

In contrast Canbaş & Kandır (2009) did not find evidence in their study that investor sentiment can forecast future stock returns; only the turnover ratio of the stock market shows the potential for predictive ability. However, the study conducted by Caferra (2022) on S&P 500 index and Bitcoin, concluded that there is a distinct sentiment-returns relationship within and between stock and cryptocurrency markets. This finding highlights the mutual influence of these two markets as they impact each other through the dissemination of sentiments among investors.

3.2. Rational and Irrational Investment Decisions

Recent literature has explored both rational and irrational sentiment across various contexts. While behavioral finance often delves into the decisions of irrational investors, known as noise traders (Uygur & Taş, 2013). Shleifer and Summers (1990) in their study on investor sentiment and limited arbitrage against traditional market efficiency views discussed how noise traders, driven by irrational sentiment, impact asset prices, causing anomalies and straying from rational expectations. These traders may enjoy short-term gains but carry higher risks from underestimating the impact of

sentiment. The study also debated government intervention, questioning whether noise traders should be shielded from their suboptimal choices and considering broader economic effects of their actions.

Ramiah et al. (2015) explored noise traders and their impact on financial markets, noting major anomalies that suggest irrational trading and attributing them to noise trader risk. The study highlights the growing interest in behavioral finance, spurring research into noise trading's influence on financial prices, driven by the acknowledgment that traders do not always behave rationally, challenging traditional neoclassical finance theories.

In their study, Zhang et al. (2010) investigated how investors' irrational behavior and psychology affect stock prices in limited arbitrage markets. The research discussed the complex relationship between investor sentiment, using the growth rate of accounts, and stock returns. They also highlighted the influence of cognitive bias in decision-making, which proved market irrationality. The findings reveal that irrational sentiment is influenced by past market performance and exerts a significant influence on both immediate and future stock returns.

However, there is a growing demand for more precise distinctions between rational and irrational decisions. Verma & Soydemir (2009) investigated the relative effects of rational and irrational sentiment of individual and institutional investors for DJIA and S&P 500 indices using the VAR model. Tseng et al. (2022) studied the rational and irrational investor sentiment on Taiwan stock market’s volatility. Demirel (2021) utilized the ARDL model to estimate investor sentiment into as rational and irrational to study the impact of investor sentiment on the BIST 100 index return and volatility.

Dash and Maitra (2018) investigated the impact of sentiment on Indian stock returns, highlighting its stronger influence on higher-return stocks like Smallcap and Midcap. They found consistent sentiment indicators—turnover, put-call ratio, and 'fear' (VIX)—and revealed bidirectional causality between sentiment and Smallcap/Midcap returns. This underscores the significant role of sentiment in shaping investor behavior and market direction.

The study by Dhaoui & Bacha (2017) examines the relationship between trading volume, stock price, and investor sentiment for the S&P 500. Using a non-linear ARDL approach, they find that stock market liquidity is non-linearly connected to these variables. Short-term trading volume reacts quickly to changes in lagged stock prices, while optimism-pessimism sentiment has a significant impact in the long term. The findings highlight the complex and asymmetric nature of these relationships.

Aiming to examine the impact of market crashes on commodity prices, Atri et al. (2021) in their study discussed the impact of panic, and news and media coverage of COVID-19 pandemic on

gold and crude oil prices. They concluded that economic uncertainty and financial volatility had a negative impact on gold and crude oil prices during the COVID-19 pandemic. Additionally, media coverage had been confirmed as one of the main factors contributing to a positive short-term reaction in commodity prices.

Ranco et al. (2015) and Hamraoui & Boubaker (2022) examined Twitter's impact on stock returns, investigating how its use affects information integration into financial asset prices and volatility. They evaluated the influence of sentiment polarity and tweet volume on stock performance. While sentiment polarity had restricted predictive value for returns, tweet volume emerged as a significant predictor of price volatility.

Furthermore, the literature underscores that rationality is more prevalent in advanced economies compared to emerging economies. In this context, Schmeling (2009) provided evidence in their study, indicating that the impact of sentiment on stock returns is particularly prominent in countries characterized by lower market integrity and a cultural tendency towards herd-like behavior and overreaction.

On the other hand, numerous studies used Consumer Confidence Index as a sentiment proxy; (CCI), published by OECD, is an economic indicator that measures consumers aspirations towards their expected financial situation. CCI serves as a measure of households' anticipated consumption and saving behavior in the future. It is derived from respondents' answers regarding their expected financial situation, sentiment about the general economic conditions, unemployment concerns, and savings capability. A value above 100 indicates heightened consumer confidence in the future economy, leading to a decreased inclination to save and an increased willingness to make significant purchases within the next year. Conversely, values below 100 suggest a pessimistic outlook on future economic trends, potentially resulting in a greater tendency to save and reduce consumption. Studies such as (Lemmon & Portniaguina, 2006; Canbaş & Kandır, 2009; Bolaman & Mandaci, 2014; Corredor, et al., 2015; Liu, 2015; Yacob et al., 2020; Duz Tan & Tas, 2021; Altuntaş & Ersoy, 2021; Demirel, 2021; Gong, et al., 2022) used CCI as a proxy of investor sentiment, the results of the studies agreed that CCI is a critical factor within stock markets.

3.3. The Impact of Investor Sentiment on Cryptocurrency Market

In the context of digital currencies and blockchain technology, sentiment analysis has emerged as a valuable tool for assessing public perceptions and sentiments surrounding cryptocurrency trading. Numerous research papers have explored the relationship between investor sentiment and cryptocurrency prices and returns. However, much of the literature primarily relies on sentiment data from Twitter.

While the focus of cryptocurrency literature has largely considered Bitcoin, the pioneering and widely recognized cryptocurrency, Anamika et al. (2023) introduced a perspective suggesting that sentiment surrounding Bitcoin influences the pricing dynamics of other cryptocurrencies. Other studies such as Kyriazis, et al. (2023), Naeem, et al. (2021), and Kraaijeveld & De Smedt (2020) implied their research on a defined set of the top cryptocurrencies in the market. While Chen & Hafner's (2019) study was one of the few that considered Cryptocurrency CRIX index by Trimborn and Karl Härdle (2018).

The digital age facilitated sentiment analysis through technology and social media platforms, allowing researchers to analyze online interactions. Social media, news articles, and online forums were utilized to gauge collective sentiment, adding a new dimension to analysis. Sentiment indicators and indices marked a significant step in understanding nuanced sentiment dynamics, providing a comprehensive assessment of market sentiment and its influence on assets. While investor sentiment has received attention in various studies, it remains understudied within the cryptocurrency ecosystem. A comprehensive indicator capturing the diverse aspects influencing investor behavior in cryptocurrency markets is lacking. Sophisticated models employing machine learning and natural language processing aim to predict market movements based on sentiment shifts.

Studies analyzed social media sentiment from several platforms like Twitter and Reddit, yielding insights into investor behavior and price predictions. Sentiment proxies are also employed; Gunay et al. (2022) used Google Trend, Fear and Greed Index, and Volatility Index as sentiment proxies to study NFT markets. The relationship between sentiment and price movements has been explored. The study of sentiment's role in market volatility has revealed insights. (Cankaya et al., 2019), studied the impact of news sentiment in cryptocurrency volatility. Where national authorities' regulations announcements in proved a significant effect on the studied cryptocurrencies.

In comparison with traditional currencies, Rognone et al. (2020) investigated the reaction of Bitcoin and traditional foreign exchange markets to high-frequency news sentiment. While conventional currencies promptly respond to economic news, Bitcoin demonstrates different behaviors. Positive news impacts Bitcoin returns, but negative news have minimal effect. Bitcoin's trading volume rises with news, but its volatility remains stable. Negative news related to cyber-attacks and fraud decrease Bitcoin's enthusiasm. Moreover, Oad Rajput et al. (2020) concluded that Bitcoin and other cryptocurrencies are significantly diverting demand from conventional currencies such as the USD, as the depreciation of Bitcoin prices is leading to an appreciation in the USD exchange rate.

Naeem et al. (2021) concluded in their study that online investor sentiment serves as a significant nonlinear predictor for returns in most cryptocurrencies. This highlights the prominence of Twitter-based sentiment over Google-based sentiment proxies. Furthermore, the study suggests

that cryptocurrency returns are influenced more by sentiment expressed through social media than by macroeconomic news. This alignment is consistent with the profile of cryptocurrency participants, primarily comprising young individuals and computer enthusiasts.

Abraham et al. (2018) found a strong correlation between both Google Trends and Tweet volume with cryptocurrency prices. This correlation held during periods of increasing and decreasing prices, suggesting robustness to high variance and non-linearity. In a similar vein, Kraaijeveld & De Smedt (2020) examined the link between Twitter sentiment and cryptocurrency price returns from 2017 to 2018. Using specialized Lexicon-based sentiment analysis and Granger-causality testing, they found that Twitter sentiment predicts returns for major cryptocurrencies such as Bitcoin, Bitcoin Cash, and Litecoin. Daily sentiment and message volume emerged as significant predictors, with intraday price returns also exerting influence. Chen and Hafner (2019) identified a pattern where volatility increases as sentiment declines, and vice versa, indicating a relationship similar to the leverage effect observed in traditional financial markets. In this context, adverse sentiment exerts a more pronounced impact on volatility compared to positive sentiment, with the sentiment index directly contributed to this phenomenon.

CHAPTER FOUR

4. RESEARCH METHODOLOGY

In this chapter, the aim, scope, and original value of this study are explained. The research design including the construction of a cryptocurrency investor sentiment index (CIST) using Principal Component Analysis (PCA) is then elaborated. Subsequently, the assessment of stationarity through Unit Root tests is discussed, followed by the estimation of Multivariable Auto Regressive Distributed Lag (ARDL) models. The definition of the data is outlined, and the results of its application, along with a model comparison, are presented within this section. Furthermore, the impact of CIST on CRIX index returns and volume is tested.

4.1. Aim of the Study

The ongoing debate between traditional and behavioral finance assumptions has triggered intensified efforts to develop a harmonious and appropriate framework that integrates behavioral factors alongside rational assumptions in order to explain the dynamics of financial markets in general. The cryptocurrency market, known for its distinct ecosystem attributes, presents a particularly unique phenomenon that remains difficult to explain through classical financial theories alone. This study aims to explore the dynamics of the cryptocurrency market in three main aspects. Firstly, generating a novel sentiment index CIST. Secondly, distinguishing cryptographic investor sentiment into rational and irrational components through an Automatic Regression of Lag (ARDL) model. Next, assessing the relationship between cryptocurrency investor sentiment and the returns and volatility of the Royalton CRIX Crypto Index using a Vector Auto Regressive (VAR) model. Finally, the Impact Response Analysis visually presents the findings, highlighting distinct dynamics in CRIX returns and volatility triggered by shocks in rational and irrational investor sentiment CIST.

4.2. Scope of the Study

The scope of the study encompasses a comprehensive exploration of the dynamics within the cryptocurrency market in the context of major financial events that occurred during the technological revolution in finance and the subsequent rise of cryptocurrencies. Despite over a decade having passed since the inception of Bitcoin and the subsequent proliferation of cryptocurrencies, the intricate nature of the cryptocurrency market remains only partially understood. Therefore, this study

contributes to filling the existing knowledge gaps by delving deep into the interactions between investors sentiment and behavior of cryptocurrencies.

Taking a behavioral finance perspective into consideration, the study recognizes the influence of social and psychological factors on the decision-making processes of investors. Emotional elements like fear and greed are integral components that can shape investment choices, diverging from the traditional approach that assumes rational behavior. This gap between market reactions and predictions based solely on fundamental analysis becomes particularly apparent during market anomalies and financial crises.

The study focuses on three primary aspects. Firstly, it aims to create an innovative sentiment index by utilizing six proxies, including the Crypto Fear & Greed Index issued by the alternative.me website, AAII Investors Sentiment Survey, Google Trends in relation to a set of positive and negative emotional terms, Tweet Volume of cryptocurrencies over time, Crypto Trading Volume Trend for the largest cryptocurrencies, and the CBOE Volatility Index (VIX). Secondly, it seeks to disentangle cryptocurrency investor sentiment into rational and irrational components through an Automatic Regression of Lag (ARDL) model. This model incorporates several variables such as EUR/USD exchange rates, S&P 500 returns, S&P Goldman Sachs Commodity Index, Cryptocurrency Volatility Index, Crude Oil WTI Futures prices, and the S&P Cryptocurrency Broad Digital Market Index, which are reputable financial benchmarks across the globe.

Furthermore, the study evaluates the connection between cryptocurrency investor sentiment and the returns as well as the volatility of the Royalton CRIX Crypto Index, using a Vector Auto Regressive (VAR) model. The CRIX cryptocurrency index includes a set of the most representative cryptocurrencies including the leading pairs: Bitcoin and Ethereum. This makes it an important tool to represent the market with a representative power that exceeds 75%. Lastly, the findings will be presented through an Impact Response Analysis, visually highlighting distinctive dynamics in CRIX returns and volatility that are triggered by shocks stemming from rational and irrational investor sentiment.

4.3. Originality of the Research

The original value of this study lies in its contribution to expanding the understanding of the influence of rational and irrational investor sentiment on the dynamics of the cryptocurrency market. This is achieved through a comprehensive exploration of the interactions between major financial factors and the cryptocurrency market's dynamics. The study introduces the cryptocurrency investor sentiment index, a novel approach that combines crypto and traditional market fear indicators, social media and search engine sentiment data, investor surveys, and trading volume trends. This unique index offers a more holistic representation compared to studies relying on single sentiment indicators

like Twitter volume or Google Trends data. For instance, Colianni et al. (2015) employed Twitter data to forecast cryptocurrency market movements through supervised machine learning. Ranco et al. (2015), Lamon et al. (2017), and Abraham et al. (2018) utilized traditional supervised learning algorithms for predicting cryptocurrency prices using the Twitter API. Smuts (2019) incorporated Google Trends and the Telegram messaging platform, while Chen & Hafner (2019) performed sentiment analysis on Twitter and Reddit. Kraaijeveld & De Smedt (2020) adopted a lexicon-based analysis approach for Twitter, and Oad Rajput et al. (2020) employed ARDL Models with Google Trends. Naeem et al. (2021), Hamraoui & Boubaker (2022), and Kyriazis et al. (2023) also relied on Twitter data in their respective studies.

The study's originality also arises from its combination of historical analysis, data-driven examination, and advanced analytical techniques. Through these approaches, the study dissects cryptocurrency responses to significant financial indicators, potentially uncovering underlying trends, correlations, and causative factors shaping market behavior. The study's distinctiveness lies in its analysis of the Royalton CRIX cryptocurrency index, offering a higher representative rate of the market compared to studies focusing on single cryptocurrencies or preselected sets. For example, Bitcoin (Colianni et al., 2015; Anamika et al., 2023), Bitcoin and Ethereum (Abraham et al., 2018; Smuts, 2019), or more than two cryptocurrencies (Lamon et al., 2017; Rognone et al., 2020; Kraaijeveld & De Smedt, 2020; Kyriazis, et al., 2023).

Furthermore, the study's practical value extends to stakeholders including investors, financial institutions, regulators, and policymakers. The insights derived from this research can guide decision-making, facilitate risk management strategies, and inform regulatory approaches within the ever-evolving cryptocurrency landscape.

4.4. Research Design

The structure of this study is designed to create a cryptocurrency investor sentiment index through the application of Principal Component Analysis (PCA). This index is constructed by considering various factors that are believed to exert an influence on overall investor sentiment in the market. The study's primary objective is to investigate the impact of crypto investor sentiment on the CRIX return and volatility. The scope of the econometric analysis encompasses weekly frequency data spanning from March 16, 2018, to July 31, 2023.

By drawing understanding from both theoretical and empirical literature, the study postulates that investor sentiment will play a role in affecting cryptocurrency returns and volatility.

To undertake this analysis, the study employs the Autoregressive Distributed Lag (ARDL) analysis method. Through ARDL, investor sentiment is deconstructed into the long-run and short-run effect of the variables, employing financial variables that are assumed to have an influence on investor sentiment (Wang, et al., 2022), including the EUR/USD exchange rate, S&P 500, Goldman Sachs Commodity Index, Cryptocurrency Volatility Index, Crude Oil WTI Futures, and the S&P Cryptocurrency Broad Digital Market Index. Additionally, the study employs the Vector Autoregressive (VAR) model analysis to comprehensively examine the effects of investor sentiment on CRIX return and volatility. To visually illustrate the dynamic reaction of returns and volatility to external shocks, Impulse-Response analysis is employed.

The selection of variables for empirical analysis in this study aligns with existing literature. However, when considering studies specifically focused on cryptocurrencies, a distinctive aspect emerges in the decision to employ a cryptocurrency index CRIX, as opposed to analyzing one cryptocurrency or a predefined set of cryptocurrencies. This approach introduces an element of originality by considering a broader market perspective.

Furthermore, the cryptocurrency sentiment index extends beyond measuring mere absolute fear and greed emotions. This innovative index is designed as a composite metric, encompassing not only the fear and greed dimension but also incorporating data from investor surveys, market confidence, trade volume, and fear indicators within the stock markets. This multidimensional sentiment index provides a comprehensive view of market sentiment, setting it apart from traditional indices.

Additionally, the research methodology employs the RALS-ADF test for stationarity testing on variables. Unlike conventional unit root tests, this approach yields more accurate outcomes, especially when errors deviate from a normal distribution. This nuanced methodology diverges from studies that exclusively rely on traditional unit root tests, thereby contributing to the originality of the study.

Moreover, the study introduces a novel perspective by dissecting investor sentiment into its long-term and short-term effects through ARDL analysis. This separation of sentiment effects adds an extra layer of originality, as it enables a deeper understanding of sentiment's influence on crypto market dynamics over different timelines.

4.4.1. Principal Component Analysis

Principal Component Analysis (PCA) is a statistical multivariate technique used to analyze a data table where observations are characterized by multiple correlated quantitative dependent variables. It is commonly applied to datasets with numerous variables to transform the data into a

new set of uncorrelated variables, known as principal components. These components capture the most significant patterns of variation in the original data, allowing for a more efficient representation while retaining essential information.

The effectiveness of the PCA model can be assessed through cross-validation methods like the bootstrap (Abdi & Williams, 2010) PCA has now gained significant recognition in the literature and has evolved into one of the most valuable tools for data modeling, compression, and visualization (Lei, 2015; Vidal, et. al. 2016; Dai, et.al., 2021).

In this context, the first step involves standardizing the data for cryptocurrency sentiment proxies using the z-score formula;

$$\boldsymbol{Z_{i(t)} = \frac{x_{i(t)} - \mu_i}{\sigma_i}} \quad \textbf{(1)}$$

Where $Z_{i(t)}$: the z-score of variables i in week t. $x_{i(t)}$: the observed value, μ_i mean and σ_i standard deviation of the variable.

Subsequently, the cross-correlation matrix C is derived by calculating the pairwise cross-correlation coefficient at any two time points in the crypto investor sentiment index.

$$\boldsymbol{C_{ij} = \langle x_i(s) x_j(s) \rangle} \quad \textbf{(2)}$$

Where the result of C_{ij} lay between -1 to 1. If C_{ij} =1 shows a perfect positive cross-correlation, or if C_{ij}=-1 shows a perfect anti-correlation, however if C_{ij}=0 it corresponds to no cross-correlation between the indices. Therefore, the covariance matrix can be created.

The third step involves performing eigenvalue decomposition on the covariance matrix. This process yields eigenvectors and eigenvalues. Eigenvectors represent the directions of maximum variance, and eigenvalues quantify the amount of variance captured by each eigenvector;

$$\boldsymbol{C_{u_1}(t) = \lambda(t) u_1(t)} \quad \textbf{(3)}$$

Where $u_1(t)$: the eigenvector of the largest eigenvalue $\lambda(t)$ of the cross-correlation matrix.

Finally, the PCA-based Composite Investor Sentiment (CIST) index is established through the eigen portfolio of the investor sentiment indices:

$$\boldsymbol{CIST_t = \frac{u_1(t).x(t)}{\sum_{i=1}^{N} u_{1i}(t)}} \quad \textbf{(4)}$$

Where $x(t) = [x_1(t), x_2(t), \ldots., x_N(t)]$

4.4.2. Unit Root Test for Stationarity Level

Many of the modeling techniques employed in time series analysis are primarily focused on assessing the stationarity of the data. The initial step involves visually inspecting the series' properties and confirming them through statistical methods. Graphs serve as the initial tool to obtain a preliminary understanding of the series' stationarity. However, for a conclusive determination, statistical tests become necessary. Unit root tests offer statistical evidence regarding the stationarity of a given series (Shrestha & Bhatta, 2018: 73). In this study, the widely obtained Augmented Dickey-Fuller (Dickey & Fuller, 1979) unit root test was utilized to evaluate the stationarity of the series and allows for higher-order autoregressive processes. The ADF unit root test Dickey and Fuller examine three differential-form autoregressive equations as part of their approach to identify the existence of a unit root:

$$\boldsymbol{\Delta Y_t = \gamma Y_{t-1} + \sum_{j=1}^{p} \delta_j \Delta Y_{t-j} + \epsilon_t} \quad \textbf{(5)}$$

$$\boldsymbol{\Delta Y_t = \alpha + \gamma Y_{t-1} + \sum_{j=1}^{p} \delta_j \Delta Y_{t-j} + \epsilon_t} \quad \textbf{(6)}$$

$$\boldsymbol{\Delta Y_t = \alpha + \beta_t + \gamma Y_{t-1} + \sum_{j=1}^{p} \delta_j \Delta Y_{t-j} + \epsilon_t} \quad \textbf{(7)}$$

Where; t is the time index, α is an intercept constant called a drift, β is the coefficient for trend over time, Y presents process root, p is the lag order of the first difference autoregressive process, and ϵ_t an independent identically distributes residual term.

The distinction among the three equations lies in the inclusion of deterministic elements a drift term (α) and a linear time trend (β_t).

The hypotheses for the models formulated in the ADF unit root test are presented as follows:

(m1) H_0: $y = 0$ or Y_t is random walk.

H_0: $y < 0$ or Y_t is stationary.

H_0: $(y = 0, a \neq 0)$ or Y_t is random walk around a drift.

(m2) H_0: $(y < 0, a \neq 0)$ or Y_t is level stationary process.

(m3) H_0: $(y = 0, \beta \neq 0)$ or Y_t is random walk around a trend.

H_0: $(y < 0, \beta \neq 0)$ or Y_t is trend stationary process.

The test for normality, Jarque-Bera, was employed to assess the normal distribution of residuals from the auxiliary regression models in the ADF unit root test. Jarque and Bera (1980) employed the Lagrange Multiplier (LM) to examine residue normality in their study. In this test, skewness and kurtosis values are computed from the sample. If the skewness is zero and kurtosis is three, the data conforms to a normal distribution.

The null hypothesis of Jarque-Bera test is:

H_0: The time series is normally distributed.

H_1: The time series is not normally distributed.

However, if the errors are not normal, and the normality of time series is rejected, Im & Schmidt (2008) determined that utilizing the Residual Augmented Least Squares (RALS) method procedure is a more suitable approach. Meng et al. (2014) highlighted novel unit root tests in their research that exhibit enhanced power when the error term departs from normal distribution. This approach leverages the insights provided by non-normal errors to examine the unit root hypothesis. Their findings indicate that the RALS-based unit root tests demonstrate a close alignment with asymptotic size and exhibit substantially improved statistical power compared to conventional Dickey-Fuller tests in cases of non-normal error distribution. Their study also underscores that unit root tests based on the RALS method offer heightened resilience and effectiveness in assessing the stationarity of financial time series. In this study, the unit root testing is conducted using RALS-LM tests based on the following formula;

$$\Delta \boldsymbol{Y_t} = \boldsymbol{\alpha} + \boldsymbol{\beta_t} + \sum_{\boldsymbol{j=1}}^{\boldsymbol{p}} \boldsymbol{\delta_j} \Delta \boldsymbol{Y_{t-j}} + \widehat{\boldsymbol{w}}_{\boldsymbol{t}} \boldsymbol{\gamma} + \boldsymbol{v_t}, \boldsymbol{t} = \mathbf{1}, \mathbf{2}, \dots, \boldsymbol{T} \quad \textbf{(8)}$$

Where the generalized term in the equation is expressed by:

$$\widehat{w}_t = h(\hat{e}_t) - \widehat{K} - \hat{e}_t \widehat{D}_2, t = 1,2, \dots, T,$$

Furthermore, in Meng, et al. (2017), the RALS-LM test formula is illustrated as:

$$\tau^*_{RALS-LM} \rightarrow \rho\tau^*_{LM} + \sqrt{1-\rho^2}Z \quad \textbf{(9)}$$

The null hypothesis of RALS-LM unit root test is stated as follows:

H_0: The time series possesses a unit root.

H_1: The time series lacks a unit root.

The study also tested for the Schmidt-Phillips unit root test (1990) with one and two structural breaks. The test developed the LM method of ADF unit root test in the absence of deterministic trend. The general form of this test model is as follows (Schmidt & Lee, 1991: 285):

$$y_t = \psi + \epsilon_t + X_t, X_t = \beta X_{t-1} + \varepsilon_t \quad \textbf{(10)}$$

The unit root restriction is $\beta = 1$, which is being test based on the LM score principle.

4.4.3. Autoregressive Distributed Lag (ARDL)

The Autoregressive Distributed Lag (ARDL) model proposed by Pesaran & Shine (1999) and Pesaran et al. (2001) is an econometric approach allows for analyzing the dynamic relationships between variables, considering both long-run and short-run dynamics in the presence of mixed orders of integration among variables.

For this study, the ARDL model has been chosen due to several merits it possesses over alternative cointegration methodologies. Firstly, the autoregressive distributed lag model excels in handling diverse sample sizes, effectively accommodating datasets with a limited number of observations ranging from 30 to 80. Secondly, the ARDL approach proves advantageous when dealing with variables that exhibit different orders of integration, such as a combination of I(0) and I(1) variables. Thirdly, by appropriately specifying the lag structure, the ARDL model effectively addresses concerns related to serial correlation and endogeneity.

Lastly, the ARDL framework allows for the simultaneous estimation of both long-run and short-run cointegration relationships, thereby providing unbiased estimates for the research inquiry (Pesaran et al., 2001).

The dynamic simulated ARDL model, necessitates a rigorous evaluation of stationarity for each individual series. Specifically, it is imperative to verify that none of the employed variables exhibit I(2) stationarity prior to conducting the dynamic ARDL simulations, as failure to do so could

yield spurious regression results. As dissuaded above stationarity tests using ADF and RALS-LM tests employed to scrutinize the stationarity of the variables, encompassing both I(0) and I(I) levels. Additionally, these tests were employed to examine the presence of a linear stochastic trend in each series. This approach is recommended for a comprehensive assessment of the relationship between the regressors (predictors) and the regressand (criterion).

Moreover, the ARDL model formula is represented as follows:

$$\Delta \boldsymbol{Y_t} = \boldsymbol{\beta_0} + \sum_{\boldsymbol{i=1}}^{\boldsymbol{p}} \boldsymbol{\lambda_i Y_{t-i}} + \sum_{\boldsymbol{i=0}}^{\boldsymbol{q}} \boldsymbol{\delta_i \Delta X_{t-i}} + \boldsymbol{\varphi_1 X_{t-1}} + \boldsymbol{\varphi_2 X_{t-1}} + \boldsymbol{\upsilon_t} \quad \textbf{(11)}$$

Where $\sum_{i=1}^{p} \lambda_i Y_{t-i} + \sum_{i=0}^{q} \delta_i \Delta X_{t-i}$ represents the short run terms or the irrational sentiment, and $\varphi_1 X_{t-1} + \varphi_2 X_{t-1}$ long run terms or the rational sentiment.

In ARDL equation the difference of the dependent variable is included in the model. Δ is the difference term, β presents the intercept, and υ_t is the error term. The optimal lag length for the model is determined through the application of the Akaike and Schwarz information criteria. Following this, a cointegration test is conducted using the Engle-Granger, (1987) method. This test aims to explore the presence of a co-integration relationship within the estimated model, based on the hypotheses outlined below:

H_0: No co-integration is present.

H_1: Co-integration is present.

The expected outcomes of the Engle-Granger cointegration test, as the framework established by Pesaran et al. (2001), are as follows: Rejection of the H_0 occurs when the calculated F statistic exceeds the critical value (F<lower value), indicating the rejection of the hypothesis of no cointegration. This suggests a lasting relationship among the variables, implying their movement together over the long term. Failure to Reject the H_0 takes place if the calculated F statistic is lower than the critical value (F>upper value), implying insufficient significant evidence to support a long-term relationship among the variables. In instances where the F statistic closely approaches the critical value (lower value<F<upper value), yielding an inconclusive result, further analysis or additional tests may be necessary to draw a conclusive inference regarding cointegration.

4.4.4. The Vector Autoregressive (VAR)

The Vector Autoregressive (VAR) model, introduced by Christopher Sims in 1980, has significantly enriched the field of macroeconometrics with its versatility. VAR offers a statistical framework to analyze and understand the intricate dynamics and relationships among multiple variables over time. It builds upon the foundation of autoregressive models, accommodating numerous variables by regressing each variable on its own past values and the lagged values of other variables within the system. This makes VAR particularly valuable in capturing interdependencies and interactions across various fields, including econometrics and finance.

Utilizing the VAR model proves to be the appropriate econometric approach for examining the correlations between sentiments and market returns and volatility (Calafiore, 2010: 64). By employing VAR models, researchers can investigate the impact of shocks, forecast future values, and explore the intricate transmission of changes across the variables in a dynamic manner. This approach is essential for comprehensively studying the complex relationships inherent in multivariate time series data. Thus, the VAR model stands as a cornerstone in time series research, facilitating the examination of dynamic interactions and contributing to a deeper understanding of the underlying mechanisms shaping these complex systems. In this study, VAR model is selected as the appropriate methodology to analyze the influence of investor sentiment on CRIX returns and volatility. The model is explained in the following equation;

$$\boldsymbol{y_t = \beta_0 + \sum_{i=1}^{k} \beta_j \, y_{t-i} + \upsilon_t} \quad \textbf{(12)}$$

Where; y_t is the $\rho \times 1$ vector of variables determined by k lags of all ρ variables, β_0 is the constant vector, υ_t is the error term.

In predicting the VAR model, determining the lagged values for the variables is crucial, as the choice of lag lengths significantly affects accurate estimation. Opting for a lag length that is too short may lead to parameter inconsistency, while selecting one that is excessively large can result in high parameter variances, leading to a loss of efficiency. In this study, the appropriate lag length is determined using the Akaike Information Criteria (AIC), which guides the VAR analysis:

$$\boldsymbol{AIC = 2k - 2ln\,(\hat{L})} \quad \textbf{(13)}$$

Where, k is the number of estimated parameters in the model, $\hat{L}$ presents the maximum value of the likelihood function for the model.

In the study, impulse response analysis is conducted to observe how variables react to shocks and interpret the results of the VAR analysis. The impulse response function determines the extent to which both the endogenous variable and other variables respond to a one-unit shock in the error term. This analysis offers insights into how variables react to future shocks and provides valuable information on their dynamic interactions.

For this study, the VAR model is applied using the returns and volatility of the CRIX. In financial research, the focus often centers on analyzing asset returns rather than their prices. Campbell, Lo, and MacKinlay (1997) highlight two primary reasons for this inclination. Firstly, an asset's return is a comprehensive and independent indicator of the investment potential, which holds significance for the average investor. Secondly, return series exhibit more favorable statistical properties and are easier to handle compared to price series.

In financial econometric analysis, the following return formula is commonly used;

$$\boldsymbol{r_{crix} = ln(1 + R_t) = lnP_t - lnP_{t-1} = ln\frac{P_t}{P_{t-1}}} \quad \textbf{(14)}$$

In this equation, P_t represents the price of the cryptocurrency at the end of day t, and P_{t-1} represents the price of the cryptocurrency at the end of day $t-1$.

Regarding volatility, the study employs the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model for its calculation. The GARCH model is an extension of the Autoregressive Conditional Heteroskedasticity (ARCH) model, as introduced by Bollerslev (1986). The general equation of the GARCH(p,q) model is as follows:

$$\boldsymbol{\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2} \quad \textbf{(15)}$$

4.5. Dataset of the Study

The data collection approach in this research involves gathering information from various sources. The study focuses on examining the impact of the cryptocurrency investor sentiment index on the returns and volatility of the Royalton CRIX Crypto Index. The dataset covers the period from March 16, 2018, to July 31, 2023, on a weekly basis. This time frame was chosen due to data availability constraints in the relatively new and emerging cryptocurrency domain. It also encompasses significant global events, such as lockdowns caused by the COVID-19 pandemic and global inflation, along with geopolitical crises such as tensions between Russia and NATO,

cyberattacks, and the strategic competition between the US and China, all of which have implications in the market during this period. Table 5 shows the study's variables list;

Table 5: The Research Variables

Symbol	Variable Name	Source
CIST	Cryptocurrency Investors Sentiment Index	The study's outcome
AAII	AAII Investor Sentiment Survey-Bull-Bear Spread	American Association of Individual Investors
VIX	CBOE Volatility Index	Investing
FGI	Crypto Fear & Greed Index	Alternative
vCRYPTO	Total Trading volume of selected cryptocurrencies	CoinMarketCap
EUR/USD	Exchange rate of EUR/USD	Investing
rSPX	Returns of S&P 500 Index	Investing
SPGSCI	S&P Goldman Sachs Commodity Index	Investing
SPBDM	S&P Cryptocurrency Broad Digital Market Index	S&P Global
NetGT	The net positive and negative terms in Goggle Trends in Financial category	Google Trends
CVI	Cryptocurrency Volatility Index	Investing
TCnt	The total number of Tweet counts for cryptocurrencies' hashtags	trackmyhashtag.com
CLU	Crude Oil WTI Futures	Investing
CRIX	Royalton CRIX Crypto Index	S&P Global
rCRIX	Returns of Royalton CRIX Crypto Index	Study's computations
vCRIX	Volatility of Royalton CRIX Crypto Index	Study's computations

4.5.1. Sentiment Indicators

Sentiment indicators are tools used to gauge the sentiment or mood of a particular market, group of people, or other entities. They are commonly used in finance, social media analysis, and other fields to assess the prevailing sentiment and make informed decisions based on that information.

In this study, a composite approach incorporating multiple variables that have been identified in the literature as sentiment proxies or potential drivers of cryptocurrency investor sentiment is

employed to create an index referred to as the Cryptocurrency Investor Sentiment Index (CIST). The sentiment proxies included in the CIST are:

- AAII Investor Sentiment Survey

The American Association of Individual Investors (AAII) was founded in 1978 by James Cloonan as a non-profit organization to deliver unbiased investment advice. AAII releases a weekly index that is derived from data obtained from their webpage. This index, known as the AAII Investor Sentiment Survey, assesses the sentiment of individual investors towards the stock market for the upcoming six months. Participants, who are AAII members, are surveyed on a weekly basis to determine their bullish, bearish, or neutral outlook. Each member is allowed to submit only one vote during each weekly voting period. The sentiment results are presented as percentage divided to bullish neutral and bearish, however, the study uses the Bull-Bear Spread as an indicator for measurement. This indicator has been used in the literature mainly in stock markets (Qiu & Welch, 2004; Chen, 2011; Waggle & Agrrawal, 2015; Maknickiene et al., 2018; Bouteska, 2019; Zeitun et al., 2023). Nevertheless, (Jo, et al., 2020; Güler, 2021) studied the impact of AAII on Bitcoin.

- CBOE Volatility Index

Chicago Board Options Exchange's CBOE Volatility Index (VIX) is a 30-day expected volatility of the U.S. stock market. VIX or also known as the Volatility Index or the Fear Index due to its association with market apprehension, plays as a gauge of investor sentiment. The VIX is a well-known measure of the expected volatility in the stock market, based on S&P 500 index options. The VIX is calculated by taking the square root of the par variance swap rate for a 30-day term that begins on the current day. Studies such as Moran, 2014; Pan, 2018; Park et al., 2023; as a prediction power of market attitude.

- Crypto Fear & Greed Index

The crypto fear & greed index (FGI), is a daily sentiment indicator run by alternative.me[9]. The index currently focuses on Bitcoin due to its significant price volatility, which forms a substantial part of the index. FGI is constructed with a composite approach, incorporating various factors. Volatility measurements, market momentum/volume analysis, and social media interactions provide insights into market sentiment. Although surveys are currently paused, they previously contributed

[9] The Alternative.me website is a platform dedicated to optimizing connections among a wide range of software and product alternatives. This platform provides essential information about the crypto market, including coin overviews, trend analysis, API documentation and the Fear & Greed Index.

sentiments from crypto investors. Coin dominance and Google Trends data further enhance the index, capturing shifts in market behavior. By combining these elements, the sentiment index offers a comprehensive perspective on the evolving sentiment within the crypto market. Studies indicated that the FGI can offer investors insights into the prevailing perception of certain facets of the cryptocurrency market. However, it is not considered a practical tool for making informed investment decisions. (Siu, 2021; Bourghelle, et al., 2022; Saggu, 2022; Johnson, 2023; Gaies, et al., 2023).

- Trading Volume Trend of Selected Cryptocurrencies

The study examined the 24-hour trading volume trend of five widely traded cryptocurrencies namely; Bitcoin (vBTC), Ethereum (vETH), Binance Coin (vBNB), Ripple (vXRB) and Cardano (vADA). The cryptocurrencies which are used also in CRIX represent75% of the total crypto market cap as of August 2023. The trading volume trend has been considered as a sentiment proxy enlightened from the literature such as (Lei, 2005; Tas & Akdag, 2012; Uygur & Tas, 2014; Mehmood & Hanif, 2014; Wang, et al., 2022).

Other sentiment indicators used in the CIST index includes; Tweet Volume, Google Trend data are discussed in the following section of social media interactions.

4.5.2. Social Media Interaction

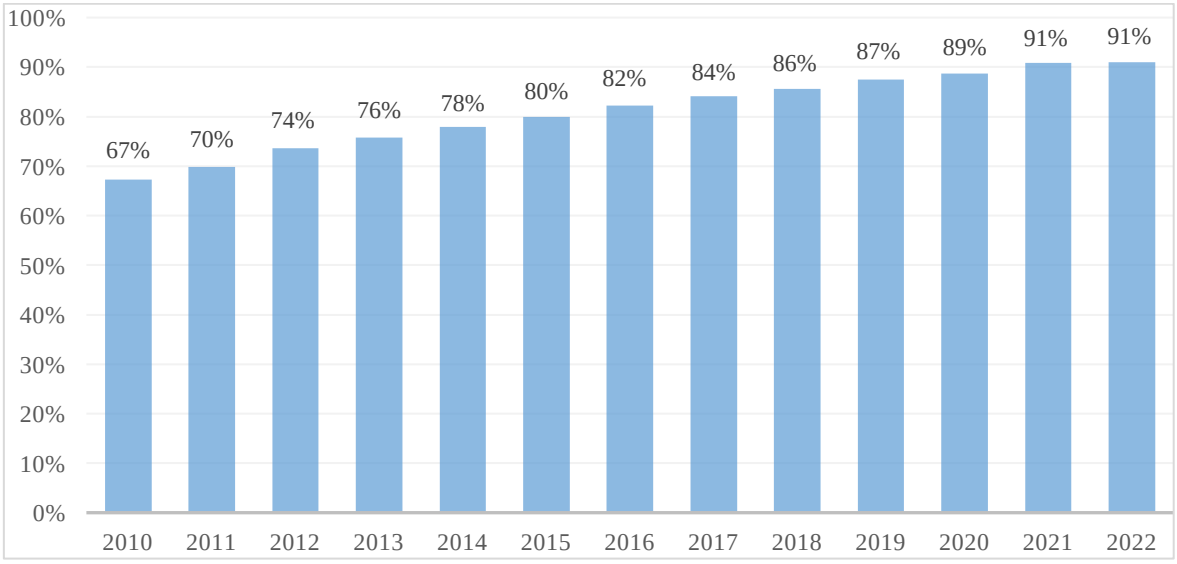
Social media platforms play an important role in modern life, serving as dynamic conduits for global communication, cross-cultural understanding, and individual expression. These platforms empower users to connect across borders, share diverse perspectives, and cultivate virtual relationships, while also facilitating self-promotion and creative endeavors that hold the potential to influence sentiment within financial markets.

In the realm of business, social media has sparked a revolution in marketing strategies and audience engagement, thereby shaping investment trends and influencing brand perceptions. Notably, the rapid surge in internet users over the past decade has significantly magnified the outreach and impact of these platforms, solidifying their status as essential components of contemporary society. Statistics reveal that global internet users exceeded 5.16 billion in 2023, compared to 1.67 billion in 2009, Figure 9, the year Bitcoin was released, showcasing a remarkable increase of 212%. This substantial growth has shed light on the widespread adoption of electronic devices to access the internet.

Moreover, social networks occupy the second place among websites and apps used by internet users, at 94.6%, following chat and messaging apps (Kepios, 2023). Online platforms have

seamlessly integrated into everyday life, continually reshaping the way individuals engage on a global scale and contributing to the expanding prominence of social media. The largely cost-free accessibility of social media underscores its inclusivity and widespread adoption. This is evidenced by the widespread popularity of social media usage, with over 4.8 billion people engaging in this online activity worldwide in April 2023, marking a 13% increase from 2021, and projections indicating a further rise to nearly six billion users by 2027 (Statista, 2023d). Noteworthy among these platforms is Facebook, which consistently emerges as a top-rated social media giant, boasting a considerable user base and a profound global impact.

Figure 9: Internet Access Indicator



Source: OECD. https://www.oecd.org

In light of this, several studies have undertaken the influence of different social networking sites on the world's financial landscape. However, in literature, Twitter and Google Trends stand out as among the most extensively examined platforms, owing to their influence on individual and market sentiment alike on one hand, and their statistical features that offer valuable insights into the popularity and interest in specific search terms over time on the other (Mao, et al., 2013; Pant, et al., 2018; Duz Tan & Tas, 2021; Aslanidis et al., 2022; Huynh, 2022; Ante, 2023).

- Tweet Volume

Twitter[10] is a widely recognized social media platform that allows users to instantly share and discover information through ‘tweets’ (digital messages) containing text, images, videos, or links. Since its establishment in 2006, Twitter has become a prominent hub for news, conversations, and

[10] Twitter has officially rebranded to "X" after it has been acquired by X Corp. On 23 July, 2023, Twitter owner, Elon Musk changed the iconic bird logo, symbolizing a new era and direction for the platform www.X.com.

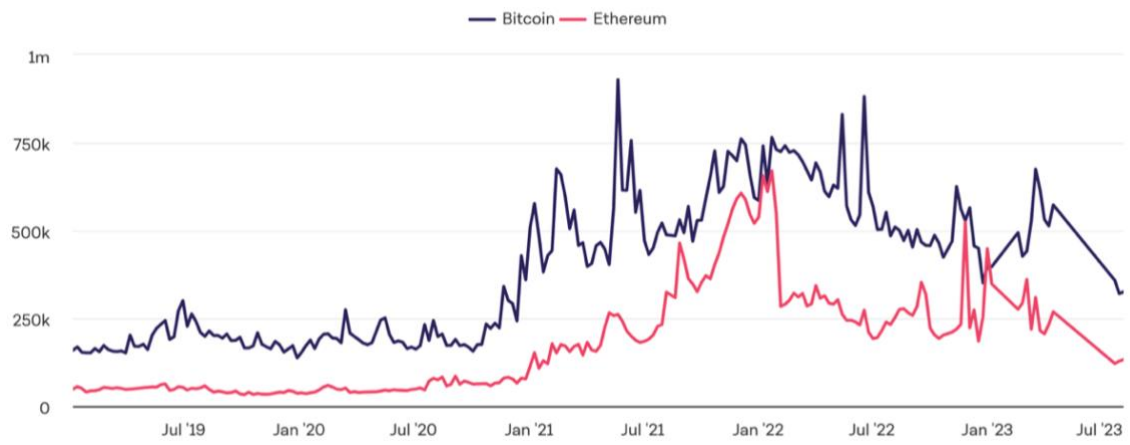
interactions in various domains. With a huge user base of over 450 million active monthly users in 2023, Twitter has firmly established itself as a global communication channel, connecting individuals, organizations, and public figures. Notably, the United States has the highest number of Twitter users, with 79.6 million users, and the largest user segment falls within the 25 to 34 age group, comprising 38.5% of Twitter's user base according to Statista (2022), as of January 2022.

Analyzing tweet volume is an essential tool in Twitter analytics, referring to the total number of tweets posted within a specific period. Tweet volume holds great significance as a statistical and analytical tool due to the platform's immense output, with approximately 500 million tweets shared daily. This wealth of data provides valuable resources for researchers, marketers, and analysts to explore public opinion, monitor trends, and assess market sentiment. Through tweet volume analysis, one can identify emerging topics, measure engagement levels, and gain insights into the impact of events or announcements on Twitter users. It also facilitates the monitoring of brand reputation and offers real-time information on ongoing discussions and events.

Furthermore, tweet volume analysis plays a crucial role in social media analytics by enabling the measurement of reach, influence, and engagement. Marketers and businesses can leverage tweet volume to identify popular hashtags, trending topics, and influential users, allowing them to customize their social media strategies and effectively target their messaging. Moreover, during crisis management situations, tweet volume analysis provides real-time insights into public sentiment amidst controversy or emergencies. By examining patterns and trends in tweet volume, researchers and analysts can gain a deeper understanding of user behavior, sentiments, and preferences on the platform.

In this study, the total average of weekly tweet count of the hashtags “#Bitcoin”, “#BTC”, “#Ethereum” and “ETH” are collected using TwitterAPI by TrackMyHashtag website. The chart in Figure 10 shows the tweet volume of the two cryptocurrencies (the Block, 2023b).

Figure 10: Tweet Volume of the Bitcoin and Ethereum



Source: The Block website on 12 August, 2023b.

- Google Trends

Google Trends (GT), introduced by Google Inc. in 2012 after merging with Google Insights, is a powerful tool for analyzing the popularity of notable search queries on Google Search. This analysis covers a wide range of categories, regions, and languages within a user-defined timeframe. Google provides a search volume index (SVI) by dividing specific data points by the total searches in a given geographic area and time frame. These values are then scaled from 0 to 100, reflecting the relative proportion of searches for a specific term compared to overall searches on different topics (Abraham et al., 2018: 8). The resulting graphical representations illustrate the trend evolution over time, offering researchers and analysts insights into the trajectory of search term trends. This visual representation serves as a valuable tool for exploring the temporal dynamics of search term popularity.

This study focuses on analyzing a set of five optimistic terms: 'success,' 'growth,' 'increase,' 'gain,' and 'profit,' alongside an opposing set of pessimistic terms: 'down,' 'crash,' 'risk,' 'crisis,' and 'loss.' This analysis is conducted on a global scale, specifically within the finance category, and is carried out for the predetermined time frame of the study. By scrutinizing the trends associated with these terms, a net Google Trends (GT) score is computed. The ensuing Figures 11 and 12 present the individual graphs corresponding to each of the aforementioned search terms, providing a comprehensive depiction of their respective trajectories and patterns.

Figure 11: The Positive Search Terms in Finance Category in Google Trends

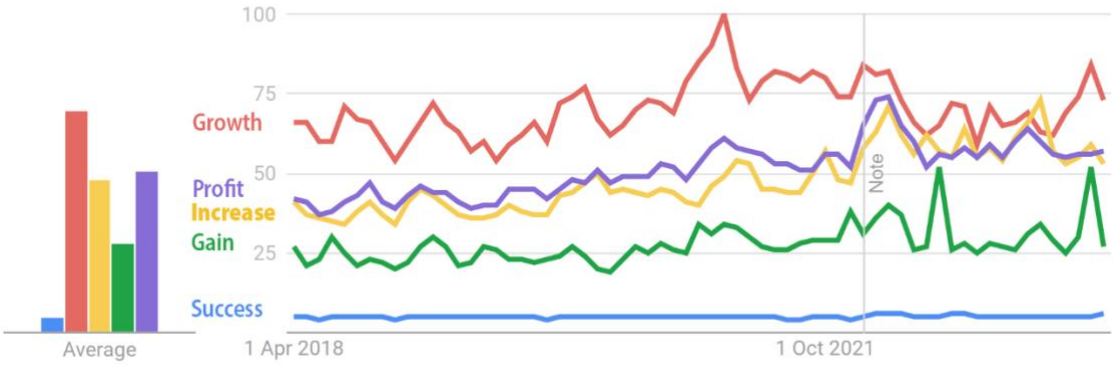
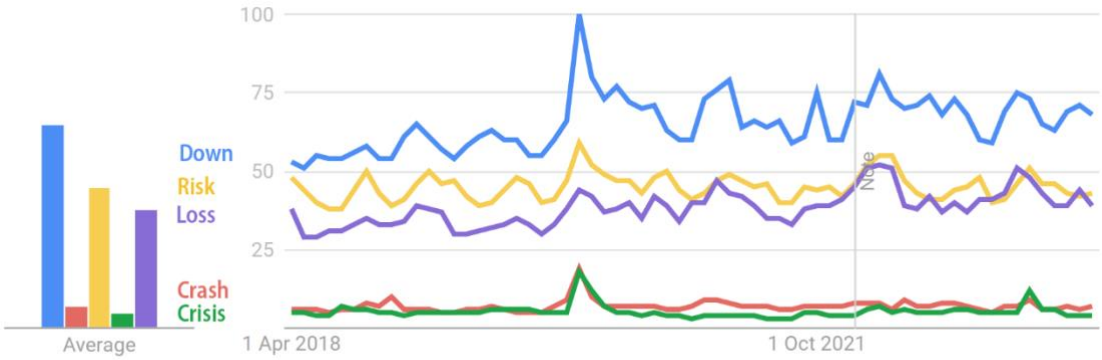


Figure 12: The Negative Search Terms in Finance Category in Google Trends



4.5.3. Financial Markets Indicators

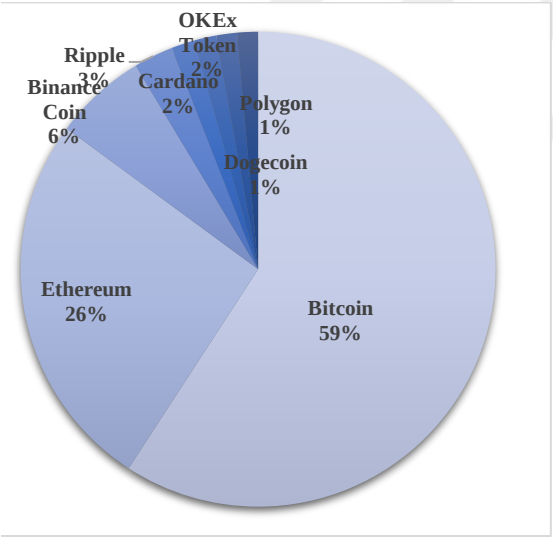
The hybrid nature of cryptocurrencies makes it difficult to categorize them. Therefore, while some analysts view cryptocurrencies as mediums of exchange, the U.S. Commodity Futures Trading Commission considers Bitcoin as a commodity. This study has considered the exchange rate of EUR/USD, Returns of S&P 500 Index and the S&P Goldman Sachs Commodity Index. This approach aims to provide insights into the intricate interplay between traditional financial indicators and the sentiments of those involved in the cryptocurrency market. It offers a more comprehensive understanding of the factors influencing investor attitudes and behaviors within this dynamic and evolving landscape.

4.5.4. Cryptocurrency Markets Indicators

- The Royalton CRIX Crypto Index (CRIX)

CRIX Index was developed by German statistician and professor Wolfgang Karl Härdle and Simon Trimborn and presented in their study 'CRIX an Index for Cryptocurrencies' (Karl Härdle & Trimborn, 2018). It was acquired by Royalton Partners in 2021. CRIX enables the monitoring of the dynamic cryptocurrency market using a limited set of components. S&P Global has been computing this index since November 2021, offering historical data traceable back to March 2018. This index strikes a harmonious balance by incorporating smaller coins to enhance tracking performance while addressing concerns related to liquidity and tradability. It encompasses eight cryptocurrencies that are updated automatically based on market dynamics. The composition includes Bitcoin, weighted at 59.17%; Ethereum, weighted at 25.91%; Binance Coin, at 6.29%; Ripple, at 2.7%; Cardano, at 1.6%; OKEx Token, at 1.49%; Dogecoin, at 1.41%; and Polygon, at 1.42%. CRIX index components are illustrated in the following Figure13.

Figure 13: The Royalton CRIX Index Components



The Royalton CRIX Index Components

Cryptocurrency	Weight
Bitcoin	59.17%
Ethereum	25.91%
Binance Coin	6.29%
Ripple	2.70%
Cardano	1.60%
OKEx Token	1.49%
Dogecoin	1.41%
Polygon	1.42%

Source: Royalton-CRIX website, 2023.

The diverse nature of the cryptocurrency market underscores the significance of including smaller coins in the index to enhance tracking performance. Professor Härdle's research demonstrates that optimizing weights assigned to constituent selections contributes to reducing the tracking error of a cryptocurrency portfolio, even when the market caps of certain constituents are considerably smaller compared to Bitcoin. Figures 14, 15 and 16 shows CRIX time series prices, returns and volatility.

Figure 14: The Royalton CRIX Index Prices

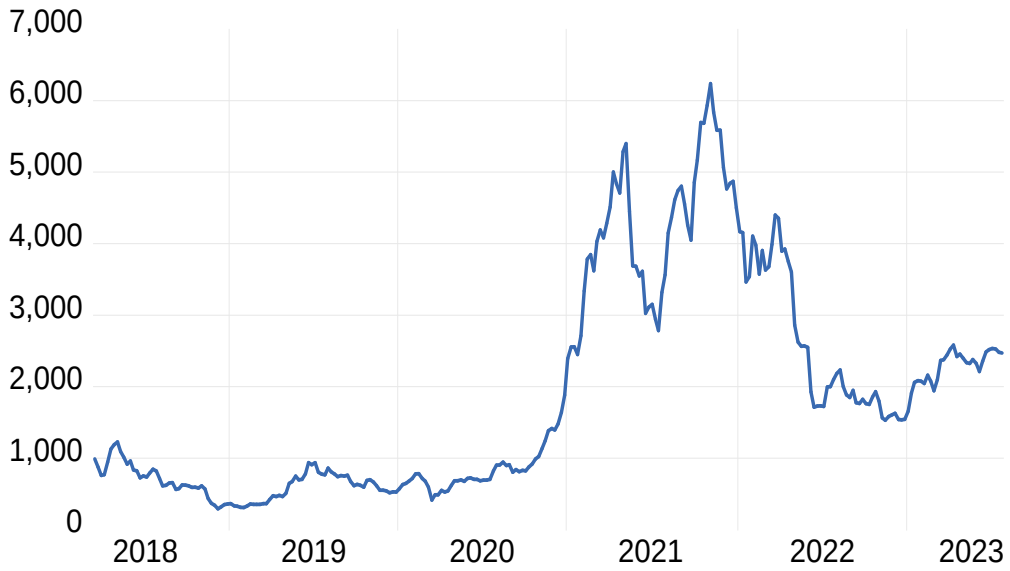


Figure 15: The Royalton CRIX Index Price Returns

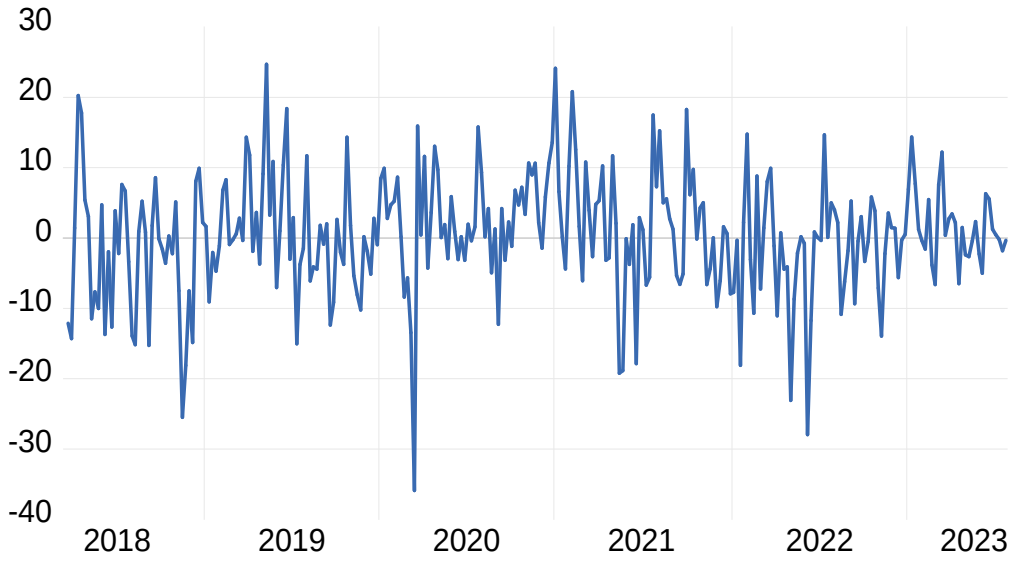
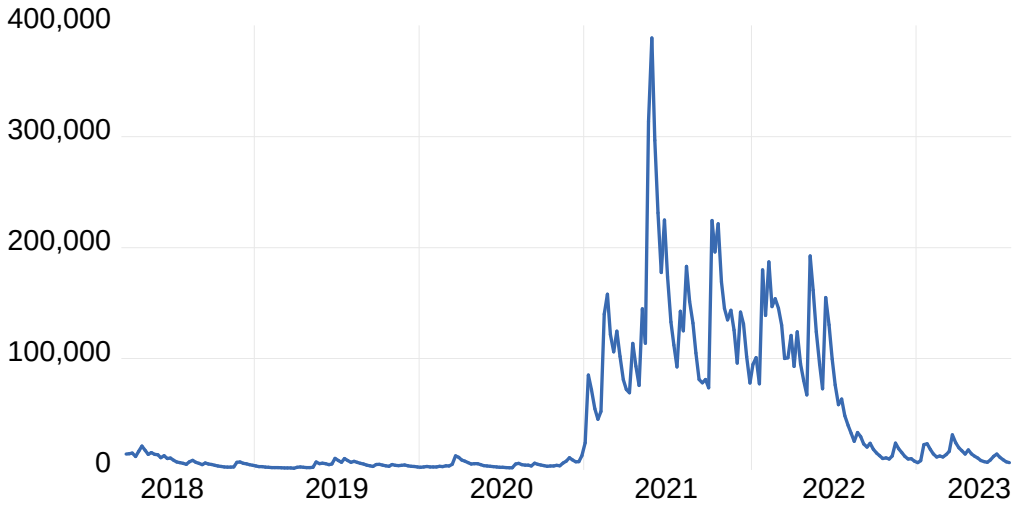


Figure 16: The Royalton CRIX Index Volatility



- Cryptocurrency Volatility Index

The Cryptocurrency Volatility Index (CVI), often known as the VIX index of the cryptocurrency market, operates as a metric for quantifying the projected magnitude of price fluctuations within the entire cryptocurrency market over a 30-day horizon. Calculated using the Black-Scholes option pricing model, the CVI index offers valuable insights into the anticipated future volatility of the cryptocurrency market. Remarkably, this index is integrated within a range spanning from 0 to 200, providing a comprehensive tool that effectively assesses and comprehends market dynamics, particularly addressing the heightened volatility inherent in the cryptocurrency domain. (Nguyen, et al., 2023).

- S&P Cryptocurrency Broad Digital Market Index

The S&P Cryptocurrency Broad Digital Market (SPCBDM) Index assesses the performance of digital assets and monitors digital assets listed on established open digital exchanges that satisfy minimum liquidity and market capitalization standards.

The following Table 6 provides a summary of the indicators that has been used in the study.

Table 6: Summary of The Study's Indicators

Indicator	Developer	Primary Users	Purpose
AAII Investor Sentiment Survey	American Association of Individual Investors	Individual investors Financial professionals Media outlets	To measure the sentiment and attitudes of individual investors towards the stock market and their investment outlook.
CBOE Volatility Index	Chicago Board Option Exchange	Investors and traders Financial professionals Market analysts Financial journalists Economists	To provide a quantitative measure of the market's expectation for future volatility in the S&P 500 Index, a widely followed benchmark of the U.S. stock market.
Crypto Fear & Greed Index	alternative.me, a crypto data analytics platform	Cryptocurrency investors Crypto analysts Cryptocurrency news outlets	To provide a representation of the emotional and psychological factors that can impact cryptocurrency markets, whether it is dominated by "fear" (indicating caution and risk aversion) or "greed" (indicating enthusiasm and risk-taking).
Google Trends	Google LLC	Wide range of Individuals, businesses, marketers, journalists, researchers, and anyone interested in analyzing search trends and patterns.	To provide a search interest tracking over time, comparing the popularity of search terms, providing geographic insights, offering real-time data on trending topics, and identifying seasonal trends.
The Royalton CRIX Crypto Index	Wolfgang Karl Härdle and Simon Trimborn	Cryptocurrency investors and analysts Researchers Cryptocurrency news outlets	To track the total market index (TMI) of cryptocurrencies using seven liquid cryptocurrencies, with significant market representation.

Table 6: (continued)

Indicator	Developer	Primary Users	Purpose
Cryptocurrency Volatility Index	CVI Finance	Cryptocurrency investors and traders Crypto analysts Cryptocurrency news outlets	To provide an estimation of the 30-day future volatility of the cryptocurrency market.
S&P Cryptocurrency Broad Digital Market	S&P Dow Jones Indices	Cryptocurrency investors Crypto analysts Cryptocurrency news outlets	To track the performance of digital assets listed on recognized open digital exchanges.

4.6. Research Model

The research model proposed in this study seeks to delineate investor sentiment into two distinct components: rational and irrational. This division aims to provide a more nuanced understanding of the intricate interplay between investor behaviors and market dynamics. The model, outlined below, serves as a framework to analyze and quantify these separate facets of sentiment:

$$\boldsymbol{CIST_{1t} = \beta_0 + \sum_{i=1}^{p} \lambda_i Y_{t-i} + \upsilon_t} \quad \textbf{(16)}$$

Where $CIST_{1t}$ represent the Cryptocurrency Investors Sentiment Index in time t, β_0 presents the intercept, λ_i the expected the predicted parameter, Y_{t-i} research variables, and υ_t the error term.

Hence, the effect of rational and irrational cryptocurrency investors sentiment on CRIX returns is calculated as the following equation:

$$\boldsymbol{rCRIX_t = a_0 + a_1 \widehat{CIST}_{1t} + a_2 \upsilon_t + \rho_t} \quad \textbf{(17)}$$

Where a_0 constant term, a_1 the coefficient of rational investor sentiment, a_2 the coefficient of irrational investor sentiment, and ρ_t represents the random error term.

The impact of CIST on CRIX volatility is modeled based on the following equation:

$$\boldsymbol{\sigma VCRIX_t = a_0 + a_1 \widehat{CIST}_{1t} + a_2 \upsilon_t + \rho_t} \quad \textbf{(18)}$$

Where a_0 constant term, a_1 the coefficient of rational investor sentiment, a_2 the coefficient of irrational investor sentiment, and ρ_t represents the random error term.

CHAPTER FIVE

5. DATA ANALYSIS AND EMPIRICAL RESULTS

5.1. Principal Component Analysis

At the first phase of the analysis, the creation of composite cryptocurrency investors sentiment index CIST is explained. CIST is created with six commonly used market sentiment measures; AAII Investor Sentiment Survey (AAII), Tweet Volume of cryptocurrencies hashtags (CTV), the trading volume trend of top eight cryptocurrencies (vBTC, vETH, vUSDT, vBNB, vXRB, vDOGE, vADA and vXRP) sympoled (vtCrypto), Crypto Fear & Greed Index (FGI), Net Positive and Negative terms in Google Trends (netGT) and CBOE Volatility Index (VIX).

After the data standardization for the crypto sentiment drivers using z-score as explained in formula (1); the sample characteristics of the sentiment proxies illustrated in descriptive statistics Table 7 below;

Table 7: Descriptive Statistics

Sentiment Proxies	Mean	Median	Maximum	Minimum	Std. Dev.
ZAAII	-1.26E-17	0.0317	2.2496	-2.3490	1.0000
ZCTV	-3.79E-17	-0.0683	6.8149	-5.2653	1.0000
ZVTCRYPTO	6.10E-17	-0.1662	5.6770	-2.4174	1.0000
ZFGI	1.86E-15	-0.1306	2.3782	-1.6319	1.0000
ZNETGT	-1.13E-16	-0.0783	3.7045	-3.8171	1.0000
ZVIX	-7.02E-16	-0.1961	6.5610	-1.2514	1.0000

The following Table 8 presents the average correlation coefficients between the sentiment proxies defined over 280 weekly observations from March 16, 2018 to July, 31, 2023; The reported numbers are the time-series averages of the cross-sectional correlations in each week.

Table 8: Transformed-Variable Correlations

	ZAAII	ZCHANGEINTV	ZCVTREND	ZFGI	ZNETGT	ZVIX
ZAAII	1					
ZCTV	-0.048013	1				
ZVTCRYPTO	0.077129	0.019581	1			
ZFGI	0.398044	0.076148	0.109258	1		
ZNETGT	0.407226	-0.071213	-0.03084	0.330959	1	
ZVIX	-0.477414	0.024621	-0.030797	-0.220283	-0.360022	1

The Transformed Variable Correlations table presents correlations between six transformed variables: ZAAII, ZCTV, ZVTCRYPTO, ZFGI, ZNETGT and ZVIX. Key observations include the provided correlation table that illustrates the relationships between various variables. Notable correlations include a weak negative association between ZAAII and ZVIX (-0.477), suggesting that as ZAAII increases, ZVIX tends to decrease slightly. ZCTV displays a weak negative correlation with ZAAII (-0.048), indicating a subtle inverse relationship. ZVTCRYPTO exhibits minimal correlations with other variables, with the highest being a weak positive correlation with ZFGI (0.077). ZFGI demonstrates moderate positive correlations with ZAAII (0.398) and a weak positive correlation with ZNETGT (0.330), hinting at potential positive associations. ZNETGT reveals moderate positive correlations with ZAAII (0.407) and a weak negative correlation with ZCHANGEINTV (-0.071), suggesting potential relationships. ZVIX displays weak negative correlations with ZAAII (-0.477), ZCTV (0.024), ZFGI (-0.220), and ZCVTREND (-0.031). Figure 17 shows the cryptocurrency investor sentiment proxies of this study and Figure 18 shows the CIST graph and data statistics.

Figure 17: Cryptocurrency Investors Sentiment Proxies

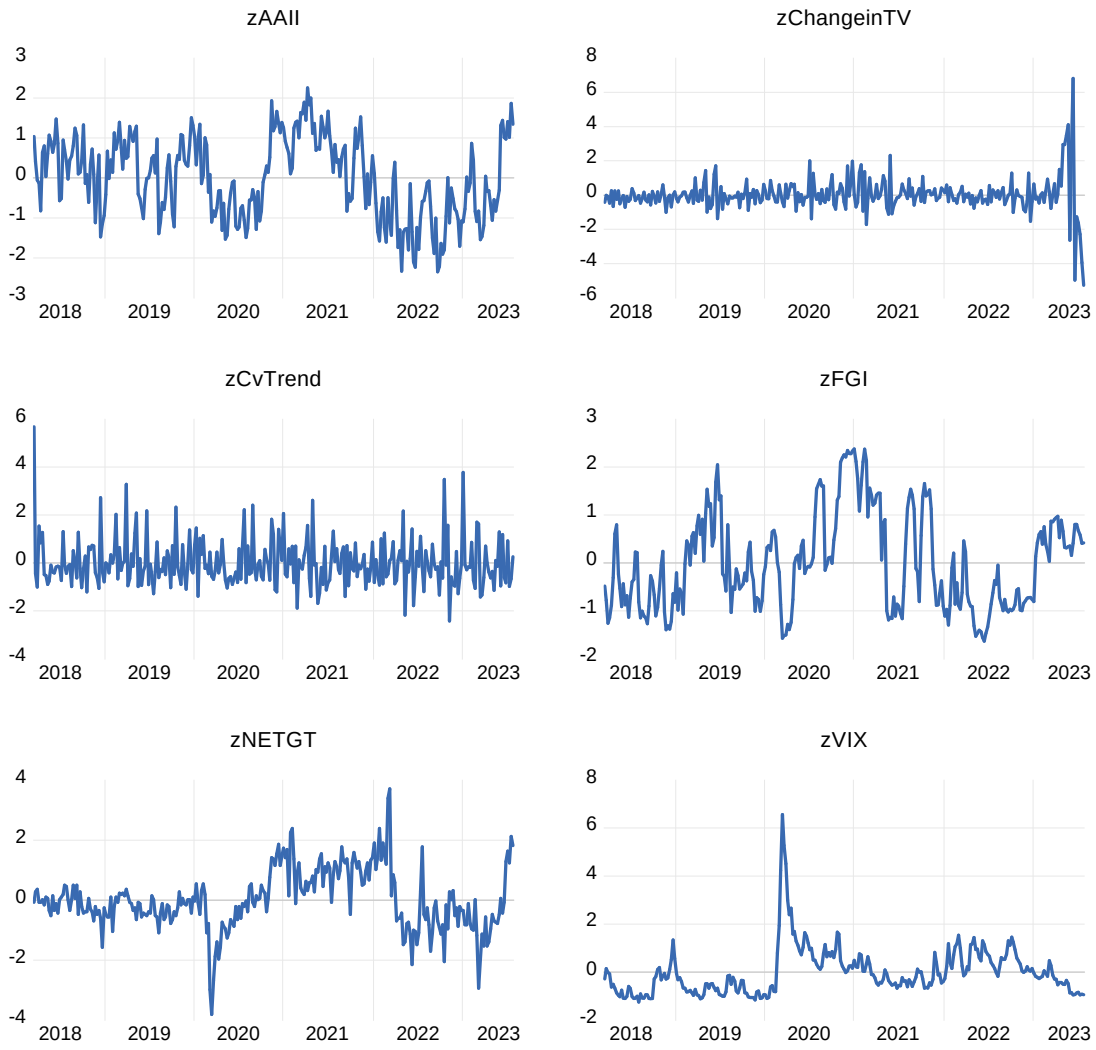
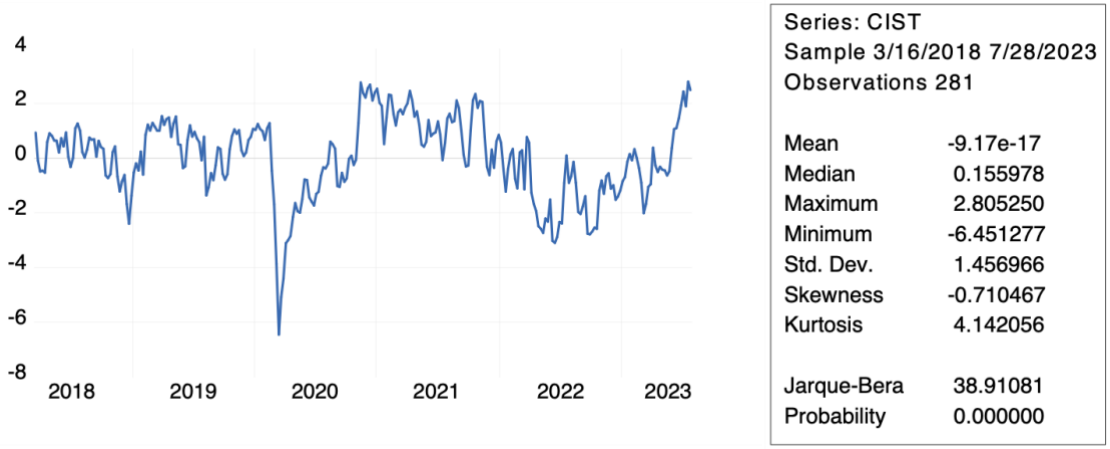


Figure 18: Cryptocurrency Investors Sentiment Index



In the second phase, the dependent (regressand) and independent (regressors) variables are defined in order to estimate ARDL model. The variables are:

Table 9: The Variables of ARDL Model

Independent Variables		Dependent Variable
EUR_USD		
rSPX		
lnSPGSCI	→	CIST
lnCVI		
CLU		
DSPBDMI		

As illustrated above in Table 9, the independent variables include the exchange rate of EUR/USD, return on the S&P 500 index, the natural logarithm of the S&P Goldman Sachs Commodity Index, the natural logarithm of the cryptocurrency volatility index, the Crude Oil WTI Futures prices, and the difference of S&P Cryptocurrency Broad Digital Market Index.

The ARDL model, provided by Pesaran et al. (2001) employs a bound testing framework to explore both long and short-term relationships among variables, complemented by an error correction model. A notable feature of this model is its ability for analyzing time series data with varying degrees of stationarity. Specifically, it accommodates series with I(0) and I(1) orders of stationarity within the analysis. However, it's important to highlight that this approach is not applicable to series possessing an I(2) order of stationarity. The study's test of stationarity results are discussed in the next section of the Unit Root Test Results.

5.2. Unit Root Test Results

In order to test for stationarity a unit root test using ADF was conducted in both level and first difference for the variables' time series. While preparing the analysis, the value of AIC has been controlled (considering the lowest value) in order to use the best ADF formula. ADF test results are shown below in Table 10.

Table 10: ADF Unit Root Test

Variables	I(0)	I(1)	Jarque-Bera	Test for Unit Root
CIST	-4.220685[N]	-13.19194 [N]	38.91081[a]	I(0)
	0.0000	0.0000		
EUR_USD	-1.760350[T]	-15.44059[T]	7.375273	I(1)
	0.7214	0.000		
RSPX	-11.86460[N]	-12.35797[N]	328.908[a]	I(0)
	0.000	0.000		
LNSPGSCI	-1.149110[I]	-12.96179[T]	1.578678	I(1)
	0.6967	0.000		
LNCVI	-5.704926[I]	-15.91041[N]	0.151031	I(0)
	0.0000	0.000		
CLU	-2.069371[T]	-8.536243[N]	4.608456	I(1)
	0.5601	0.0000		
DSPBDMI	-13.17079[N]	-17.73154[N]	770.2879[a]	I(0)
	0. 0000	0.0000		

[N] ADF tests include intercept, [T] ADF tests include trend and intercept and [N] ADF tests are conducted without trend or intercept.

[a] Indicates that the residuals are not normally distributed based on Jarque-Bera test.

The outcomes displayed in Table 10 explain the stationarity characteristics of the variables. Specifically, CIST, RSPX, LNCVI and DSPBDMI exhibit a stationary pattern at level I(0) at significance level of 1%. Conversely, EUR_USD, LNSPGSCI, and CLU demonstrate stationarity at first difference I(1), implying that a single differencing step is necessary to establish stationarity. This observed stationarity profile makes the dataset well-suited for ARDL estimation.

However, Jarque-Bera test of normality results suggest deviations from normal distribution for CIST, RSPX and LNSPBDMI with statistical significance indicating that the null hypothesis cannot be accepted.

In response to these considerations, Im & Schmidt (2008) and Meng et al. (2014) determined that the RALS method is a more suitable approach. In this approach the RALS-LM Unit Root test as an alternative is a better approach to test for stationarity. This test is suggested as a more appropriate choice when dealing with non-normally distributed time series data. The RALS-LM unbreakable, at

first break and at a second break is tested. The results of the RALS-LM tests are presented in the subsequent Table 11, Table 12 and Table 13.

Table 11: Unbreakable RALS-LM Unit Root Test Results

			Critical Values		
Variables	**ρ2**	$\tau_{RALS-LM}$	**1%**	**5%**	**10%**
CIST	0.878	-4.748	-3.532	-2.981	-2.705
RSPX	0.836	-12.717	-3.520	-2.962	-2.684
DSPBDMI	0.741	-13.079	-3.489	-2.918	-2.631

Based on the unbreakable RALS-LM test, the null hypothesis rejected at level 1% the variables CIST and RSPX do not have a unit root thus they are stationary at unbreakable RALS-LM.

Table 12: First-Break RALS-LM Unit Root Test Results

			Critical Values		
Variables	**ρ2**	$\tau_{RALS-LM}$	**1%**	**5%**	**10%**
CIST	0.875	-5.235	-3.531	-2.979	-2.703
RSPX	0.821	-7.635	-3.516	-2.956	-2.677
DSPBDMI	0.729	-8.284	-3.484	-2.912	-2.623

In the Table 12 results, the null hypothesis rejected at level 1% the variables CIST and RSPX do not have a unit root thus they are stationary at first break RALS-LM.

Table 13: Second-Break RALS-LM Unit Root Test Results

			Critical Values		
Variables	**ρ2**	$\tau_{RALS-LM}$	**1%**	**5%**	**10%**
CIST	0.869	-5.476	-3.529	-2.977	-2.700
RSPX	0.866	-12.354	-3.528	-2.975	-2.698
DSPBDMI	0.745	-13.923	-3.490	-2.920	-2.633

The outcomes of the second break RALS-LM test lead to the rejection of the null hypothesis for all variables. This compellingly indicates that all variables show stationarity.

5.3. ARDL Limit Test Model

The results obtained from the ADF and RALS-LM unit root tests have confirmed the stationarity properties of the variables employed in the analysis, establishing their integration at both I(0) and I(1) levels. Consequently, in light of these findings, it has been concluded that the ARDL model is the most appropriate choice for the analysis. The process of determining the optimal lag length selection has been diligently carried out, as evidenced by the employment of the AIC criterion as illustrated in Table 14.

Table 14: Lag Order Selection Criteria for ARDL Method

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-3144.114	NA	27.24348	23.16995	23.26275	23.20721
1	-1575.321	3045.303	0.000382	11.99501	12.73738*	12.29305
2	-1473.305	192.7816	0.000259	11.60518	12.99713	12.16400*
3	-1420.289	97.45580*	0.000252*	11.57565*	13.61717	12.39525
4	-1385.296	62.52339	0.000280	11.67865	14.36974	12.75903
5	-1348.620	63.64311	0.000308	11.76927	15.10994	13.11043
6	-1318.755	50.28874	0.000357	11.90996	15.90021	13.51191
7	-1290.353	46.36173	0.000420	12.06142	16.70124	13.92414
8	-1268.324	34.82470	0.000520	12.25974	17.54913	14.38324

According to AIC value the optimal lag length is 3.

Drawing upon Equation (11), ARDL model has been estimated as follows;

Figure 19: The Best 20 ARDL Models

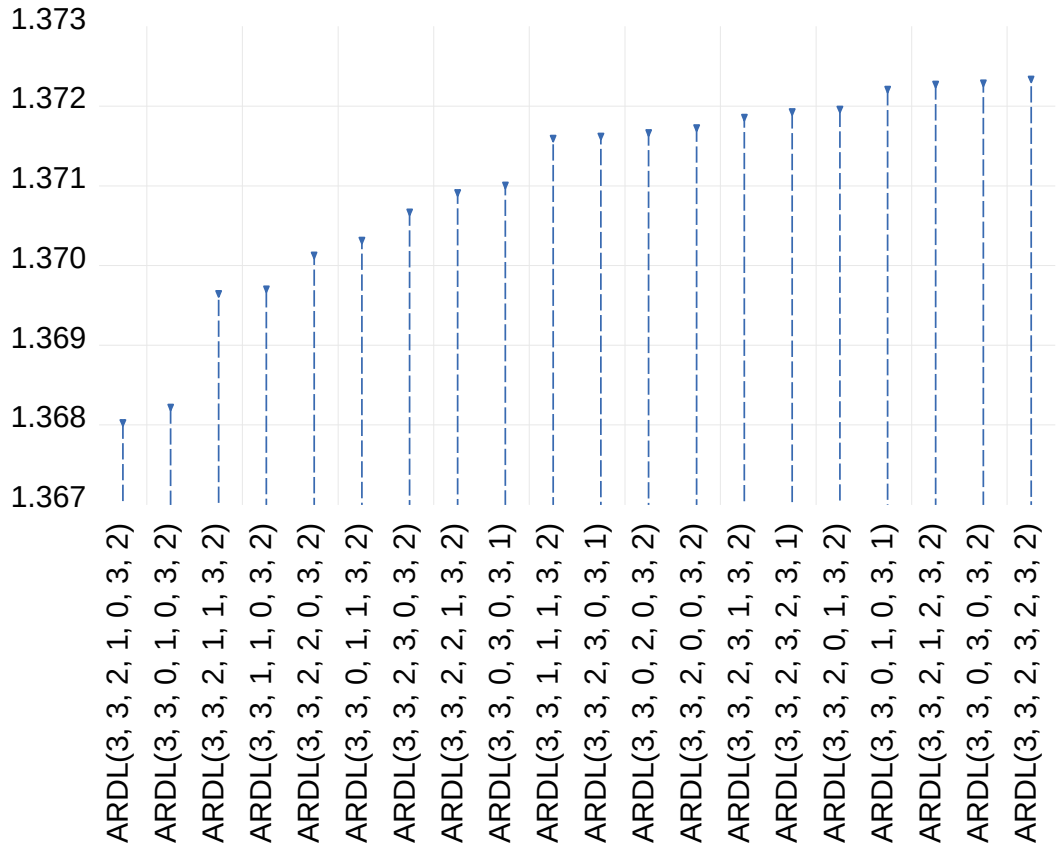


Figure 19 presents a listing of the top 20 models, ranked according to their AIC values, with lower AIC values indicating better model fit. Notably, within this study, the ARDL (3, 3, 2, 1, 0, 3, 2) model emerges as the most optimal ARDL model in terms of the AIC criterion. This signifies that among the considered models, ARDL (3, 3, 2, 1, 0, 3, 2) demonstrate the strongest balance between explanatory power and model complexity, making it the most suitable choice.

Table 15: ARDL (3, 3, 2, 1, 0, 3, 2) Model Results

Variables	Coefficient	t-Statistic	P-Value
CIST(-1)	0.623011	10.61523	0.0000
CIST(-2)	0.017200	0.258507	0.7962
CIST(-3)	0.181602	3.496804	0.0006
CLU	0.017714	1.763745	0.0790
CLU(-1)	0.003848	0.315582	0.7526
CLU(-2)	0.016453	1.260147	0.2088
CLU(-3)	-0.040766	-3.490019	0.0006
LNCVI	-0.466479	-2.289078	0.0229
LNCVI(-1)	0.355499	1.496540	0.1357
LNCVI(-2)	-0.223322	-1.143862	0.2537
EUR_USD	-3.364722	-1.025508	0.3061
EUR_USD(-1)	5.459617	1.708469	0.0888
DSPBDMI	0.000669	4.309727	0.0000
LNSPGSCI	0.226397	0.132635	0.8946
LNSPGSCI(-1)	-1.364106	-0.650436	0.5160
LNSPGSCI(-2)	-3.361391	-1.680526	0.0941
LNSPGSCI(-3)	4.998165	3.967229	0.0001
RSPX	0.132365	7.647400	0.0000
RSPX(-1)	0.108650	5.805203	0.0000
RSPX(-2)	0.037147	1.950006	0.0523

Table 16: ARDL (3, 3, 2, 1, 0, 3, 2) Model Diagnostic Test

R-squared	0.907009
Adjusted R-squared	0.899772
F-statistic	125.34 (0.00)*
Akaike Information Criterion	1.3717
Schwarz Criterion	1.6457
Durbin-Watson Statistic	2.0804
Jarque-Bera	0.5303 (0.767)*
Breusch-Pagan-Godfrey	0.9602 (0.511)*

*Probability is significant at 5% level.

Table 16 presents a comprehensive set of results that assess the performance and diagnostic aspects of the estimated model. The key findings are as follows:

- R-squared and Adjusted R-squared: The model achieved R-squared and Adjusted R-squared values of 0.9070 and 0.8998, respectively. This indicates that the model is capable of explaining approximately 91% of the variation in the dependent variable, suggesting a strong level of accuracy.

- F-Statistic: The F-statistic probability is reported as 0.000, which indicates that the model possesses significant explanatory power. This suggests that the included independent variables collectively contribute to explaining the variation in the dependent variable.

- Akaike Information Criterion (AIC) and Schwarz Criterion (BIC): The AIC and BIC values are recorded as 1.3717 and 1.6246, respectively. These values are the lowest among the considered models. Since lower AIC and BIC values indicate better model performance, this suggests that the estimated model is favored in terms of its goodness of fit and complexity.

- Durbin-Watson Statistic: The Durbin-Watson statistic value of 2.0804 is close to 2, implying that there is no significant evidence of autocorrelation in the residuals. This suggests that the model has accounted for temporal dependencies effectively.

- Jarque-Bera Test of Normality: The model's residuals were subjected to the Jarque-Bera test of normality, which indicated significant evidence of normality at a 5% significance level. This suggests that the assumption of normality for the residuals is met.

- Breusch-Pagan-Godfrey for Heteroskedasticity: The Breusch-Pagan-Godfrey test yielded a F test statistic of 0.9602, indicating that there is no significant problem of varying variance (heteroskedasticity) in the model's residuals.

Table 17: F-Bounds Test Results

F-statistic	**Value**	15.9101
	k	6
	Critical Values	
Significance	**I(0)**	**I(1)**
10%	1.99	2.94
5%	2.27	3.28
2.50%	2.55	3.61
1%	2.88	3.99

The assessment of cointegration relationships between variables using the bounds test involves using critical values in both upper I(1) and lower level I(0). The comparison of the calculated F-statistical value against these critical values aids in determining the presence of cointegration. Specifically, if the calculated F-statistic surpasses the upper critical value, as indicated in the critical value table, it signifies the existence of a cointegration relationship among the variables.

In the results of the bound test presented in Table 17, the computed F-statistic is 15.91. Importantly, this value exceeds the upper critical value corresponding to the 10% significance level. This outcome suggests that a cointegration relationship exists between the variables under consideration. In light of this observation, it can be inferred that there is a long-term relationship among the variables and this implies that the model is exhibiting some form of trend, seasonality, or other systematic variation over time.

CUSUM and CUSUM Q tests are used to investigate whether there is a structural break in the model for the period of analysis. Both CUSUM and CUSUM Q tests are used to identify points in time where there might be a structural break in the relationships between variables. It helps determine

if the model's parameters remain stable over time or if there are indications of changing relationships. The results of the CUSUM and CUSUM Q tests are shown in Figure 20 and Figure 21.

Figure 20: Cumulative Sum (CUSUM) Test

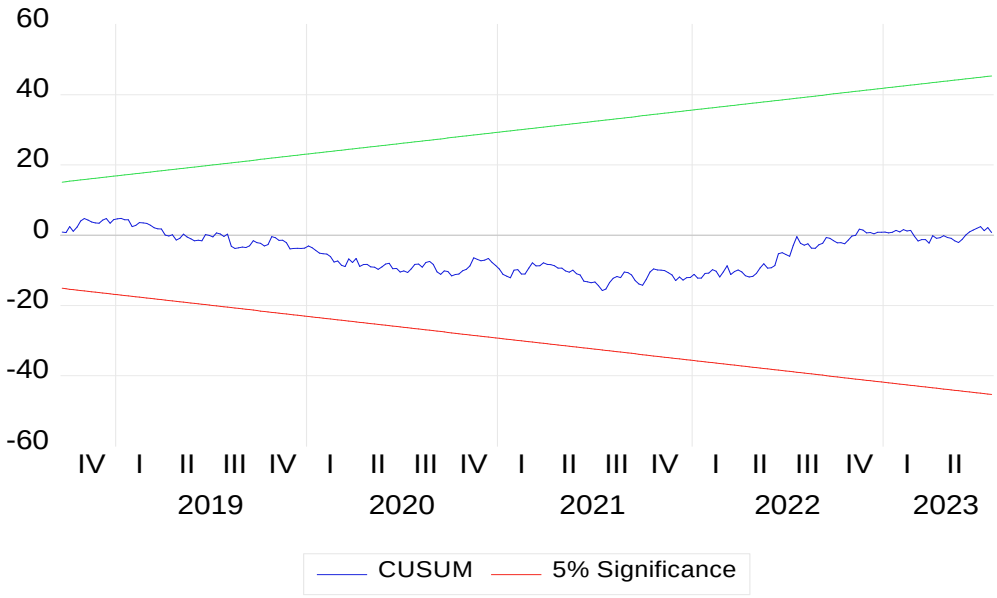
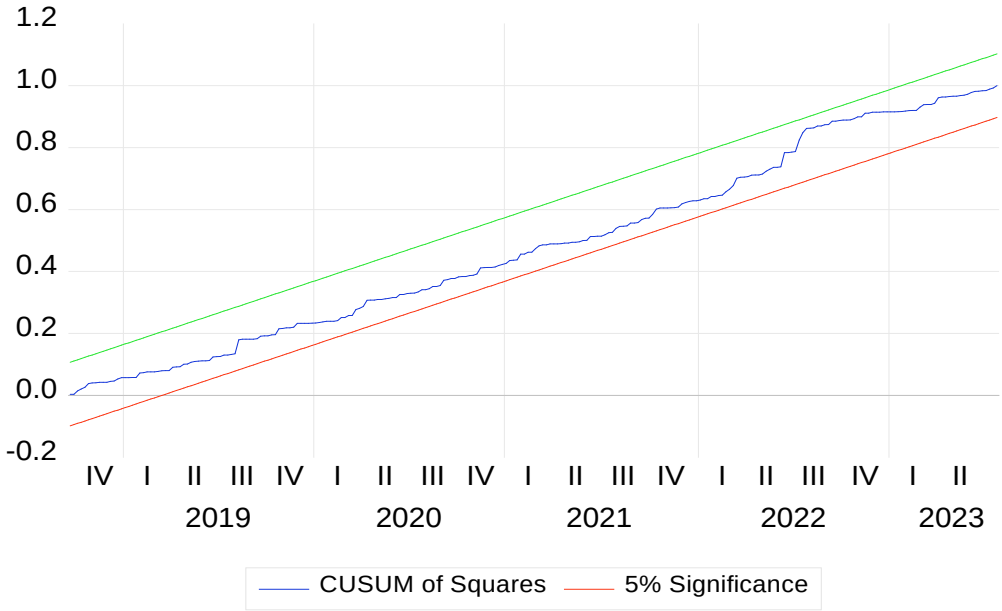


Figure 21: Cumulative Sum of Squares (CUSUM) Q Test



Following the diagnostic tests, it has been established that the model holds significance and is free from concerns such as autocorrelation, heteroskedasticity, and deviations from normal

distribution. Furthermore, no evidence of structural breaks within the model has been identified. With these findings in mind, the model conforms to the stipulations outlined in Equation 11, effectively partitioning investor sentiment into its rational and irrational components. This analysis enhances the validity of the model's results and allows for a more nuanced understanding of the factors driving investor attitudes and behaviors.

5.4. VAR Model Analysis Results

Upon the division of cryptocurrency investor sentiment into rational and irrational components in accordance with Baker and Wurgler (2006), the subsequent phase entails an examination of the impact exerted by these sentiments on CRIX return and volatility. This analysis is carried out through the utilization of a Vector Autoregression (VAR) model. Prior to embarking on this analytical endeavor, the initial step involves ascertaining the stationarity levels exhibited by the variables in question. The study used two tests of stationarity Augmented ADF test and Philips Perron PP. The results are presented in Table 18.

Table 18: Unit Roots Test Results

	ADF			**PP**		
Variables	**Intercept**	**Intercept and Trend**	**None**	**Intercept**	**Intercept and Trend**	**None**
sh-CIST	-12.808*	-12.799*	-12.831*	-12.516*	-12.488*	-12.542*
lo-CIST	-11.369*	-11.354*	-11.390*	-11.344*	-11.158*	-11.199*
rCRIX	-12.323*	-12.301*	-12.326*	-12.323*	-12.301*	-12.332*
vCRIX	-3.451*	-3.594*	-2.850*	-3.070*	-3.214	-2.757*

*Significant at the 5% level.

In Table 18, the results of the unit root tests for CRIX return, CRIX volatility, lo-CIST (rational sentiment), and sh-CIST (irrational sentiment) are presented. Based on these outcomes, it is evident that the variables have attained stationarity at the I(0) level. This fulfillment of stationarity requirements is crucial for conducting VAR model analysis, as it is imperative for all variables to possess stationarity characteristics.

After assessing the stationarity of the series, the impact of rational and irrational investor sentiment on CRIX return is elucidated in Equation 14, while their effect on CRIX volatility is

described in Equation 15. Prior to delving into VAR model analysis, it is essential to first ascertain the suitable lag length.

Table 19: Lag Order Selection Criteria for VAR Method

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-5462.369	NA	4.52e+12	40.49162	40.54493	-5462.369
1	-4906.632	1090.892	8.30e+10*	36.49357*	36.76012*	-4906.632
2	-4895.814	20.91398	8.63e+10	36.53196	37.01175	-4895.814
3	-4877.937	34.03247	8.51e+10	36.51805	37.21108	-4877.937
4	-4868.594	17.50976	8.94e+10	36.56736	37.47363	-4868.594
5	-4853.680	27.50791	9.02e+10	36.57541	37.69492	-4853.680
6	-4834.462	34.87732*	8.81e+10	36.55157	37.88432	-4834.462
7	-4826.239	14.67954	9.35e+10	36.60918	38.15517	-4826.239
8	-4816.504	17.08994	9.81e+10	36.65559	38.41482	-4816.504

As shown in Table 19, based on AIC value the optimal lag number is 1.

Table 20: Vector Autoregression Estimation

	LO_CIST	SH_CIST	RCRIX	VCRIX
LO_CIST(-1)	0.690068 (0.37494) [1.84048]	-0.801677 (0.34436) [-2.32803]	0.265335 (0.97416) [0.27237]	1050.004 (3136.05) [0.33482]
LO_CIST(-2)	0.016963 (0.07136) [0.23772]	0.003003 (0.06554) [0.04582]	-0.059497 (0.18541) [-0.32090]	385.7842 (596.864) [0.64635]
SH_CIST(-1)	1.335463 (0.39699) [3.36400]	-0.557167 (0.36461) [-1.52812]	0.088452 (1.03144) [0.08576]	2014.706 (3320.46) [0.60675]
SH_CIST(-2)	-0.538628 (0.36035) [-1.49472]	0.685706 (0.33096) [2.07186]	-0.147194 (0.93626) [-0.15721]	-476.7109 (3014.05) [-0.15816]
RCRIX(-1)	-0.034416 (0.02687) [-1.28071]	0.040896 (0.02468) [1.65699]	0.258531 (0.06982) [3.70287]	-147.1658 (224.765) [-0.65476]

Table 20 (continued)

	LO_CIST	SH_CIST	RCRIX	VCRIX
RCRIX(-2)	-0.011028	0.005135	0.010540	173.5031
	(0.02428)	(0.02230)	(0.06307)	(203.053)
	[-0.45425]	[0.23031]	[0.16711]	[0.85447]
VCRIX(-1)	-2.59E-06	2.61E-06	1.58E-05	-0.101722
	(7.4E-06)	(6.8E-06)	(1.9E-05)	(0.06180)
	[-0.35057]	[0.38433]	[0.82242]	[-1.64602]
VCRIX(-2)	1.02E-05	-9.63E-06	3.33E-06	-0.048490
	(7.4E-06)	(6.8E-06)	(1.9E-05)	(0.06153)
	[1.38922]	[-1.42548]	[0.17429]	[-0.78811]
C	0.023790	-0.014884	0.190220	-60.01199

To conduct impulse-response analysis within the VAR model, model stability is a prerequisite. Specifically, the characteristic roots of the model are anticipated to lie within the unit circle. Figure 22 visually illustrates the characteristic roots of the estimated VAR model plotted on the unit circle. Additionally, Table 20 provides the numerical values of the inverse roots of the characteristic polynomial for the VAR model. These evaluations contribute to ensuring the stability of the model, an essential condition for meaningful impulse-response analysis.

Figure 22: Inverse Roots of AR Characteristic Polynomial

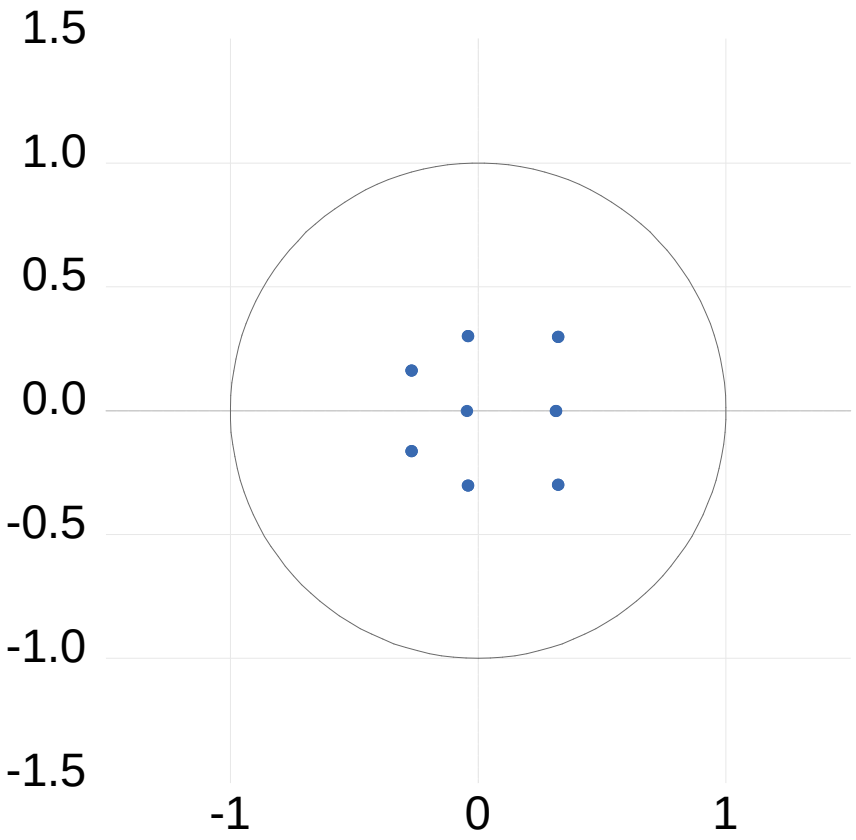


Figure 22 shows that there no root lies outside the unit circle. Thus, VAR satisfies the stability condition.

Table 21: Roots of Characteristic Polynomial of the VAR Model

Root	Modulus
0.322106 - 0.299342i	0.439725
0.322106 + 0.299342i	0.439725
-0.269724 - 0.163026i	0.315164
-0.269724 + 0.163026i	0.315164
0.312708	0.312708
-0.041087 - 0.302038i	0.304820
-0.041087 + 0.302038i	0.304820
-0.045586	0.045586

Table 21 shows that all roots are less than 1, which means that the estimated VAR model fulfills the stability and stationarity conditions. In this context, it is appropriate to complete the analysis by calculating impulse-response functions.

5.5. Impact Response Analysis Results

In VAR model analysis, the interpretation of coefficients within the regression equation can be challenging, often falling short of capturing the full impact of independent variables. In response, impulse response analysis emerges as a valuable tool to illuminate how variables react in the face of shocks. Impulse responses encapsulate the dynamic behaviors of variables within a model when confronted with sudden disturbances. This methodology seeks to clarify how a specific variable responds to an external shock or disruption.

Illustrated through generalized impulse-response functions, these graphs present a clear depiction of these variable reactions. These graphical representations consist of both horizontal and vertical axes. The horizontal axis delineates the timeline, showcasing the duration of the variable's response post-shock. Simultaneously, the vertical axis quantifies the magnitude of the response. Monte Carlo methods were used to establish confidence bands around the mean response.

Below, the following figures explain the responses of CRIX return and volatility to a standard deviation shock in both rational and irrational cryptocurrency investor sentiments. The dashed lines on each graph depict the upper and lower 95% confidence intervals. When both upper and lower bounds have the same sign, the response becomes statistically significant.

Figure 23: Responses of Return on CRIX Index to Shock of Rational Sentiment

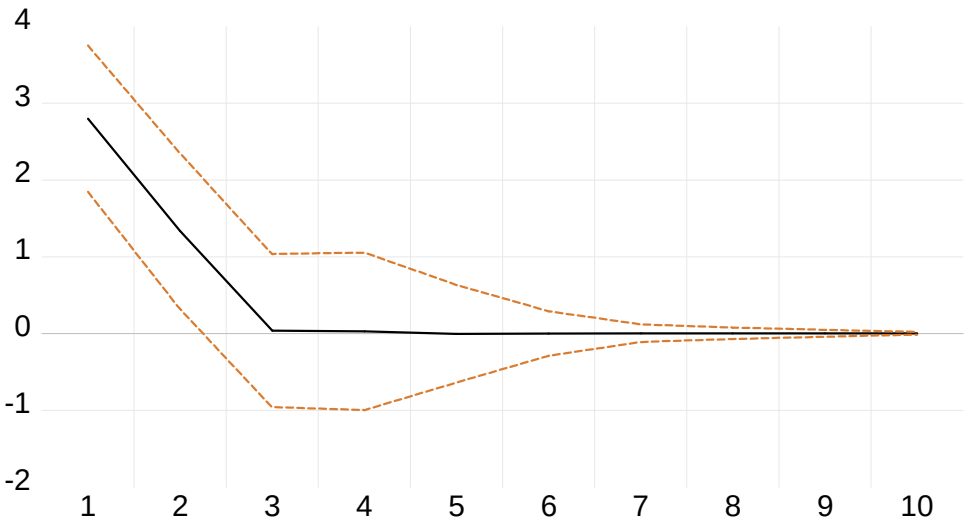


Figure 24: Responses of Return on CRIX Index to Shock of Irrational Sentiment

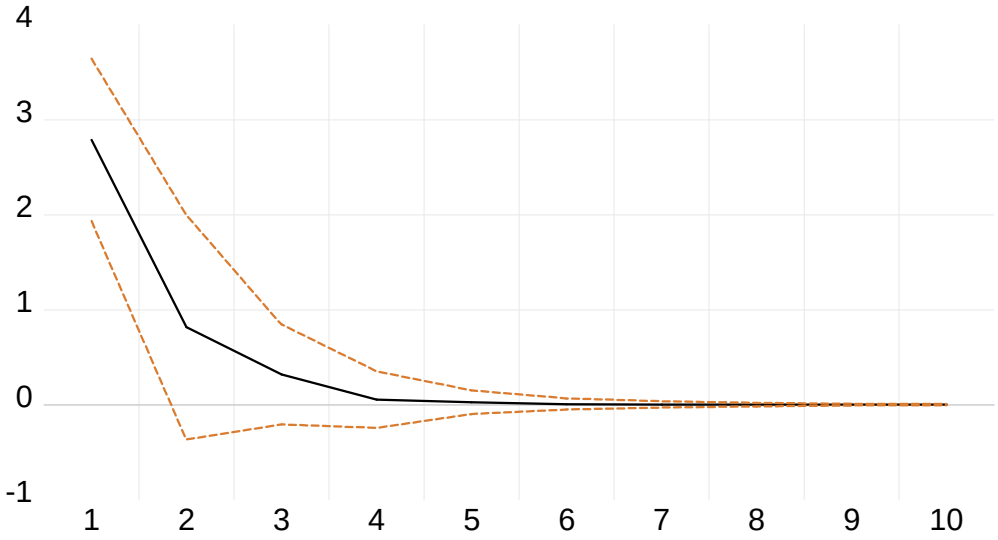


Figure 25: Responses of Volatility of CRIX Index to Shock of Rational Sentiment

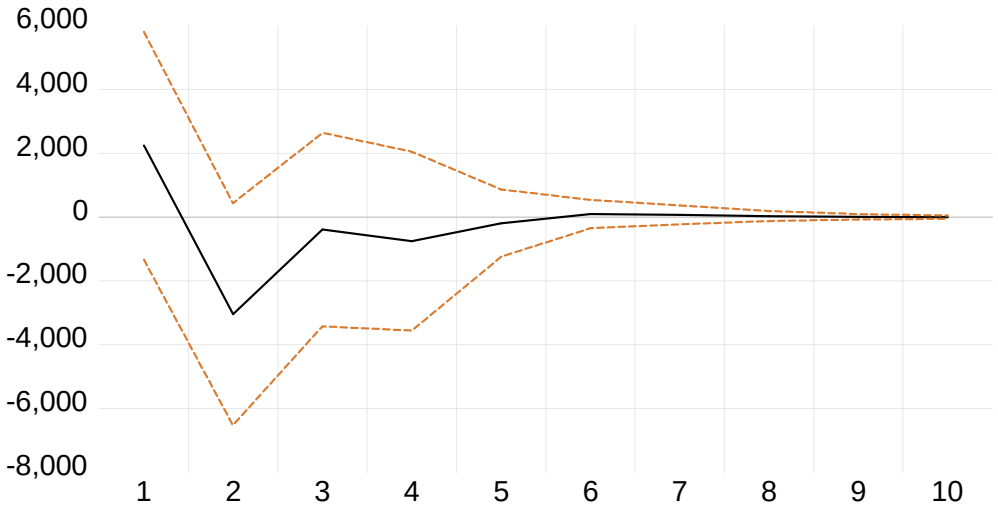


Figure 26: Responses of Volatility of CRIX Index to Shock of Irrational Sentiment

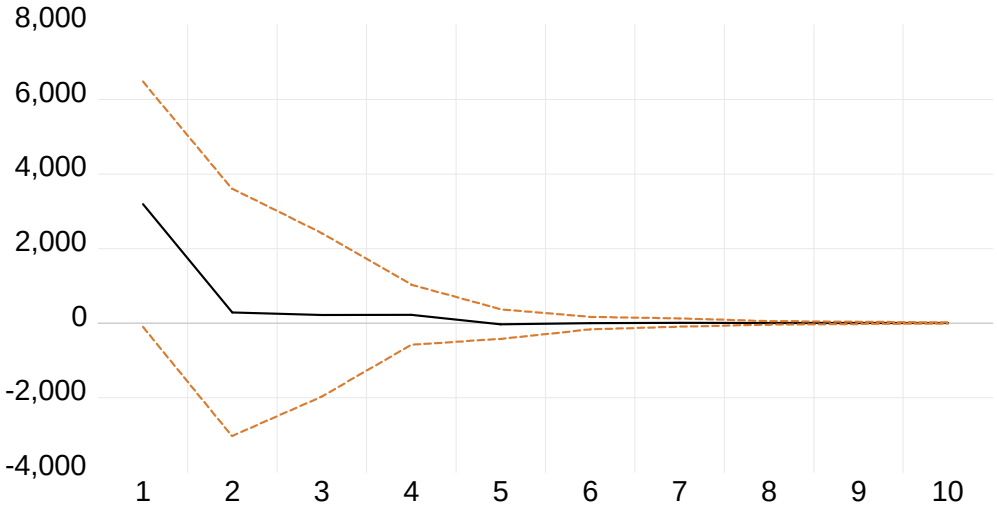


Figure 23 shows the response of CRIX index return to a standard deviation shock in rational investor sentiment, Figure 24 shows the response of CRIX index return to a standard deviation shock occurring in irrational investor sentiment, Figure 25 shows CRIX index volatility in rational investor sentiment. In Figure 26, the response of CRIX index volatility to a standard deviation shock in irrational investor sentiment is shown.

CONCLUSION AND RECOMMENDATIONS

The aim of this study is to investigate the impact of cryptocurrency investor sentiment on cryptocurrency index (CRIX) returns and volatility. To achieve this, a dataset covering the period from March 2018 to July 2023, at a weekly frequency, was analyzed. Cryptocurrency investor sentiment has been measured using six different sentiment proxies: AAII Investor Sentiment Survey Bull-Bear Spread, CBOE Volatility Index (VIX), Crypto Fear & Greed Index, Cryptocurrencies Trading Volume, Tweet Volume of Cryptocurrency hashtags, and Net positive and negative term frequency in Google Trends.

Other variables utilized to decompose investor sentiment into rational and irrational components varied from social platform data to financial market data. These variables included Exchange Rates of EUR/USD, S&P 500 returns, S&P Goldman Sachs Commodity Index, Cryptocurrency Volatility Index, Crude Oil WTI Futures prices, and S&P Cryptocurrency Broad Digital Market Index.

In contrast to previous studies, the ARDL method was employed to differentiate sensitivity. Subsequently, the effects of rational and irrational investor sentiment on CRIX returns and volatility were estimated using VAR models. The findings were then visually represented using Impact Response Analysis, and the resulting graphs are presented in Figure 18, Figure 19, Figure 20 and Figure 21, respectively.

Figure 23 illustrates the impulse responses resulting from a standard deviation shock of rational cryptocurrency investors' sentiment on the returns of the CRIX index. The graph reveals significant dynamics in the CRIX index returns following a shock in rational sentiment. Notably, the impact of the rational sentiment shock triggers a substantial decline in the CRIX index returns, persisting for four periods before gradually regaining stability over the ensuing timeframe after the sixth term. This finding underscores the pronounced influence of rational sentiment on the performance of the CRIX index. The immediate and sustained reduction in return highlights the cryptocurrency market's sensitivity to shifts in investors' rational outlook.

In Figure 24, the impulse responses stemming from a standard deviation shock of irrational cryptocurrency investors' sentiment on the volatility of the CRIX index display a noteworthy dynamic. Similar to the response observed with rational sentiment, a shock in irrational sentiment leads to a substantial decline in the CRIX index returns. However, in this case, the effect is slightly

shorter, lasting for two periods before gradual stabilization over subsequent periods. This observation reaffirms the significant influence of irrational sentiment on the CRIX index's performance. The rapid and sustained reduction in volatility underscores the cryptocurrency market's susceptibility to shifts in investors' irrational sentiment.

Comparing the two figures, it becomes evident that while both rational and irrational sentiment play substantial roles in shaping the cryptocurrency market, rational sentiment appears to exert a stronger impact. This discrepancy indicates that the dynamics of cryptocurrency markets, particularly the returns, are more closely intertwined with rational sentiment than with its irrational counterpart. These insights shed light on the intricate relationship between investor sentiment and the cryptocurrency market's behavior and its sensitivity to outsider factors.

As for the volatility of the CRIX index, Figure 25 illustrates the impulse responses stemming from a standard deviation shock of rational cryptocurrency investors' sentiment. The horizontal axis of the graph represents rational cryptocurrency investors' sentiment, while the vertical axis represents the volatility of the CRIX index.

The graph showcases the substantial impact of a standard deviation shock in rational investor sentiment on the CRIX index volatility. Initially, this shock triggers a negative effect on CRIX index volatility, which persists for a span of two periods. Following this, the volatility experiences a minor uptick, succeeded by a subsequent decline extending for one period, spanning up to the fourth term. Subsequently, the impact gradually vanished. This observed pattern underscores the noteworthy significance of CRIX index volatility's response to shocks induced by shifts in rational investor sentiment. The initial reduction, followed by a brief surge and ensuing decline in volatility, firmly substantiates the intricate interplay between rational sentiment and market volatility. Importantly, the presence of a four-period damping effect further accentuates the profound influence of rational sentiment shocks on the dynamics of CRIX index volatility.

Figure 26 illustrates the impulse responses caused by a standard deviation shock of irrational cryptocurrency investors' sentiment on the volatility of the CRIX index. The graph unveils significant dynamics in CRIX index volatility subsequent to an irrational sentiment shock displaying significant negativity in the first month followed by insignificance. In a parallel pattern to the impact of rational sentiment on CRIX volatility, the shock's effect is discernibly swift, spanning two periods. However, beyond the fourth period, the response to irrational investor sentiment gradually subsides. These outcomes align with behavioral finance theory, suggesting links between irrational sentiment and market dynamics. The results indicate significant associations between investor sentiment and both the CRIX index returns and volatility. These findings suggest that irrational sentiment triggers market

volatility, consequently reducing the mean variance ratio and leading to a decrease in the CRIX index.

Traditional financial theories posit that individuals act as rational decision-makers, basing their investment choices on a comprehensive analysis of available market information. However, previous studies have unveiled the limitations of these conventional theories in explaining market anomalies and price movements, particularly neglecting the irrational factors that influence certain investor decisions. This discrepancy paved the way for the emergence of behavioral finance, a field that emphasizes the role of human emotions and intuitions in shaping decision-making processes.

The advent of the cryptocurrency market, which has emerged as a robust competitor to central and traditional financial markets, has escalated the need to revisit prevailing financial paradigms. Behavioral finance theories propose that individuals' investment decisions are driven not solely by rational factors, but also by their emotional responses. This perspective has gained prominence in deciphering the intricacies of cryptocurrency market dynamics through the lens of behavioral finance. However, it's important to acknowledge that models within behavioral finance do have limitations, predominantly centered around elements of irrationality.

In earlier studies exploring the impact of investor sentiment—characterized as either excessively optimistic or pessimistic—on stock markets, sentiment was often perceived as existing somewhere between complete irrationality and absolute rationality. While labeling investor sentiment as entirely irrational implies that investors base their investment decision on rumors, characterizing it as completely rational suggests that trading occurs solely based on factual information. Both of these extreme viewpoints fail to fully interpret the complexities of real-world investor behavior.

As a response, there emerged a need for a more nuanced model that acknowledges the interplay between rational and irrational sentiments inherent in human decision-making. This necessitated subsequent research efforts aimed at dissecting investor sentiment into distinct rational and irrational components. This study contributes to this analytical framework by striving to elucidate the intricate interplay between rational decision-making and emotional influences across the broader landscape of financial markets.

The study's outcomes establish that both rational and irrational sentiments among investors wield a substantial influence on the returns and volatility of the cryptocurrency index. These findings align with prior investigations which classify and distinguish investor sentiment into rational and irrational categories (Verma & Soydemir, 2009; Demirel 2021; Tseng et al., 2022).

The research casts a spotlight on the nuanced duality inherent in cryptocurrency investors' behaviors. Investment decisions materialize through both diligent analysis and the sway of market rumors. As a consequence, individuals contemplating cryptocurrency investments must remain attuned to the interplay between rational and irrational elements that impact cryptocurrency returns and volatility.

Upon scrutinizing existing literature, a prevalent focus emerges on singular cryptocurrencies, particularly Bitcoin, due to its seniority and dominant market share. However, the application of the CRIX cryptocurrency index, representative of over 70% of the market, renders findings more reflective of reality. Furthermore, diverse variables have been employed to dissect investor sentiment. The absence of consensus regarding variable selection beckons future studies to explore the integration of macroeconomic and geopolitical factors into analyses, unraveling their influence on cryptocurrency market dynamics.

While this study employs a composite six-factor index to gauge investor sentiment, forthcoming research endeavors hold promise in crafting sentiment indicators via surrogate variables or leveraging artificial intelligence mechanisms and intricate calculations. Such advancements could elevate precision in identifying the impact on cryptocurrency returns and volatility, thereby illuminating unexplored facets within the realm of behavioral finance.

These outcomes provide benefits to various stakeholders, including the academic community, where efforts are paid on understanding and solving the complexities of cryptocurrency dynamics. Researchers and scholars interested in the role of behavioral finance in cryptocurrency market dynamics would find value in exploring the relationship between investor sentiment and cryptocurrency markets. This study presents a novel cryptocurrency investor sentiment index, that researchers can utilize in different research objectives and variables.

Additionally, investors in both cryptocurrency markets and the wider financial arena can obtain valuable insights to shape their investment decisions by understanding how investor sentiment influences market behavior. The study demonstrates both the rational and irrational impacts on cryptocurrency market dynamics, that would encourage more investors to enter the market and integrate cryptocurrencies into their financial portfolios. Moreover, regulators and policymakers are important stakeholders in the cryptocurrency domain as well. Given the undeniable existence of cryptocurrencies, this study encourages regulators and policymakers in the financial sector to increase their efforts to maintain a more trustworthy cryptocurrency trading environment, and to ensure compliance with the regulatory frameworks that protect investors and achieve market stability.

Finally, future studies possess the potential to yield profound contributions, particularly within the landscape of cryptocurrency markets. By delving deeply into the intricate dynamics of investor sentiment and its multifaceted influence on these emerging markets, these endeavors will undoubtedly enrich our comprehension of investor behavior while facilitating an integration of behavioral finance with traditional finance theories.

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APPENDICES

Appendix 1: List Of The Top 100 Ranked Cryptocurrencies

Rank	Name	Symbol	Rank	Name	Symbol	Rank	Name	Symbol
1	Bitcoin	BTC	35	Mantle	MNT	68	Pepe	PEPE
2	Ethereum	ETH	36	Arbitrum	ARB	69	Chiliz	CHZ
3	Tether USDt	USDT	37	Cronos	CRO	70	KuCoin Token	KCS
4	BNB	BNB	38	VeChain	VET	71	Rocket Pool	RPL
5	XRP	XRP	39	NEAR Protocol	NEAR	72	Gala	GALA
6	USD Coin	USDC	40	Quant	QNT	73	Curve DAO Token	USDP
7	Dogecoin	DOGE	41	Maker	MKR	74	Pax Dollar	CRV
9	Solana	SOL	42	Optimism	OP	75	Klaytn	KLAY
10	TRON	TRX	43	The Graph	GRT	76	Zcash	ZEC
11	Polygon	MATIC	44	Aave	AAVE	77	IOTA	MIOTA
12	Shiba Inu	SHIB	45	XDC Network	XDC	78	PAX Gold	PAXG
13	Litecoin	LTC	46	Algorand	ALGO	79	Tether Gold	XAUt
14	Polkadot	DOT	47	Axie Infinity	AXS	80	Frax Share	RUNE
15	Dai	DAI	48	Stacks	STX	81	THORChain	FXS
16	Toncoin	TON	49	The Sandbox	SAND	82	Terra Classic	LUNC
17	Wrapped Bitcoin	WBTC	50	EOS	EGLD	83	Mina	MINA
18	Bitcoin Cash	BCH	51	Multivers X	EOS	84	BitTorrent (New)	BTT
19	Avalanche	AVAX	52	Immutable	IMX	85	Sui	SUI
20	Chainlink	LINK	53	Tezos	XTZ	86	Casper	CSPR
21	Stellar	XLM	54	ApeCoin	APE	87	Compound	COMP
22	UNUS SED LEO	LEO	55	Theta Network	THETA	88	Huobi Token	HT
23	Uniswap	UNI	56	USDD	USDD	89	GMX	GMX
24	Binance USD	BUSD	57	Decentraland	MANA	90	GateToken	GT
25	TrueUSD	TUSD	58	Bitcoin SV	BSV	91	Trust Wallet Token	TWT
26	Cosmos	ATOM	59	Fantom	FTM	92	Dash	DASH
27	Monero	XMR	60	Synthetix	SNX	93	Gemini Dollar	GUSD
28	OKB	OKB	61	Injective	INJ	94	Nexo	NEXO
29	Ethereum Classic	ETC	62	Render	RNDR	95	Bone ShibaSwap	BONE
30	Hedera	HBAR	63	Neo	NEO	96	Arweave	AR
31	Filecoin	FIL	64	Flow	FLOW	97	dYdX	DYDX
32	Internet Computer	ICP	65	Kava	KAVA	98	APENFT	NFT
33	Aptos	APT	66	eCash	XEC	99	WOO Network	WOO
34	Lido DAO	LDO	67	Conflux	CFX	100	Zilliqa	ZIL

Appendix 2: Top 100 Countries in Cryptocurrency Ownership

No	Country	Population	Ownership	Ownership Percentage
1	United Arab Emirates	9,516,871	2,633,001	27.67%
2	Vietnam	98,858,950	20,945,706	21.19%
3	United States	339,996,563	48,820,972	14.36%
4	Iran	89,172,767	12,000,000	13.46%
5	Philippines	117,337,368	15,761,549	13.43%
6	Singapore	6,014,723	664,627	11.05%
7	Ukraine	36,744,634	3,885,037	10.57%
8	Venezuela	28,838,499	2,970,365	10.30%
9	South Africa	60,414,495	6,041,450	10.00%
10	El Salvador	6,364,943	636,494	10.00%
11	Thailand	71,801,279	6,902,630	9.61%
12	Brazil	216,422,446	15,585,940	7.20%
13	Germany	83,294,633	5,632,393	6.76%
14	Pakistan	240,485,658	15,879,216	6.60%
15	India	1,428,627,663	93,537,015	6.55%
16	Turkey	85,816,199	5,605,841	6.53%
17	Russia	144,444,359	8,749,780	6.06%
18	Nigeria	223,804,632	13,261,259	5.93%
19	United Kingdom	67,736,802	3,888,092	5.74%
20	Argentina	45,773,884	2,620,664	5.73%
21	Kenya	55,100,586	2,796,738	5.08%
22	Morocco	37,840,044	1,921,753	5.08%
23	Colombia	52,085,168	2,582,764	4.96%
24	France	64,756,584	3,056,511	4.72%
25	Nepal	30,896,590	1,410,342	4.56%
26	Saudi Arabia	36,947,025	1,682,561	4.55%
27	Indonesia	277,534,122	12,205,132	4.40%
28	Canada	38,781,291	1,656,474	4.27%
29	China	1,425,671,352	59,134,683	4.15%
30	Japan	123,294,513	5,096,970	4.13%
31	South Korea	51,784,059	2,120,185	4.09%
32	Ecuador	18,190,484	695,148	3.82%
33	Israel	9,174,520	332,622	3.63%

No	Country	Population	Ownership	Ownership Percentage
34	Mexico	128,455,567	4,484,795	3.49%
35	Cambodia	16,944,826	582,232	3.44%
36	Spain	47,519,628	1,452,158	3.06%
37	Egypt	112,716,598	3,423,723	3.04%
38	Belarus	9,498,238	285,325	3.00%
39	Malaysia	34,308,525	1,011,146	2.95%
40	Poland	41,026,067	1,200,394	2.93%
41	Netherlands	17,618,299	489,182	2.78%
42	Australia	26,439,111	726,241	2.75%
43	Portugal	10,247,605	276,185	2.70%
44	Peru	34,352,719	881,811	2.57%
45	Bangladesh	172,954,319	4,318,791	2.50%
46	Italy	58,870,762	1,469,892	2.50%
47	Lebanon	5,353,930	132,845	2.48%
48	Hong Kong	7,491,609	180,991	2.42%
49	Tanzania	67,438,106	1,621,947	2.41%
50	Georgia	3,728,282	89,055	2.39%
51	Taiwan	23,923,276	567,594	2.37%
52	Palestine	5,371,230	126,293	2.35%
53	Honduras	10,593,798	241,679	2.28%
54	Bulgaria	6,687,717	150,302	2.25%
55	Algeria	45,606,480	1,022,874	2.24%
56	Ghana	34,121,985	759,162	2.22%
57	Seychelles	107,660	2,347	2.18%
58	Chile	19,629,590	421,831	2.15%
59	Dominican Republic	11,332,972	243,632	2.15%
60	Moldova	3,435,931	72,498	2.11%
61	Tunisia	12,458,223	257,623	2.07%
62	Jamaica	2,825,544	58,011	2.05%
63	Bolivia	12,388,571	252,801	2.04%
64	Switzerland	8,796,669	177,525	2.02%
65	Somalia	18,143,378	351,706	1.94%
66	Czech Republic	10,495,295	200,955	1.91%
67	Sri Lanka	21,893,579	416,339	1.90%
68	Iraq	45,504,560	845,138	1.86%

No	Country	Population	Ownership	Ownership Percentage
69	Mozambique	33,897,354	630,991	1.86%
70	Ivory Coast	28,873,034	537,819	1.86%
71	Serbia	7,149,077	131,775	1.84%
72	Ethiopia	126,527,060	2,259,197	1.79%
73	Belize	410,825	7,366	1.79%
74	Costa Rica	5,212,173	92,614	1.78%
75	Kazakhstan	19,606,633	341,971	1.74%
76	Armenia	2,777,970	48,266	1.74%
77	DR Congo	102,262,808	1,758,920	1.72%
78	Kyrgyzstan	6,735,347	115,621	1.72%
79	Cameroon	28,647,293	481,930	1.68%
80	Romania	19,892,812	333,758	1.68%
81	Bahamas	412,623	6,638	1.61%
82	Sweden	10,612,086	170,092	1.60%
83	Jordan	11,337,052	178,935	1.58%
84	Estonia	1,322,765	20,564	1.55%
85	Greece	10,341,277	157,757	1.53%
86	Myanmar	54,577,997	806,426	1.48%
87	Rwanda	14,094,683	208,229	1.48%
88	Slovakia	5,795,199	85,537	1.48%
89	Uzbekistan	35,163,944	512,332	1.46%
90	Guatemala	18,092,026	263,422	1.46%
91	Belgium	11,686,140	168,588	1.44%
92	Mongolia	3,447,157	49,553	1.44%
93	Zimbabwe	16,665,409	238,138	1.43%
94	Finland	5,545,475	77,263	1.39%
95	Laos	7,633,779	105,579	1.38%
96	Barbados	281,995	3,856	1.37%
97	Uruguay	3,423,108	46,251	1.35%
98	Albania	2,832,439	38,109	1.35%
99	Austria	8,958,960	120,181	1.34%
100	Hungary	10,156,239	134,603	1.33%

Appendix 3: List of OECD Member Countries

no	Country	Joining Date
1	Australia	June 7, 1971
2	Austria	September 29, 1961
3	Belgium	September 13, 1961
4	Canada	April 10, 1961
5	Chile	May 7, 2010
6	Colombia	April 28, 2020
7	Costa Rica	May 25, 2021
8	Czech Republic	December 21, 1995
9	Denmark	May 30, 1961
10	Estonia	December 9, 2010
11	Finland	January 28, 1969
12	France	August 7, 1961
13	Germany	September 27, 1961
14	Greece	September 27, 1961
15	Hungary	May 7, 1996
16	Iceland	June 5, 1961
17	Ireland	August 17, 1961
18	Israel	September 7, 2010
19	Italy	March 29, 1962
20	Japan	April 28, 1964
21	Korea	December 12, 1996
22	Latvia	July 1, 2016
23	Lithuania	July 5, 2018
24	Luxembourg	December 7, 1961
25	Mexico	May 18, 1994
26	Netherlands	November 13, 1961

no	Country	Joining Date
27	New Zealand	May 29, 1973
28	Norway	July 4, 1961
29	Poland	November 22, 1996
30	Portugal	August 4, 1961
31	Slovak Republic	December 14, 2000
32	Slovenia	July 21, 2010
33	Spain	August 3, 1961
34	Sweden	September 28, 1961
35	Switzerland	September 28, 1961
36	Türkiye	August 2, 1961
37	United Kingdom	May 2, 1961
38	United States	April 12, 1961

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Alongside her academic achievements, Basma has established a successful professional career in the field of finance. She served as the Chief of Finance at the Palestinian Center for Human Rights, demonstrating her proficiency in leadership and accounting. In 2019, she began her PhD studies in the Department of Business Administration at Karadeniz Technical University. Basma is fluent in Arabic and English, and proficient in Turkish.

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