Cryptocurrency volatility, volatility spillovers and the effect of global investor sentiment

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GLOSSARY OF ACRONYMS

AIC	Akaike's Information Criterion
ALTCOINS	Alternative cryptocurrencies
AAII	American Association of Individual Investors
ADCC-GARCH	Asymmetric Dynamic Conditional Correlation GARCH
ADF	Augmented Dickey-Fuller
ARCH	Autoregressive Conditional Heteroskedasticity
ARMA	Autoregressive–moving-average
BTC	Bitcoin
BCI	Bloomberg Commodity Index
CAPM	Capital Asset Pricing Model
CBDC’s	Central Bank Digital Currencies
CCC-GARCH	Constant Conditional Correlation GARCH
CRIX	Cryptocurrency Index
DeFi	Decentralised Finance
DCC-GARCH	Dynamic Conditional Correlation GARCH
EMH	Efficient Market Hypothesis
ETH	Ethereum
EGARCH	Exponential GARCH
FOMO	Fear Of Missing Out
FRA	Factor Regression Analysis

GARCH	Generalised Autoregressive Conditional Heteroskedasticity
GED	Generalised Error Distribution
GJR-GARCH	Glosten Jagannathan Runkle – GARCH
HQIC	Hannan–Quinn Information Criterion
ICO	Initial Coin Offering
IPO	Initial Public Offering
II	Investor Intelligence
KPSS	Kwiatkowski–Phillips–Schmidt–Shin
LB	Ljung-Box
PCA	Principal Component Analysis
SBIC	Schwarz's Bayesian Information Criterion
S&P 500	Standard & Poor’s 500 Index
TY	Toda-Yamamoto
USD	United States Dollar
USDI	US Dollar Index
VAR	Vector Autoregression
VIX	Volatility Index

ABSTRACT

Cryptocurrencies continue to enjoy attention from investors and policymakers and their growing usage has fortified this attention. However, it is their volatility and the volatility spillovers among the cryptocurrencies have been most intriguing. Various factors such as susceptibility to speculative pressures, uncertainty regarding their valuation, and the lack of regulation have been forwarded as possible explanations. However, these factors have not fully explained cryptocurrency volatility and volatility spillovers, suggesting that there could be other salient factors. In this study, investor sentiment, described as the noise-driven investors' perception of the risk and cash flows of an asset, was forwarded as one of those salient factors.

Specifically, this study sought to examine the nature of volatility and volatility spillovers among currencies and their subjectivity to global investor sentiment. Bitcoin, Ethereum and Ripple and an investor sentiment index constructed from a set of five proxies over a period spanning February 2018 to August 2021 were employed. For the analysis, the study employed GARCH models to examine the nature of cryptocurrency volatility, the ADCC-GARCH framework and the Diebold-Yilmaz spillover index to examine the nature of cryptocurrency volatility spillovers, and the Toda-Yamamoto model to examine the causality between cryptocurrencies and investor sentiment.

The study found evidence of significant sentiment effects in both mean and variance equations of the cryptocurrencies. Similarly, the analysis of comovements and spillovers showed that there were significant sentiment effects on the phenomena. Failure to account for investor sentiment could, therefore, lead to poor estimation of volatility and volatility spillovers. The results have implications for investors, speculators, and policymakers alike. The results obtained provided an insight on the effect of investor sentiment on cryptocurrency volatility and showed how the market reacts to the investors' behaviour where their actions influence volatility. The investors and speculators may then use the insight on sentiment to determine the market volatility to earn returns accordingly. Further, policymakers can use this to determine the optimal regulations to prevent excessive volatility in this market. The study, therefore contributes to the debate on the drivers of cryptocurrency volatility. It also contributes to literature by introducing a measure of investor sentiment.

Keywords: Cryptocurrency; volatility; spillovers; sentiment; GARCH; ADCC

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CHAPTER 1: THE SCOPE AND PURPOSE OF THE STUDY

1.1 Background

Currency, both in form and as a concept, has changed significantly over the years. According to Velde (1998), the first form of currency was lumps of gold in uniform sizes imprinted with a stamp. This formed the basis of a money-based bartering system. Coins were then created from multiple forms of minerals such as silver and gold over the years. In China, 960 AD, paper currency was created in addition to the coins used, which thereafter was adopted by the rest of the world (Yu and Yu, 2004). Numerous factors influenced the adoption of paper currency. For instance, counterfeiting became difficult, the paper currency and coins were interchangeable, the production of paper currency was easier and larger amounts of trade could be done using paper currency as it held a larger value (Silk Road Foundation, 2021). This form of currency continued over many years to what is known as fiat currency presently.

In the same vein of transformation of currency, cryptocurrencies are the newest form that is based on modern technology. They represent currency that any government or central bank has not issued but are accepted for the payment of goods and services, almost similar to traditional forms of currency (El Bahawry et al., 2017). They have low transaction costs, they can easily be transferred internationally, and they have a more secure platforms for those transfers than other traditional platforms. More advantages such as divisibility and fungibility, transaction irreversibility, predictability of money supply and the readily available implementations make cryptocurrencies particularly attractive (Barber et al., 2012). By eliminating the shortcomings of traditional forms of currencies, the popularity of cryptocurrencies has continued to increase exponentially over time (Hari & Lakshman, 2016).

Aside from their use as currency, investors use cryptocurrency as a form of investment due to the high return properties they offer. To date, the cryptocurrency market has exceeded $1 trillion in market capitalisation, with thousands of cryptocurrencies active in the market. This is astonishing, considering that cryptocurrencies were simply an idea before the first cryptocurrency was actually introduced in 2009 (Gandal & Halaburda, 2016). According to Gil-Alana et al. (2020), the cryptocurrency market does not move with other markets and can be used to diversify risk. Further, as cryptocurrencies do not correlate with other traditional assets, they can hedge a portfolio to overcome risks in the market that affect the investors' anticipated returns. As cryptocurrencies offer these benefits based on diversifying and hedging, the popularity of cryptocurrency has risen among investors.

It is thus not surprising that there is increasing investment in the cryptocurrency market by institutional investors, a welcome development in the cryptocurrency market because these investors who bring more stability in the pricing of the cryptocurrencies (Forbes, 2018). This is due to institutional investors being able to 'anchor' the large cryptocurrency investors, preventing them from manipulating the markets on a large scale. However, cryptocurrencies have also become popular among speculators because of their large returns. For instance, Bitcoin had a return on investment of 46000% over the past decade, while Ethereum had a return of 890% in 2020 (Businesstech, 2021). The substantial incidence of these investors may offset the stabilising effect of institutional investors. As Alam (2017) found, the speculative attacks from these investors generate large volatility periods in cryptocurrency prices.

It is the cryptocurrencies' extremely high and persistent volatility that has captured much attention recently (Chu et al., 2017; Klein et al., 2018; Walther et al., 2019). Numerous factors have been forwarded to try and explain this volatility. For instance, the uncertainty of cryptocurrency's future regarding widespread adoption (Colon et al., 2021), high-profile losses which create fear among smaller investors (Bloomberg, 2021) and noise in pricing and returns which creates market pricing bubbles (Kristoufek, 2015; Rognone et al., 2020). The disagreement regarding the intrinsic value of cryptocurrencies may also contribute to their volatility. Per Bartos (2015) and Alam (2017), other financial assets like stocks have easily accessible fundamental information. However, this is not the case with cryptocurrencies, thus making it complex to estimate their market value and exposing them to speculative pricing (Hayes, 2017; Romanchenko et al., 2018).

In addition to the extreme volatility, it has been noted that the volatility in one cryptocurrency or a group of cryptocurrencies can easily spillover to another cryptocurrency or group of cryptocurrencies. Natarajan et al. (2014) describe these volatility spillovers as one-way causal relationships between the past volatility of one market to the current volatility of another market. Often, the correlation between the two markets results from contagion, where speculation and noise trading are present (Natarajan et al., 2014). The price movements are driven by fads or herding instincts among these investors, resulting in volatility spillovers. Studies have reported an increase in volatility spillovers among cryptocurrencies (Katsiampa, 2018; Koutmos, 2018; Yi et al., 2018). Together with extreme volatility, the volatility spillovers among cryptocurrencies has significantly limited their growth and usage.

In addition to the explanation on volatility above, there is a growing number of studies that attempt to link cryptocurrency volatility and volatility spillovers to behavioural biases such as the disposition effect, overconfidence, and the confirmation bias (Hidajat, 2018; El Jebari & Hakmaoui, 2018; Haryanto et al., 2019). In other asset markets, focus has mounted on investor sentiment as a possible driver of volatility and volatility spillovers. Baker and Wurgler (2006) describe investor sentiment as the investors' perception of the risk and cash flows of an investment that is not validated by fundamental information. They argued that financial assets that are hard to value and arbitrage are susceptible to investor sentiment. As cryptocurrencies are hard to value and arbitrage due to the lack of consensus on their intrinsic value, it is possible that investor sentiment may be a good explanation for their volatility and volatility spillovers.

This assertion contradicts traditional finance theory, particularly Fama's (1970) efficient market hypothesis (EMH) wherein he argued that the market reflects all available information. Any mispricing is arbitraged away by the actions of rational traders instantaneously. Fama (1970) acknowledged different market efficiency forms and categorised these into the weak form, semi-weak form and strong form of market efficiency depending on the type of information – past prices, fundamental factors and inside information – that prices reflect. Several studies have examined the theory as a framework for cryptocurrency. For instance, Alam (2017) found cryptocurrencies price patterns dispute the weak form efficiency whereas Kyriazis (2019) and Noda (2020) found that cryptocurrencies generally go against the predictions of all levels of efficiency. There is, thus, strong debate between behaviouralists and traditionalists.

1.2 Research problem

Cryptocurrencies currently experience high volatility and volatility spillovers. As a result, they are considered very risky investments and an unstable form of currency. There are various explanations that have been forwarded for these volatility patterns, ranging from the complexity in determining intrinsic values, to uncertainty regarding their regulation and susceptibility to speculative pressures (Bartos, 2015; Alam, 2017; Hayes, 2017; Romanchenko et al., 2018). However, there has not been a consensus regarding the explanation of the volatility and volatility spillovers among cryptocurrencies, despite these numerous assertions.

As a contribution to this debate concerning the drivers of cryptocurrency volatility and volatility spillovers, this study sought to determine whether investor sentiment is a major contributing factor to the volatility and volatility spillovers among cryptocurrencies.

1.3 Research aim, questions and objectives

This study sought to determine the influence of investor sentiment on the volatility and volatility spillovers of cryptocurrencies. To achieve this aim, the study sought to answer the questions:

a) What is the nature of volatility and volatility spillovers among cryptocurrencies?
b) To what effect does global investor sentiment drive cryptocurrency volatility and volatility spillovers?

To answer this question, the study sought to:

- Examine the nature of volatility and volatility spillovers among cryptocurrencies
- Determine sentiment's influence on cryptocurrency volatility and volatility spillovers.

1.4 Theoretical framework

1.4.1 Efficient market hypothesis

According to Sewell (2011), despite the Fama's (1970) EMH being criticised for its stringent demand for information efficiency, it is considered asymptotically accurate, making it a strong theory in finance. Within the EMH, Fama (1970) explained that financial assets are always efficiently priced as they immediately adjust to reflect any new information as it enters the market. Shiller (1981) elaborated those prices always match their true, unbiased intrinsic values as investors adjust their expectations accordingly when faced with the arrival of new information within efficient markets. Thus, no group of investors can consistently find mispriced assets with any strategy. In other words, by holding a portfolio of diversified assets at the prevailing market price, an average investor would not be able to earn any extra returns compared to an expert analyst (Malkiel, 2003).

For the theory to hold, vital conditions have to be met, primarily the rationality of investors and the ability of investors to arbitrage away mispricing. Certain investors may deviate from common rationality; however, market efficiency requires these deviations to be random rather than systematic (Shleifer and Vishny, 1997). However, different levels of efficiency were identified. In the first one, the weak-form efficient market, current prices fully reflect all information contained in historical prices. The markets are semi-strong efficient, the second level, if prices instantly reflect new publicly available information. Lastly, in the strong form efficient market, prices reflect all types of information – public and private (Poshakwale, 1996). As is the case with any theory, Fama's (1970) theory of efficient markets has been a source of contention regarding its applicability on markets.

In this regard, various studies have assessed the efficiency of cryptocurrency markets and findings generally indicate that they are inefficient. For instance, Alam (2017) found that Bitcoin and Litecoin are subject to speculative bubbles and inconsistent with weak-form efficiency. Brauneis and Mestel (2018) and Wei (2018) found smaller market capitalized cryptocurrencies were less efficiently priced and that efficiency of cryptocurrencies was positively related to liquidity. In addition, liquid markets with more active traders led to price efficiency and lower volatility. Köchling, Müller and Posch, (2018) found that price reaction delays had decreased significantly in cryptocurrencies and, while the cryptocurrency market is inefficient, its efficiency had increased over time. However, most studies surveyed by Kyriazis (2019) showed significant evidence of inefficiency in the cryptocurrency market.

1.4.2 Behavioural finance

As an alternative, behavioural finance has been forwarded. This was a result of the failure of the former to explain a number of pricing patterns on various financial markets. In behavioural finance, investors' behavioural biases - psychological and sociological - are recognised as impactful on their investment decisions (Tseng, 2006). This school of thought disputes the assertion of investor rationality (Guzavicius, 2014). While traditional finance deals with how investors are expected to behave, behavioural finance analyses why investors behave in a certain way (Lo, 2007). In the latter, investors are said to be influenced by the manner in which information is presented to them, which leads to cognitive and emotional biases that create inefficient markets (Lo, 2007). This accords with Tversky and Kahneman's (1974) explanation that human behaviour is based on simplified procedures or heuristics.

Various studies have identified a myriad of behavioural biases in the cryptocurrency market. For instance, El Jebari and Hakmaoui (2018) found that the overconfidence bias was present in the Bitcoin market, proving that investors tend to overestimate their knowledge, underestimate risks and exaggerate their ability to control events. Yang (2019) found that behavioural theories could explain cryptocurrency anomalies that emphasised noise trader risks than fundamental risks. Calderón (2018) found that investors frequently deviated from the rational asset pricing benchmark and instead followed the consensus in market stress situations. Hidajat (2018) found that the bubbles in Bitcoin were a result of herding, optimism, overconfidence, confirmation bias, loss aversion, and gamblers' fallacy among investors. Bouri et al. (2019) found that the cryptocurrency market was subject to herding behaviour that varied over time.

Bouri et al. (2019) also found evidence of high degree of co-movement in the cross-sectional returns' dispersion within the cryptocurrency market, implying mimicking behaviour among investors. Da Gama Silva et al. (2019) also reported herding behaviour among cryptocurrency investors. The study further found that negative news in the cryptocurrency market was related to herding behaviour, indicative of risk aversion in the loss domain. Haryanto et al. (2019) found a reverse disposition effect in bullish periods and a common positive disposition effect in bearish periods based on a round trip and survival analysis of Bitcoin bullish and bearish periods. Further, the authors found evidence of herding behaviour in bullish and bearish markets, with low trading volume as a cause of herding. Similarly, Ballis and Drakos (2020) found evidence of herding that investors in the cryptocurrency market.

Overall, evidence suggests that cryptocurrencies are generally subjective to behavioural biases and, therefore, contradict the theory of efficient markets. Of note, most studies on asset pricing either support or provide evidence against Fama’s (1970) theory. This study was no exception; the examination of the nature of cryptocurrency volatility, the nature of cryptocurrency volatility spillovers and the impact of investor sentiment on volatility and volatility spillovers was essentially based on a comparison of what patterns would be expected in an efficient cryptocurrency market versus an inefficient cryptocurrency market. That is, there are expectations regarding what volatility features – persistence, asymmetry, mean-reversion, risk premium and spillovers – should look like in an efficient market versus an inefficient market. An attempt was thus made to explain any departures from the expected patterns using behavioural biases.

1.5 Scope and method of this study

1.5.1 Scope of the study

Although many studies have documented various reasons for cryptocurrency volatility, this study focuses on investor sentiment as the most prominent explanation. While cryptocurrencies have been in existence since 2009, virtual currency's popularity has only materialised many years later. Herein, the study utilised cryptocurrencies during a period of an uptrend in their usage, where higher volatility began to emerge. Further, a single cryptocurrency could not be used as the study would be biased towards the dominating cryptocurrency. Accordingly, the starting period was chosen as a result of the top three cryptocurrencies sharing a common starting point in terms of trading to get a precise indication of the market movements. Specifically, the common date was February 2018 and the period extended to August 2021, which presents a sufficient period to assess the effects of investor sentiment. As cryptocurrency prices fluctuate exceptionally frequently, daily prices were considered to be more appropriate.

1.5.2 Methodology and data

To examine the impact of sentiment on cryptocurrency volatility and volatility spillovers, three highest market capitalised cryptocurrencies – Bitcoin, Ethereum and Ripple – were used. The Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models were used to examine these cryptocurrencies' nature of volatility, with the focus on volatility asymmetry, volatility clustering, volatility mean reversion and the risk-return relationship. To examine the volatility spillovers among the cryptocurrencies, the Asymmetric Dynamic Conditional Correlation (ADCC)-GARCH framework and the Diebold-Yilmaz spillover index were used. Subsequently, the new sentiment index constructed using a set of global proxies based on similar cryptocurrencies, sample period, and methods – GARCH, ADCC-GARCH and the Diebold-Yilmaz spillover index – was used to examine the impact of investor sentiment on volatility and volatility spillovers among the three cryptocurrencies.

1.6 Importance of the study

The study sought to add to the knowledge of the nature of volatility and volatility spillovers amongst cryptocurrencies. The motivation was due to the high volatility experienced in this market, coinciding with many nations seeking to regulate digital currency while others try to ban its usage (Bucko, Pal'ova and Vejacka, 2015). In some cases, there are volatility spillovers observed from one cryptocurrency to another (Liu and Serletis, 2019). Investors who invest in cryptocurrencies should be able to understand the consequences of investing in cryptocurrencies. It is crucial to their portfolio construction as they can use this to diversify their portfolios. Investors may obtain independent financial assets and cryptocurrencies that are not correlated with the financial assets to prevent the entire portfolio from decreasing in value due to the high volatility experienced therein.

The high volatility in cryptocurrencies is also a concern to policymakers. Therefore, policymakers need to develop regulations to control the problems that have arisen and prevent future issues such as a crash on the cryptocurrency market. Cryptocurrencies currently vary across the world in terms of their legal status within specific countries. By understanding cryptocurrency, policymakers will, therefore, recognise ways on how to regulate it. Firstly, its volatility will need to be understood to instil regulations such as price manipulation. Secondly, the financial system's protection will be crucial as individuals will use cryptocurrencies to make international payments or transfers to evade taxes. Further, regulations will be needed to prevent bubbles and financial crises from occurring. Also, there is a need to protect other asset classes in the financial system from spillovers from the cryptocurrency market. Therefore, the regulation will help avoid the failure of cryptocurrencies and provide legal methods that benefit the investors and authorities involved.

There are gaps in the literature concerning the volatile nature of cryptocurrencies. The first is about how investor sentiment influences the volatility of cryptocurrencies. the second is about how the spillovers among the cryptocurrencies can be explained by investor sentiment. Prior studies have researched these two concepts individually concerning cryptocurrency; however, this study aims to combine the concepts and explain the effect investor sentiment has on cryptocurrency volatility and spillovers. The study resolved this by firstly examining the essence of volatility in the cryptocurrency market. Secondly, investigating the relationship amongst cryptocurrencies, the volatility similarities amongst cryptocurrencies, and the volatility spillovers that occur. Lastly, examining investor sentiment influence on the volatility of cryptocurrencies.

1.7 Structure of this study

The remainder of the study is as follows: Chapter 2 presents an in-depth analysis of cryptocurrencies, the volatility present within this market and the literature pertaining to cryptocurrency volatility and spillovers. Chapter 3 examines the effects of the global investor sentiment dynamics and provides empirical evidence of investor sentiment within the cryptocurrency market. Chapter 4 specifies the cryptocurrency and investor sentiment data used in this study and explains analysis methods employed in detail. Chapter 5 examines the results from the tests conducted and determines whether global investor sentiment explains cryptocurrency volatility and volatility spillovers. Chapter 6 concludes the study, outlining the implications for investors and the cryptocurrency market regarding the results obtained in the analysis and providing future research recommendations.

1.8 Conclusion

Overall, cryptocurrency volatility patterns may continue to grab the attention of various market participants for a long time. As the cryptocurrency market continue to develop and as more institutional funds continue to flow into market, significant changes to volatility and pricing of cryptocurrencies may occur. In this study, the nature of volatility and volatility spillovers across cryptocurrencies were examined. This chapter contains the background of the study, the statement of the problem and the research aim, objectives and questions directed at examining nature of volatility and volatility spillovers across cryptocurrencies and the impact of investor sentiment on the two phenomena. The theoretical and methodological scope as well as the significance of the study were also defined in this chapter. Lastly, the structure of the study – including the structure of each chapter – was described.

CHAPTER 2: THE CRYPTOCURRENCY MARKET

2.1 Introduction

The chapter provides a theoretical background on cryptocurrencies and introduces the major elements that define this market. Multiple aspects of cryptocurrencies are looked at, including their history, how they work, competition in the market, cryptocurrency users, benefits and limitations, the risks and regulation, and the issue of volatility. The latter part of the chapter proceeds to review the literature pertaining to cryptocurrency volatility. The aspects analysed in this chapter aim to relate to the study's two objectives – the nature of volatility and volatility spillovers – with a particular interest in identifying what it is, the cause, and the effects on the cryptocurrency market.

2.2 An overview of cryptocurrencies

Abu-Bakar (2018) defined cryptocurrencies as digital assets that are designed to operate as a medium of exchange using cryptography to secure financial transactions, verify the transferring of assets, and control the creation of additional units of the virtual currency. According to Mukhopadhyay et al. (2016), it is any form of currency that exists purely digitally and does not have a central authority but rather a decentralised system that records transactions. The crucial difference between fiat currency and cryptocurrency is that the latter does not take a tangible form such as paper or coins but rather a digital representation of value (Mokhtarian and Lindgren, 2017). Cryptocurrencies operate on an underlying technology termed blockchain. This digital distributed ledger takes a record of all virtual currency transactions, with each cryptocurrency having its own blockchain (Makarov and Shoar, 2020). The ledger is public, which means it is transparent to all network users (Crosby et al., 2016).

To acquire the cryptocurrencies, users need to purchase existing cryptocurrencies on a cryptocurrency exchange, receive them by selling goods or services or mine their own cryptocurrency. The latter involves using computer processing power to solve a cryptographic puzzle, which adds a block onto the blockchain (Konoth et al., 2018). After that, the user receives a reward in the form of cryptocurrency, which transfers to the cryptocurrency address provided, similar to that of a bank account. The profitability of cryptocurrency mining, however, is dependent on the user. Paneet, Deepika, and Kaur (2017) stated that the mining of cryptocurrencies is expensive. This is especially in terms of acquiring hardware to mine, such as specialised computers with sufficient processing power, cooling systems, and the costs of mining itself. Thus, places such as Canada and China showed significant mining amounts due to the cheap electricity cost that make mining profitable (Hileman and Rauchs, 2017).

Bitcoin was created by an unknown programmer, known by the pseudonym Satoshi Nakamoto, who published a paper on the peer-to-peer system in 2008. The goal was to create a disconnected system that is not dependent on any financial institution or the government (Bhosale and Mavale, 2018). By 2009, Bitcoin emerged as the first publicly available cryptocurrency. It should be noted that despite cryptocurrencies being released public in 2009, the initial concept had emerged in 1998, but with numerous failed attempts of a virtual currency. The idea of virtual currencies did not catch on, leading to the bankruptcy of the businesses that created them. However, as of 2011, over a thousand cryptocurrencies had been developed and by the end of 2020, more than 6500 were in existence (Coinmarketcap, 2020). Similar to companies holding an initial public offering (IPO) event, companies and individuals' cryptocurrencies host an initial coin offering (ICO) to finance projects in the blockchain development arena (Fenu et al., 2018).

In 2017, the cryptocurrency ICO market reportedly generated approximately $1.2 billion in start-up capital (Clements, 2018). The rapid increase in the number of cryptocurrencies is due to very low entry barriers and the need to fix predecessor currencies' shortcomings, mostly in terms of transactions processing (Hayes, 2015; Finextra, 2021). Some cryptocurrencies often gain a competitive advantage over others by having higher price stability, more media attraction, a better reputation, faster transaction speeds, higher liquidity and market capitalisation (Bornholdt and Sneppen, 2014). However, Bitcoin remains the most prominent and valuable virtual currency with a market capitalisation of approximately $900 Billion as of 25 August 2021 (Coinmarketcap, 2021). Much of its success is based on its first-mover advantage in the cryptocurrency market. In comparison, Ethereum, the second-highest in terms of market capitalisation, had a value of $376 Billion, and Ripple was third with $53 Billion.

The dominance of Bitcoin is depicted in Figure 2.1. At some point, Bitcoin's dominance decreased considerably as other virtual currencies were entering the market during the cryptocurrency boom. However, Bitcoin regained its dominance as it has become more widely adopted in the real world. In contrast, other cryptocurrencies are more widely used as an investment vehicle for profits and not for transactions. According to Gandal and Halaburda (2014), the cryptocurrencies' growth patterns reveal two effects - the substitution effect and the reinforcement effect. As cryptocurrencies get more popular and expensive with the substitution effect, investors believe they may be overvalued and invest in alternative cryptocurrencies. However, investors believe large cryptocurrencies will prevail in the 'winner-takes-all' race with the reinforcement effect and demand more of the most popular cryptocurrency. In their study to investigate these two effects, the authors found that the reinforcement effect was more dominant than the substitution effect. The reinforcement effect can then be used as an explanation of Bitcoins' continued dominance.

Figure 2. 1 Market capitalisation of Bitcoin, Ethereum and Ripple

Source: Coinmarketcap (2020)

Many economists and authorities have been debating the classification of cryptocurrencies. Cryptocurrencies have often been referred to as virtual assets or digital assets, or virtual currencies. However, many researchers classify cryptocurrencies as an alternative investment vehicle rather than a form of currency despite these names (Oziev and Yandiev, 2017; Danila and Loan-Bogdan, 2019). Researchers such as Yermack (2015) and Baur et al. (2018) focused their studies on determining whether cryptocurrencies can be regarded as assets or a form of currency. Both studies found that cryptocurrencies behaved more of a speculative investment rather than currency. The classification arguments relate to the high volatility experienced in this market, together with the detachment from the real economy, which go against any typical characteristics of money or currency. Per Krugman (1984:263), a currency should serve three main functions – "a medium of exchange, a unit of account, and a store of value." So, for cryptocurrencies to be considered as actual currency, they should meet these criteria.

As a medium of exchange, currencies should allow for the exchange of money for goods and services. Presently, several merchants have accepted cryptocurrencies as a form of payment in physical stores (Acheson, 2018). Further, many popular international company websites such as Microsoft, Wikipedia, Subway and Burger King, as well as South African companies such as Bidorbuy, Raru and Shopify, among others, accept Bitcoin as a means of payment (Luno, 2020). Further, cryptocurrencies as a medium of exchange have allowed for faster transactions, lower transaction costs, and high divisibility. However, Rubin (2019) explained that presently, most of the cryptocurrency transactions are for trading purposes while only a minimal amount is used for goods and services. They are also not officially approved as a form of currency, and there are no laws that compel merchants to accept cryptocurrencies as a form of payment (Library of Congress, 2021). Further, there are no goods explicitly expressed in terms of cryptocurrency units, thereby leading to a dependency on traditional currency.

Per Berentsen and Schaer (2017), the success of cryptocurrency as an official medium of exchange is tied to the network size and the number of users that adopt cryptocurrencies as a form of payment. Due to the increase in the adoption of virtual currencies in businesses, cryptocurrency should be accepted as a medium of exchange, similar to fiat currencies. An earlier characterisation of cryptocurrency by the European Central Bank (2015) as a digital representation of value, not issued by a central bank, credit institution or e-money institution, which, in some circumstances, can be used as an alternative to money, suggests that cryptocurrencies may potentially be widely used as a form of payment in the future. Nevertheless, the drawbacks of the cryptocurrency, such as very high volatility, will need to be addressed to allow the implementation. The USD coin introduced in 2018, a cryptocurrency pegged to the US Dollar based on the Ethereum blockchain, is a step in that direction (Luno, 2021). Termed the stablecoin, it is very stable compared to other cryptocurrencies.

A unit of account is essentially a measurement of value (Binance Academy, 2020). A unit of account has three essential characteristics: divisibility, fungibility and countability (Study, 2021). Divisibility refers to the currency's ability to be divided, with the component parts equal to the original value. Fungibility is where one unit is viewed as the same as any other without a change in value. Countability is where the unit of account can be counted using mathematical operations. These characteristics of currency allow for the measurement and comparison of the value of different items. Cermak (2017) explained that it is a monetary unit that can value goods, services and other transactions. With cryptocurrencies, fractions are used due to the predominantly high prices of the single unit of each cryptocurrency. This is particularly the case with Bitcoin and Ethereum. This, however, makes daily life more difficult as the amounts are less intuitive. For example, as of 15 October 2020, $1 of Bitcoin is equivalent to 0.0000877193 BTC. Similarly, $1 of Ethereum is equal to 0.0026315789 ETH (Coinmarketcap, 2020). The fractions, therefore, make cryptocurrencies more difficult in everyday situations in comparison to fiat currency.

Claeys et al. (2018) analysed cryptocurrency, specifically Bitcoin, to determine its usability as a unit of account. The analysis found that Bitcoin could not perform well as expected from a currency. Claeys et al. (2018:7) stated that “Bitcoin's inflation and deflation rates were closer to that of Venezuela than those observed in the Euro area, making it a poor unit of account.” Similarly, in a study by Demertzis and Wolff (2018), it was stated that cryptocurrencies are not valid as units of account due to their extraordinary price volatility. The study explained that central banks agreed that cryptocurrencies such as Bitcoin could not be considered as a unit of account due to their volatility. In contrast, Demertzis and Wolff (2018) explained that the German Federal Financial Supervisory Authority (2018) classified cryptocurrency as a unit of account, comparable to foreign exchange, with the difference that cryptocurrencies are not referred to as legal tender. From a banking perspective, the Bank of International Settlements found that 86% of the 65 central banks examined are working on central bank digital currencies (CBDC's), including research on cryptocurrency, proof of concept or pilot development (CNBC, 2021).

The store of value is the ability to save and accumulate wealth into future periods. This is an essential element of money. Cryptocurrencies are faced with a limited supply, thereby imposing a natural scarcity. Carrick (2016) explained that the supply is limited as cryptocurrencies; for instance, Bitcoin has a total of 21 million coins to be mined. Thereafter, no more coins will be allowed to be mined as controlled by the developers of Bitcoin. The scarcity, together with great demand, produces inflationary effects and makes cryptocurrencies much more valuable. However, a crucial factor of a good store of value is stability, as individuals expect their assets to be equal to or higher than the value today in the future. According to Yermack (2015), there are arguments that although cryptocurrencies act as a medium of exchange and sometimes as a unit of account, investors can hardly use cryptocurrencies as a store of value and a unit of account due to their excess volatility.

Kubat (2015) stated that Bitcoin, for instance, has the potential to succeed as a good store of value based on the fact that it possesses a non-inflation characteristic. This characteristic is explained as fiat money, which the government rules, has a risk of losing value when more money is printed. However, Kubat (2015) demonstrated that cryptocurrencies might succeed as they will store value compared to fiat currency. Hayes (2017) examined Bitcoin and proposed that the cryptocurrency may have some fair value due to the similar properties of money, such as a store of value and a medium of exchange. However, Bitcoin's historical volatility compared to traditional assets such as currency, shares, and gold makes it very risky to hold onto it as a store of value. For instance, as of 21 March 2021, Bitcoins' average 30 and 60-day average volatility was 4.16% and 4.98%, respectively, which was in a lower volatility period. In comparison, gold averages 1.2% and major currencies between 0.5% and 1%, which is significantly lower (BuyBitcoinWorldwide, 2021). This, therefore, cancels the store of value function of Bitcoin. In a more recent analysis, Claeys et al. (2018) explained that a critical feature of being a successful currency is the ability to be a good store of value. Specifically, Claeys et al. (2018) demonstrated that unless the value of money is stable over time, it will not be used as a medium of exchange.

The high volatility experienced in the cryptocurrency market leads to significant price fluctuations daily, resulting in an increased risk for customers and merchants. Lowering volatility will allow cryptocurrencies to be used as a unit of account and a store of value. Perhaps the control of cryptocurrency volatility lies in establishing stronger regulation (Berentsen and Shaer, 2017). According to Glaser et al. (2014), the inability to use cryptocurrency as an actual currency has resulted in users acquiring it as an alternative investment vehicle rather than for its use in transactions. However, Selgin (2015) and Blau (2017) proposed that cryptocurrencies are a hybrid between commodities and currency. The claim was based on the reasoning that cryptocurrency shared properties of both, with the addition of connectedness among these assets. Based on this, cryptocurrencies experience volatility in the market as it is an attraction to investors. This means investors use virtual currency for speculative purposes, which contributes to their volatility.

2.4 Cryptocurrency users

The cryptocurrency users are classified into three categories based on their investment goals. The first category is active users. This category of users purchases cryptocurrencies for transactional purposes and the purchasing of goods and services. They are tech enthusiasts and early adopters who then use this form of payment for the sake of using the more recent technology (Glaser et al., 2014). Baur et al. (2018) explained that there are three types of cryptocurrency investors: active, passive and hybrid. The active users keep the lowest balance of cryptocurrencies compared to the other groups but make the most frequent transactions. The second category is the long-term investors, also classified as passive investors in the cryptocurrency market. They utilise cryptocurrencies as an investment vehicle with a long-term oriented goal. The third category, the hybrid investor, is short-term investors who exhibit both active and passive attributes. Short-term investors are deemed risk-takers and adopt a risk-taking strategy to earn higher returns, despite the high volatility encountered (Andrianto and Diputra, 2017). As these investors are profit-driven, they tend to keep their cryptocurrencies on their exchange wallets and not use virtual currency to make purchases.

The composition of cryptocurrency users influences the level of volatility in the market. For instance, active users accept cryptocurrencies as a medium of exchange and promote the acceptance of virtual currencies. Both active users and short-term investors share a common aspect where cryptocurrencies are frequently traded, for instance, multiple times a day, contributing to the price fluctuations. Papadopoulos (2015) pointed out that there is a limited supply of most cryptocurrencies. This, therefore, creates deflationary effects, which in turn increases volatility and speculation. However, as speculators benefit from a volatile situation, the active and short-term investors favour cryptocurrency volatility. Speculative investors are contrasting to rational traders. Tsai and Tsai (2021) explained that speculators are uninformed traders who purchase financial assets for a short term for profit. The uninformed characteristic involves these traders making decisions using behavioural biases such as herding behaviour (Hidajat, 2019). Based on the investor's trades, many within these groups contribute to market efficiency by exploiting arbitrage possibilities.

Pertaining to the age demographic, Figure 2.2 represents the data adapted from Google Analytics on the age groups of Bitcoin users, which is used as a cryptocurrency market proxy. The data reveals that a higher portion of cryptocurrency users are within the 25-34-year age group. The unequal distribution is most likely due to the technological affinity of younger investors. The higher share within the more youthful age category may indicate higher speculative behaviour. Therefore, they are more likely to be less experienced and not consider all risk factors. Furthermore, the age group may point out a lower trust in traditional investments. As depicted in Figure 2.2, as the ages increase, the use of cryptocurrencies decreases. This may reveal that older investors may not believe that virtual currencies are worthy investments, or the understanding of cryptocurrencies may be inadequate.

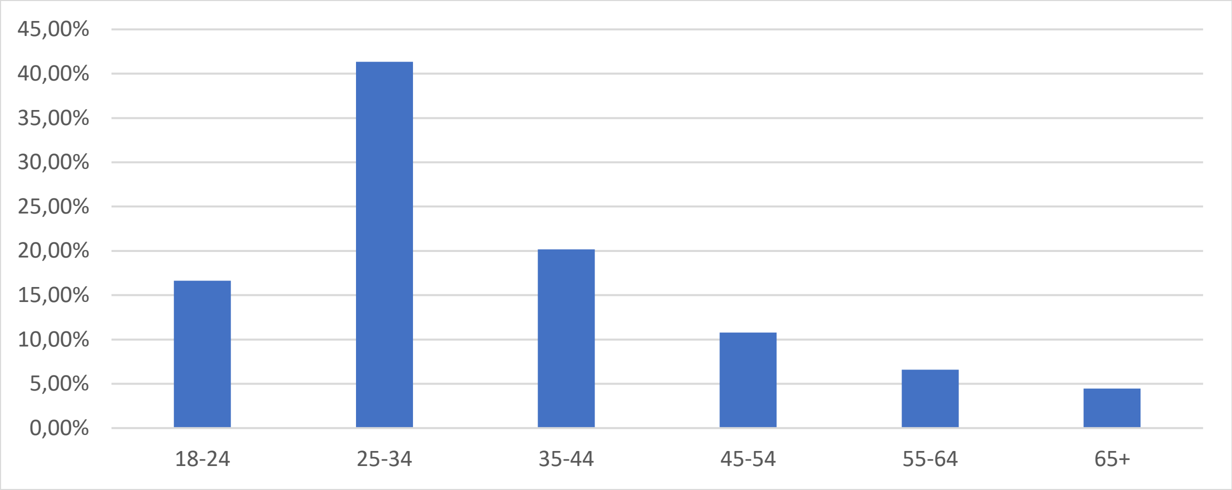

Figure 2. 2 Analytics of Bitcoin users

Source: Own illustration based on Coindance (2020)

As cryptocurrencies develop in the financial markets, institutional investors are now beginning to use cryptocurrency in their funds to earn higher returns. The addition of well-known cryptocurrencies, for example, Bitcoin, can provide substantial returns for a fund. For instance, Liew and Hewlett (2017) examined the outcome of adding Bitcoin in many different institutional funds to determine the returns. The study found that the addition of cryptocurrency provides unique diversification advantages due to its low correlation with other financial assets. Over a seven-year period, Bitcoin was found to have 298% annual returns, while the closest traditional asset that is a large US stock, had 14.5% returns. The returns were due to the high volatility of the Bitcoin market, which was 253% compared to 11.3% of the same stock. On that note, a $1000 investment in an institutional fund without cryptocurrency would increase to $1586 over seven years, while with the inclusion of Bitcoin, the investment would increase to $6801. This, therefore, makes cryptocurrency a remarkable addition to a fund.

Despite the large increase in returns offered to institutional investors, the use of cryptocurrencies in a fund will influence both its liquidity and volatility. Based on the liquidity of cryptocurrency, Momtaz (2019) stated that the buying and selling of cryptocurrency tokens increase liquidity in the market. Fisch and Momtaz (2020:10) explained that "institutional investors seek higher liquidity as it is associated with lower risk and enables investors to exit their investments easily." As previously mentioned, the increase in liquidity will reduce the volatility in the cryptocurrency market. With the notion of institutional investors entering the cryptocurrency market, the cryptocurrency returns would be significantly reduced as volatility would be lowered.

2.5 Benefits and limitations of cryptocurrency

Cryptocurrency offers several advantages compared to traditional currency, which may explain the growth in its total market capitalisation. For instance, according to Al Shehhi et al. (2014), cryptocurrency offers anonymity. Further, as stated by Inshyn, Mohilevskyi, and Drozd (2018), cryptocurrency has the advantage of quicker transactions and lower transaction costs as it does not require intermediaries. Dumitrescu (2017) explained that cryptocurrencies benefit users as transaction costs are minimal; there are no banking fees involved, international trade is simplified, and the security of transactions is robust. In emerging markets, the demand for cryptocurrency has been driven by instability in the local currencies, various capital restrictions, and high inflation.

Cryptocurrencies have easy convertibility to the world's major currencies (Gangwal, 2016). Kaminskaya and Kurbanova (2018) also found that cryptocurrencies are an accessible avenue for crowd-funded start-up ventures in terms of investments. The public ledger on which the cryptocurrencies are based enhances and promotes transparency within the blockchain network (Gangwal, 2016). Per Dumitrescu (2017), the private user keys utilised within the network further enhance users' personal data protection. Maloumbey-Baka and Kingombe (2016) postulated that presently, currency transfer costs are high, particularly in Africa, and cryptocurrencies can remedy this. Dumitrescu (2017) explained that cryptocurrencies reduce the costs of transacting by up to a fifth to that of credit card fees, with some cryptocurrencies significantly reducing processing times.

Investors further benefit from cryptocurrencies as an attractive investment. The first significant benefit is the use of cryptocurrency as an alternative investment vehicle. Due to their high volatility, cryptocurrencies are ideal for speculative purposes (Dallyn, 2017). Relating to portfolios, cryptocurrency can be used for diversification and hedging purposes. Briere et al. (2015) stated that Bitcoin could be used as a diversifier based on its low correlation with traditional assets. To safeguard investors, cryptocurrencies are minimally affected by extreme market events, making them a safe haven. According to Bouri et al. (2020), this property allows investors, that are reluctant to invest due to political and economic stability to shelter their wealth. The benefits of being a safe haven are of particular interest to the investors who invest in gold or stable currencies such as the Swiss Franc.

Despite all these advantages, cryptocurrencies also have some demerits that constrain the growth of the market further. A large factor that continues to affect cryptocurrencies is their scalability. Scalability refers to the ability to cope with an influx of a large number of transactions at a time (Medium, 2018). Scalability relates to the fact that despite cryptocurrencies are continuously increasing in adoption, it is still dwarfed by payment giants such as VISA processes (Herrera-Joancomarti and Perez-Sola, 2016). Bitcoin, for instance, operates at a rate of seven transactions per second (Medium, 2018). At the same time, Visa can authorise up to 56000 transactions per second (Visa, 2021). Therefore, cryptocurrencies cannot compete in terms of transactions presently. An additional factor that has a significant effect is trust. Dumitrescu (2017) explained that adopting cryptocurrency and trusting it with savings and earnings could be a difficult choice for many people, especially the older generation who are accustomed to traditional money such as cash and bank cards. Dumitrescu (2017:69) further explained that “the complicated algorithms and the idea of a virtual wallet might be daunting for the general public.”

As cryptocurrencies are relatively new, many are reluctant to jump into the unknown, including many businesses. The most significant issue from the creation to present times is the legal issues. Cryptocurrency's pose risks for government institutions, such as the inability to control money supply to account for monetary risks, and it may be used potentially as a method to perform tax evasion (Inshyn, Mohilevskyi, and Drozd (2018). Ivaschenko (2016) further explained that cryptocurrencies have substantial volatility. Thus, it is disadvantageous as it creates issues in the short-term price movements. Ivaschenko (2016) also stated that within the medium to long term, it may lead to illegal activities, for instance, money laundering and illicit financing activities such as the dark web.

The disadvantages of cryptocurrencies contribute to the volatility within the market. For instance, Wu and Pandey (2014) and Gandal and Halaburda (2016) explained that despite cryptocurrencies fixed supply nature mitigating the current systems inflationary pressure, it raises deflation concerns. In addition, cryptocurrencies are found different from traditional assets to which they do not have a fundamental value to support their pricing. Sellers become profitable when new buyers are willing to purchase the virtual currency at a market premium (Wu and Pandey, 2014). Despite some countries recognising cryptocurrencies as a form of payment, only a few countries legally recognise cryptocurrencies as a form of money (Srokosz and Kopyscianski, 2015). If a central bank states that cryptocurrencies are unacceptable as a means of payment, they will be rendered worthless and risky to hold (Pichet, 2017).

2.6 Regulation of cryptocurrencies

Pertaining to regulation, Gainsbury and Blaszczynski (2017) and Chohan (2017) stated that various countries have contrasting views on cryptocurrencies. Shanaev et al. (2020:2) explained that country regulation is categorised into two categories, "mainstream risk-averse regulation bulls" and "crypto-anarchist regulation bears." The first group speculates that the anticipated gains associated with the increased adoption and decline in volatility, as a result, exceed the potential efficiency losses. However, the second group believes that the government regulation of cryptocurrency and Blockchain technology contradicts the concept of decentralisation. Multiple countries, such as Egypt, Pakistan, and the United Arab Emirates, have banned virtual currencies. In contrast, countries such as Australia, Canada, and Switzerland promote virtual currencies. Other countries such as India, Nigeria, and South Africa do not have a legal status for cryptocurrencies (Library of Congress 2020).

Inshyn, Mohilevskyi, and Drozd (2018) investigated the legal regulations of cryptocurrencies in various countries. Within the European continent, Germany is regarded as the most technologically friendly country. The country regards virtual currencies as an official financial instrument that can be taxed as capital as it is viewed as private money. If the virtual money is sold, it is considered a financial instrument, which needs licencing according to the German Banking Act. In Germany, Bitcoin has been deemed an analogue of other investments, such as bonds and stocks. In the United Kingdom, the government stated in 2015 that it would regulate Bitcoin and promote innovation in the country. In 2017, a financial innovation plan was published, which said that the government would support a digital currency exchange. A report from the Bank of England (2014) further noted that they do not consider virtual currencies a threat to the monetary and financial stability of the United Kingdom, but rather a possibility of integrating it into their current payment system.

In the United States of America, Bitcoin is regarded as a form of payment in e-commerce (Gup, 2017). Some civil servants' salaries are paid in Bitcoin, and many restaurants, hotels, and stores accept Bitcoin as a form of payment (Barkan and Tapliashvili, 2018). Inshyn et al. (2018) stated that exchanges, large hedge funds, and other companies related to cryptocurrency are incorporated in the country; thus, individuals may use fiat currency or electronic money and virtual currency for many goods and services. Concerning regulation, California was the first state to authorise the usage by adopting Assembly Bill 129 (Nahorniak, Leonova, and Skorokhod, 2016). This law allows individuals, associations, and corporations to participate in the usage of virtual currencies. Further, in New York 2015, the Department of Financial Services provided the legal regulation of cryptocurrency. This was the adoption of Bitlicence, which is a license that businesses require to permit the use of cryptocurrency.

On the Asian continent, Japan has legalised Bitcoin (Artemov et al., 2020). It's believed that the creator of Bitcoin, Satoshi Nakamoto, has his roots within this country. From 2018, thousands of Japanese traders accepted cryptocurrency as a form of payment. In accordance with their laws, cryptocurrencies are of value similar to other assets. Due to the legalisation of virtual currencies, from 2018, there was a 'cryptocurrency boom,' as many purchased virtual currencies as their primary form of payment. Contrary to Japan, China banned cryptocurrencies (Bloomberg, 2019). By September 2017, China completely banned the sale of cryptocurrencies (Library of Congress, 2019). As a result, Bitcoin prices declined sharply internationally, especially considering that China mined two-thirds of all Bitcoin. However, as of 2021, China has then implemented a rollout plan to establish digital currency as a form of payment (CNBC, 2021). Although a digital currency is being tested, popular cryptocurrencies such as Bitcoin will not be used as China's digital currency will be controlled by a single power, that is, China's central bank, rather than a decentralised system.

Presently, there is a lack of regulation on cryptocurrencies. This issue immensely contributes to the volatility in the market. For instance, compared to the stock market, cryptocurrencies do not have any regulating agencies that can control investor behaviour. Investors can easily manipulate the market by performing pump and dump schemes on cryptocurrencies, which is illegal when trading other regulated securities. Pump and dump schemes are caused when investors buy cryptocurrencies to raise prices and spread misinformation on prices, and thereafter sell them off in large quantities to create a significant price decrease for profits (Kamps and Kleinberg, 2018). Li, Shin and Wang (2020) explained that these schemes create short term bubbles, which increases volatility in the market. However, if cryptocurrencies become regulated, these illegal activities will be prevented, leading to a stabilisation in this market. The stabilisation will allow cryptocurrencies to fluctuate in value based on fundamentals rather than manipulation and news.

2.7 Cryptocurrency market

According to Hayes (2017), cryptocurrency value is derived from their demand and supply interaction. In terms of supply, cryptocurrencies have a fixed supply. Satoshi Nakomoto explained the limitation of supply that as there will be a limited value of cryptocurrency, it will be valued substantially more per unit than a traditional currency that can be frequently produced, which reduces its value (Luno, 2021). Burnie et al. (2018) explained that the supply of cryptocurrencies is determined formulaically by the cryptocurrency codebase. Further, Jakub (2015) stated that based on the current mining speed, the mining limit would only be reached by the year 2140. The maximum mining value delay is that as each block of cryptocurrency is mined, the mathematical calculation to mine the following block is more complex, slowing down the process. Therefore, an increase in demand with a fixed supply causes a price surge.

Often investors demand cryptocurrencies for use as hedging tools against poorly managed national currencies and geopolitical instability (Clements, 2018). Hedging is described as a strategy used to protect an individual's finances from being exposed to a risky situation, leading to a loss in value (Corporate Finance Institute, 2021). Abid et al. (2020) explained that investors hedge their exposure by adding an asset to their investment portfolio, which has a lower or negative correlation with their initial position. Wong et al. (2018) found cryptocurrencies to have two essential characteristics for hedging. The study found that cryptocurrencies have zero correlation with other asset classes, allowing the benefit of hedging a portfolio. Further, Wong et al. (2018) found that cryptocurrency high intrinsic volatility will add variance to a portfolio, increasing the portfolio's risk, which rewards the portfolio with higher returns. Dyhrberg (2016) found cryptocurrency a useful hedge against the US Dollar. Tiwari et al. (2019) found that cryptocurrencies have low correlations, which was found useful as a hedge against the S&P 500. While Bouri et al. (2020) examined multiple cryptocurrencies and found that they can hedge the US equity index.

The cryptocurrency investments presently offer portfolio diversification opportunities for investors (Corbet et al., 2018). Andrianto and Diputra (2017) and Gangwal (2017) explained that adding cryptocurrencies to a portfolio, particularly Bitcoin, enhances a portfolio risk-adjusted return. Due to the high risk – high return property of cryptocurrency, the digital asset will increase the portfolio's risk while subsequently increasing portfolio returns. However, Brauneis and Mestel (2018) demonstrated that a significant risk reduction could only be achieved when there is a diverse basket of virtual currencies within the investment portfolio. Based on Andrianto and Diputra (2017) 's findings, the suggested minimum cryptocurrency capital allocation should be 5%, while the maximum in the portfolio should be 20%. This has then increased the demand due to the increase in interest of a portfolio containing a cryptocurrency. The demand has not primarily promoted Bitcoin but a vast number of cryptocurrencies due to large returns anticipated from various cryptocurrencies.

Li, Shin and Wang (2020) found liquidity as a driver of demand and supply on a larger market capitalised cryptocurrencies such as Bitcoin and Ethereum; high market capitalisation means more liquidity. However, a less popular cryptocurrency with lower market capitalisation had lower liquidity. The illiquid cryptocurrencies were found to have a pump and dump scheme present, increasing the market volatility. The higher liquidity was found to lower volatility in the market as it makes mispricing easy to arbitrage. Valenzuela et al. (2015) explained that assets could be sold easily without large price variations during high liquidity periods as there is a greater demand, which maintains low volatility. Whereas in lower liquidity periods, asset prices vary due to the higher spread in the bid-ask prices, which is caused by lower demand, thereby increasing volatility. In contrast, Będowska-Sójka et al. (2019) examined the more popular cryptocurrencies and found that high liquidity leads to high volatility, and low liquidity leads to low volatility. This result contradicts illiquid cryptocurrencies and traditional financial assets such as stock returns, as Chan et al. (2013) found. Będowska-Sójka et al. (2019) explained that this phenomenon of the liquidity-volatility relationship is typical for highly speculative cryptocurrencies. Therefore, the higher market capitalised cryptocurrencies are prone to this relationship.

Further, the demand for cryptocurrency is influenced by the preferred choice of investments by the users. Al Shehhi et al. (2014) examined the factors behind choosing a cryptocurrency. The analysis found that the majority of the participants believe that the cryptocurrency name and logo affect their choice of currency. The participants mentioned that the ease of mining was one of the most important factors affecting their choice. The study explained that mining was an important factor based on the value earned from the mined cryptocurrency. After that, anonymity, privacy, value, popularity and potential as a new technology were further factors of choice. However, Katsiampa (2019) pointed out that the increased popularity of specific cryptocurrencies leads to a rise in volatility. This meant that based on the users' preferences explained by Al Shehhi et al. (2014), the particular cryptocurrencies would have higher volatility compared to others due to the number of investors within that specific currency. A possible explanation for the rise in the volatility of popular cryptocurrencies is the investors' irrational behaviour.

2.8 Cryptocurrency volatility

2.8.1 Volatility within the cryptocurrency market

The cryptocurrency market is known for its excessive volatility. For instance, the cryptocurrency market peaked at $828.5 billion in January 2018; however, exactly a month later, the market fell to $330.5 billion in February 2018. Further, during the month of February 2018, the market partially recovered to a value of $513.7 billion before falling to a low of $249.6 billion in April 2018 (Coinmarketcap, 2020). Based on this, there is significant evidence of cryptocurrencies being a highly volatile asset (Latif et al., 2017). This, therefore, creates concern for investors participating in the market, together with companies and governments who wish to adopt cryptocurrencies as an official form of payment.

Further, cryptocurrency is an asset whose pricing does not have an agreed-upon intrinsic value to support it (Hayes, 2017). Tobin (1984) explained that intrinsic value is a fundamental value, whereas Shiller (1981) stated the intrinsic value is the true investment and economic value. More recently, McGoun (2007) described intrinsic value as a financial asset's value based upon the cash flows and the asset's fundamental values. In a study, Romanchenko et al. (2018) attempted to determine the intrinsic value of cryptocurrencies. The study found the cryptocurrency intrinsic value consists of two parts: the commodity-based part and the currency-based part. The commodity-based part consists of using computational labour to mine the currency, thereby giving cryptocurrency value. The currency-based part consists of the fact that people use cryptocurrency with the intention to buy goods and services, which then applies an intrinsic value to it. However, Romanchenko et al. (2018) further found that investors' behaviour substantially helps in the determination of an intrinsic value based on their buying and selling trends. The sentiment of the investors and the differences in opinion of the value by the investors then leads to the instability of its pricing.

However, investors tend to use this highly volatile property to their advantage. Ji et al. (2019) emphasised that fund managers have viewed cryptocurrencies as an investible asset capable of generating high returns. According to Ji et al. (2019), investors have maximised their returns by investing in Bitcoin and other smaller cryptocurrencies prone to significant volatility. For instance, smaller cryptocurrency alternatives in 2017 outperformed 1300% price appreciation for Bitcoin, where the returns ranged from 5000% for Litecoin to 36000% with Ripple (Ji et al., 2019).

Figure 2.3 depicts a graph in the study by Conrad, Custovic, and Ghysels (2018). The chart illustrates the realised volatility of multiple assets and indices: S&P 500, Nikkei 225, Gold, Copper, and Glux, which are compared to Bitcoin volatility. Evidently, Bitcoin volatility is conspicuously higher at 73% compared to the other assets and indices, the S&P 500, which had a realised volatility of 11%. Even in 2017, where the stock markets were unusually characterised by low volatility with the Volatility Index (VIX) at its lowest since the mid-1990s, the volatility of Bitcoin was continuously increasing.

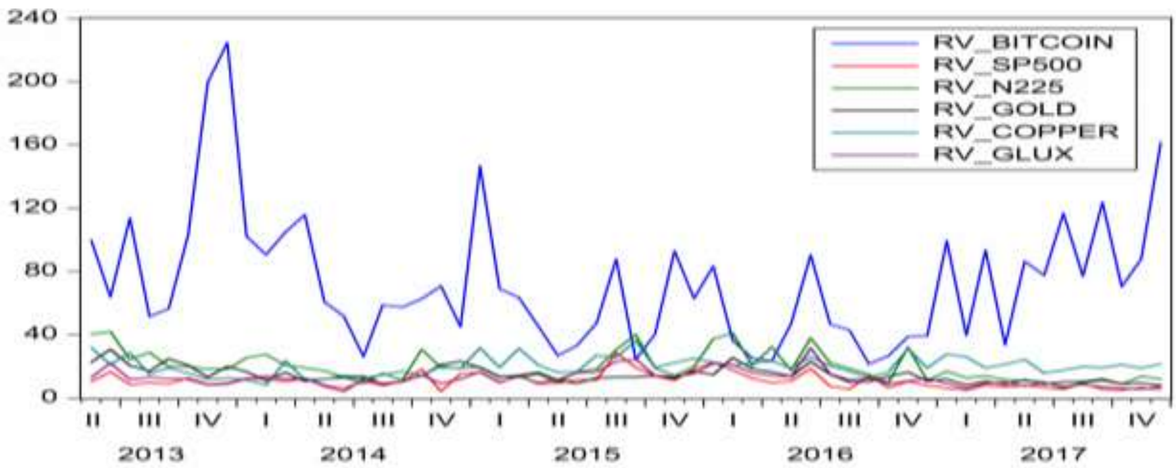

Figure 2. 3 Realised volatility of assets and indices

Source: Conrad, Custovic, and Ghysels (2018)

2.8.2 Cryptocurrency volatility literature

As alluded to in the preceding discussion, cryptocurrencies exhibit extreme volatility in their prices. This was confirmed in the findings by studies such as Baker and Rosbi (2017), who used the standard deviation of logarithmic returns, Shapiro-Wilk normality test, box-whisker plot and statistical process control chart to evaluate the volatility condition of Bitcoin. The study's results showed that Bitcoin experienced very high volatility with its returns varying continuously, and thus, it should be categorised as a high-risk investment. Similarly, Klein et al. (2018) sought to compare Bitcoin and gold based on their volatility, correlation, and performance in a portfolio. In their findings, Bitcoin returns had an asymmetric response to market shocks, similar to precious metals. The price increases led to a rise in volatility, and periods of elevated volatility led to a higher persistence. Based on linkages, it was discovered that Bitcoin behaved differently to that of gold, particularly in market distress, thereby concluding that Bitcoin may be used as a hedge for gold.

Corbet et al. (2018) examined the relationship between news coverage of macroeconomic statistics announcements and Bitcoin volatility. The study found that news associated with unemployment and durable goods sales announcements were significantly linked to Bitcoin volatility but not gross domestic product or consumer price index announcements. Further, regarding macroeconomic factors, Bitcoin shares similar links to equities, interest rates and commodities when determining future economic conditions. Relating to external factors, Jabontinsky and Sarel (2020) studied the Coronavirus pandemic's effects on cryptocurrencies. The study used the top one hundred cryptocurrencies and a comparison of pre-pandemic and during the pandemic. Naturally, the traditional markets responded negatively to a global pandemic's news, leading to plummeting share prices. The study found a pump and dump scheme present, as cryptocurrencies are unregulated, which led to further volatility in the cryptocurrency market despite the economic downturn.

Baur and Dimpfl (2018) analysed the volatility found in the twenty highest market capitalised cryptocurrencies using the TGARCH model. The study found that noise traders significantly influenced cryptocurrency volatility. Further, contrary to usual beliefs, the findings established that positive shocks increased cryptocurrency volatility more than negative shocks. Pump and dump schemes were found to be another significant driver of volatility. Cheikh et al. (2019) examined the top four cryptocurrencies' volatility dynamics using several GARCH models. The authors found a similar result to Baur and Dimpfl (2018), which showed that positive shocks increased volatility more than negative shocks. Periods with positive shocks were found to have higher noise trading activity, but informed traders' increased trading activity followed negative shocks. The authors stated that cryptocurrencies supported the safe-haven hypothesis, in which investors would transmit volatility and uncertainty to the cryptocurrency market in financial turmoil.

Conrad et al. (2018) investigated short and long-term volatility drivers of Bitcoin volatility. The study used Bitcoin price data and tested it against Commodity ETF's, GLUX, S&P 500, Nikkei 225, VIX, SPDR Gold Shares ETF and the Bloomberg Copper ETF using the GARCH-MIDAS model. The study found that the S&P 500 realised volatility had a negative and highly significant impact on Bitcoin volatility. Bitcoins volatility decreased during the flight to safety periods in the stock markets. This, therefore, confirmed a link between Bitcoins volatility and global economic activity. Sovbetov (2018) focused on examining the factors that influence the five most common cryptocurrencies' prices. The study used five cryptocurrencies, the S&P 500 index, Euro/USD exchange rate, US interest rate and Gold prices. The study found that cryptocurrency market-related factors, such as market beta, trading volume, and volatility, appeared significant determinants in both the short and long run. Further, the cryptocurrencies' attractiveness matters in terms of the price determination; however, only based on its long run.

Zhang et al. (2018) conducted a comprehensive study analysing the stylised facts on eight of the largest cryptocurrencies, based on the GJR-GARCH model and a detrended fluctuation analysis. Based on the volatility of returns, cryptocurrency returns displayed strong volatility clustering and leverage effects, thereby indicating that large price changes tend to be followed by large price changes. Based on leverage effects, Ethereum and Ripple were prone to leverage effects. The study concluded there were exist power-law correlations among the cryptocurrencies' price and trading volume. Further examining volatility, Hafner (2020) examined the eleven largest cryptocurrencies and the Cryptocurrency Index (CRIX) to determine if bubbles exist and whether volatility is time-varying. The study found extensive evidence of bubbles in the cryptocurrency market, especially with Bitcoin. This was due to Bitcoin attracting investors as it is the largest cryptocurrency and having the most extensive media coverage. Hafner (2020) stated that the Bitcoin market had fallen steadily over the years, and the configuration of the leading cryptocurrencies is changing rapidly.

Chaim and Laurini (2019) examined the volatility dynamics, and returns of the nine highest market capitalised cryptocurrencies. The analysis found that cryptocurrencies experienced excessive volatility periods in 2017 and 2018. The permanent volatility component was driven by significant market developments and the widespread interest in cryptocurrencies. In addition, transitory mean jumps became larger and frequent over time which suggested shifts in cryptocurrency return dynamics. Będowska-Sojka et al. (2019) examined the dependency between the top twelve cryptocurrencies' volatility and liquidity using the Toda-Yamamoto model. The empirical results indicated that volatility Granger cause liquidity, and not the other way around. This implied that high volatility attracts cryptocurrency investors into the cryptocurrency market. The studies implications showed that high volatility causes higher liquidity, while low liquidity improved the forecast of low volatility. This was found more pronounced in daily data tests than weekly.

Bouri et al. (2019) examined the internal factors to determine the predictability of returns and volatility in cryptocurrencies. The study used daily price returns of seven large cryptocurrencies, their return volatility, and detrended volume. Using the Granger causality test, their results showed that trade volume indicated the cryptocurrencies' returns; however, it cannot determine volatility. The study's findings support the hypothesis, which assumed that volume volatility relation depends on the rate of informational flow in the market. Chan et al. (2020) studied the volatility features based on a sizable investable subset of cryptocurrencies. The results revealed that volatility persistence and leverage effects improve cryptocurrencies' predictability, reduce risk, and reduce speculation in the cryptocurrency market. The authors stated that despite predictability presents evidence of market inefficiency, the predictability helped evaluate risk and reduce speculation and bubble creation. However, findings showed that factors such as cyber criminality, market correlation, regulatory disorientation and social media impact affected the level of market speculation.

Walther et al. (2019) examined the exogenous volatility drivers using the top five cryptocurrencies based on the GARCH-MIDAS model. The study found that the global business cycle drove cryptocurrency volatility rather than country-specific economic and financial variables. Further, unforeseen policy changes had a significant but short-term influence on cryptocurrencies. The study concluded that the cryptocurrency market is predictable using the global real economic activity, regardless of the global market's sentiment orientation. Akyildirim et al. (2019) examined the relationship between the implied volatility of the United States and European financial markets and twenty-two cryptocurrencies using GARCH models. The results of the study showed a positive time-varying interrelationship between cryptocurrencies and financial market stress. Further, correlation increased during high financial market stress, indicative of contagion of fear between these markets. The study also found that by using high-frequency data, evidence was found that supported the influence of option denoted implied volatility on the price volatility of cryptocurrencies.

2.9 Cryptocurrency volatility spillovers

2.9.1 Volatility spillovers within the cryptocurrency market

Hong (2001) described volatility spillovers as an event where a shock increases volatility in its own asset or market and other assets or markets. Yi et al. (2018) explained that there are two groups of volatility spillovers, the visible transmission mechanism and the invisible transmission mechanism. The visible transmission mechanism believes that "the correlation between economic fundamentals leads to the co-movement of asset prices" (Yi et al., 2018:98). The invisible transmission mechanism considers the market inefficiency and investors behaviour to assess other markets performance, thereby causing contagion via a correlated information channel. Recently, it has been noted that there are volatility spillovers and interconnectedness within the cryptocurrency market. Huynh (2019) demonstrated that shocks in some cryptocurrencies often lead to spillovers to other cryptocurrencies. Many studies, for instance, Katsiampa (2018), Koutmos (2018), Ji et al. (2018) and Bouri et al. (2019), have analysed the spillover effects among cryptocurrencies.

It is worth noting studies found the spillovers do not necessarily originate from the highest market capitalised cryptocurrencies but also from smaller cryptocurrencies. For instance, Ji et al. (2018), in an analysis on volatility spillovers, found that apart from Bitcoin, Litecoin, which is a significantly smaller cryptocurrency, was the second most influential cryptocurrency. The study found that as the cryptocurrency is evolving, the smaller cryptocurrencies begin to affect larger ones based on those markets' volatility. However, Bitcoin was generally dominant in this regard (Ji et al., 2018). Nguyen et al. (2018) explained that Bitcoins' dominance could be attributed to the cryptocurrency market's first-mover advantage. As Bitcoin was the first cryptocurrency, investors and the general public believe that Bitcoin is the most renowned, making it a preferred investment choice.

2.9.2 Cryptocurrency volatility spillover literature

2.9.2.1 Volatility spillovers among cryptocurrencies

Various studies have reported significant volatility spillovers among cryptocurrencies. One such study was conducted by Koutmos (2018), who employed a vector autoregression model and eighteen cryptocurrencies. The study found the spillovers and interdependencies had risen over the years and news about cryptocurrencies increased the degree of spillovers. Further findings showed that Bitcoin was the dominant contributor to return interdependency and volatility spillovers. Ji et al. (2018) conducted a similar study to examine the interdependencies amongst the six major cryptocurrencies based on market capitalisation. A similar result was found where Bitcoin dominated in the transmission of volatility shocks to other cryptocurrencies. However, contrary to Koutmos (2018), returns and volatility connectedness was not necessarily related to market size.

Yi et al. (2018) used variance decomposition functions to examine the volatility connectedness among the top eight cryptocurrencies. The study showed that the connectedness fluctuated cyclically when the markets experienced unpredictable exogenous shocks or unstable economic conditions. Further, using fifty-two cryptocurrencies, there was evidence that larger market capitalised cryptocurrencies were more likely to propagate volatility shocks to others. The authors forwarded herding behaviour in the market as an explanation for the spillovers. Katsiampa (2018) examined the volatility dynamics between Bitcoin and Ethereum using the BEKK-GARCH model. The study found interdependencies between Bitcoin and Ethereum. However, the study also found that Ethereum could be used as a hedge for Bitcoin in a portfolio. Katsiampa (2018) found that the conditional correlation between Bitcoin and Ethereum ranged from -0.70 to 0.96. Therefore, in an average portfolio, 82% should be invested in Bitcoin, while 18% should be invested in Ethereum as a hedge.

Antonakakis et al. (2019) examined the contagion effects between the top nine cryptocurrencies and a composite index consisting of 45 cryptocurrencies. The study found that periods of high market uncertainty corresponded to strong connectedness and vice versa. Bitcoin was found to be the most prominent influencer, and Ethereum the number one net transmitter. Katsiampa et al. (2019) examined spillovers among Bitcoin, Ethereum and Litecoin and found evidence of a bi-directional link between Bitcoin and both Ethereum and Litecoin. However, there were unidirectional spillovers from Ethereum to Litecoin. Bouri et al. (2019) examined eight cryptocurrencies and found that spillovers did not necessarily originate from Bitcoin but rather other smaller cryptocurrencies. This suggests the growing importance of other cryptocurrencies. Smaller cryptocurrencies, such as Dash and Stellar, were relatively segmented and thus offer diversification potential.

Katsiampa (2019) investigated the volatility dynamics and interdependencies in the cryptocurrency market using the top five cryptocurrencies. The study revealed a correlation between cryptocurrencies. However, the correlation patterns differed in certain periods. Conditional covariances were significantly affected by cross products of previous error terms and previous covariance terms. Huynh (2019) investigated spillovers using the cryptocurrencies used by Katsiampa (2019). The study found that Bitcoin was a spillover recipient from Ethereum, Ripple, Litecoin and Stellar when faced with a simultaneous downside trend of bad news. Also, Ethereum was independent of other cryptocurrencies. The

Student t Copulas test implied that all cryptocurrencies had a joint distribution in extreme value, which causes a simultaneous downside trend when faced with bad news.

Omane-Adjepong and Alagidede (2019) sought to determine volatility linkages using the top seven cryptocurrencies using the Granger causality and wavelet-based methods. The findings showed that any potential diversification benefits were most likely found within intra-week to intra-monthly time horizons for specific market pairs. They also found that the volatility linkages between cryptocurrencies were sensitive to the market's time scale, liquidity, and volatility. Canh et al. (2019) analysed the structural breaks and volatility spillovers also among the seven largest cryptocurrencies. The study revealed structural breaks present, and the breaks tend to spread from smaller market capitalisation cryptocurrencies. Further, using the DCC-MGARCH model showed significant strong and positive correlations, indicative of a lack of diversification scope among the cryptocurrencies.

Kumar and Anandarao (2019) analysed four major cryptocurrencies using the DCC-IGARCH model. The study found spillovers from Bitcoin to Ethereum and Litecoin. Initially, the spillovers were negligible, but the latter part of the study period showed volatility spillovers. Kumar and Anandarao (2019) explained that spillovers could be caused by herding behaviour in the market. The explanation by Kumar and Anandarao (2019:457) was that "the correlation structure gets weakened between the cryptocurrency pairs during moments of a market crash, especially Bitcoin, which indicated investor panic." Based on a wavelet approach, volatility spillovers were found moderate and existing in the short run during the initial periods. Overall, the study found that cryptocurrencies are primarily influenced by the turbulence found within the Bitcoin market, which indicated Bitcoins' influence on other smaller cryptocurrencies.

2.9.2.2 Cryptocurrency and traditional currencies

Baumohl (2018) analysed the connectedness between forex and cryptocurrencies. The study used six traditional currencies and six major cryptocurrencies. The analysis established some significant negative dependencies between forex and cryptocurrencies from both the short - and long-term perspectives. Further, the connection was not as strong as widely believed as correlations were practically zero; thus, making cryptocurrency a diversifier for foreign exchange. Drożdż et al. (2019) examined the cross-correlation between the US Dollar, Euro, Bitcoin and Ethereum over two years. A significant finding was that the measure applied to detect cross-correlations between the dynamics of EUR/USD and BTC/ETH exchange rates did not show any noticeable relationship. This was an indication that the cryptocurrency market had decoupled itself from the forex market. The decoupling could be explained that as the cryptocurrency market is evolving, as the cross-correlations decrease due to the market becoming more mature and independent.

Grobys and Saptoka (2018) examined the potential impact of news that originated from the Bitcoin market onto the traditional G-10 currencies over eight years using a VAR model. An equally weighted index was created using the G-10 currencies and Bitcoin as a cryptocurrency market proxy. The findings showed that only hacking incidents which occurred in the Bitcoin market resulted in high levels of co-movement in the risk of both cryptocurrencies and the G-10 currencies. The good news did not have an impact. Andrada-Félix et al. (2019) examined the volatility interconnection between the four highest market capitalised cryptocurrencies and four major currencies over four years. They found that traditional currencies and cryptocurrencies are mostly disconnected, with periods of mild net volatility spillovers. Furthermore, volatility connectedness varied over time, with a surge during periods of increasing financial and economic stability.

Kostika and Laopodis (2019) took a different approach. They examined short and long-run dynamic linkages between cryptocurrencies, which exceeded $1 billion market capitalisation, and multiple traditional currencies paired with the US Dollar. The study found that cryptocurrencies did not interact with each other as their correlations were weak, established from the VAR model and the DCC-GARCH. Based on VAR models, the impulse response indicated that cryptocurrencies appear to be isolated from market-driven shocks from exchange rates. Further, the DCC-GARCH indicated that all cryptocurrencies were susceptible to speculative attacks and market events from the cryptocurrency market. The study concluded that despite sharing common characteristics, the cryptocurrency market did not reveal any short and long-term stochastic trends with the traditional currencies.

2.9.2.3 Cryptocurrency and traditional assets

Linkages among traditional financial assets are often experienced, as turbulent market conditions lead to volatility linkages. However, as cryptocurrencies are relatively new assets, among others, studies have analysed the spillovers between cryptocurrencies and traditional assets.

Dyhrberg (2016) reviewed the similarities of Bitcoin to gold and the US Dollar. Based on the GARCH (1,1) and the EGARCH, the author found that Bitcoin had similarities with both gold and the Dollar indicating hedging capabilities and advantages as a medium of exchange. Bitcoin was shown to react significantly to federal funds rates similar to the Dollar and have similar hedging capabilities to gold as they react symmetrically to good and bad news. This finding proved that Bitcoin might be ideal for risk-averse investors in anticipation of negative shocks to the market, making Bitcoin useful in risk management. However, Bitcoin was traded more frequently, and reactions to market sentiment were shown faster. Therefore, Dyhrberg (2016:92) stated that "Bitcoin is between a currency and a commodity due to its decentralised nature and limited market size." Based on a portfolio, Bitcoins' position would be useful as a store of value, and a medium of exchange assumed from gold and the US Dollar properties, respectively.

Bouri et al. (2018) examined the volatility and return spillovers between Bitcoin and five asset classes, namely equities, stocks, commodities, currencies, and bonds in bear and bull market conditions. Principal findings indicated there were spillovers found where the recipient was usually Bitcoin. Evidence showed that Bitcoin was closely related to the chosen asset classes; however, Bitcoin had a greater connection with returns than volatility. Vadar and Aydogan (2019) sought to determine the return and volatility transmission between Bitcoin and other traditional asset classes, namely stock, bond, and currencies, from Turkey's standpoint. The results revealed the existence of the positive unilateral return spillovers from the bond market to the Bitcoin market. Further, there was evidence of bidirectional cross-market shock and volatility spillover effects between Bitcoin and all other financial asset classes, except the US Dollar exchange rate. Additionally, the effects of the US Dollar were transferred onto Bitcoin.

Based on examining spillovers in the market, Trabelsi (2018) examined the connectedness amongst cryptocurrencies and between cryptocurrencies and traditional assets. The study used four cryptocurrencies, a Bitcoin index, the S&P 500, NASDAQ, FTSE100, Hang Seng, and Nikkei225. Further, five currency pairs with Crude oil and Gold futures were used. The study found that there were no signs of spillovers between cryptocurrencies and traditional assets. However, spillovers between cryptocurrencies were found based on specific times. Similarly, Tiwari et al. (2019) investigated the time-varying correlations between six cryptocurrencies and the S&P 500 index over three years. The analysis found that the overall time-varying correlations were low, thus indicating that the cryptocurrencies could be used as a hedge against the S&P 500. Further, volatility responded more to negative shocks compared to positive shocks in both markets. Findings showed that cryptocurrencies play a role in stock market hedging, providing a guideline on designing an optimal portfolio.

Kurka (2019) analysed the asymmetric transmission mechanisms of shocks between the most liquid representatives of traditional asset classes, such as commodities, foreign exchange, stock, and financials, against Bitcoin as a cryptocurrency market proxy. The author found that the unconditional connectedness between cryptocurrencies and traditional assets were negligible. The study concluded that market disruptions could spread from Bitcoin to traditional assets, thereby undermining the potential of Bitcoin as a hedging tool. Okorie and Lin (2020) examined the volatility connectedness between crude oil spot prices and cryptocurrencies. For the study, the Crude oil spot prices and the top and bottom five cryptocurrencies were used. The authors found a bi-directional spillover between Crude oil and Bit Capital Vendor, together with a unidirectional spillover from Crude oil to Bitcoin Cash. Further, Ethereum, Ripple, and ReddCoin had a significant unidirectional volatility spillover to the Crude oil markets.

2.10 Chapter summary

This chapter examined cryptocurrencies and their respective elements that define the new virtual currency. The chapter reviewed the classification of cryptocurrency as a financial asset, the market in which it operates and is used for investment purposes, the users of cryptocurrencies and the regulation pertaining to cryptocurrency. Presently, cryptocurrencies have been valuable as a form of investment due to their high returns. Evidently, cryptocurrencies can be seen as a potential candidate as a new form of currency for the future. However, presently, cryptocurrencies are being used as a form of investment due to the high returns that this market offers. The chapter further examined the literature relating to cryptocurrencies. The literature comprises cryptocurrency volatility and the volatility spillovers based on other cryptocurrencies and other financial assets such as forex, equities, stocks and commodities. The studies reviewed showed that the cryptocurrency market is very volatile, and those volatility spillovers exist among cryptocurrencies. In the following chapter, the analysis considers global investor sentiment as a potential explanation for the volatility and spillovers experienced in this market.

CHAPTER 3: INVESTOR SENTIMENT IN THE CRYPTOCURRENCY MARKET

3.1 Introduction

Traditional financial theories are based on an underlying assumption – the rationality of investors (Muhammad, 2009). Specifically, investors are presumed to use all available information and form rational expectations about the future. As explained in the prior chapter, cryptocurrencies constantly experience extensive, frequent periods of volatility. It has been hypothesised that the volatility experienced within the cryptocurrency market is due to the effect of global investor sentiment. As such, traditional financial theories such as the EMH may be challenged in explaining cryptocurrency price movements based on the rationality of the investors in this market. This chapter thereby consists of the theoretical framework and empirical evidence to justify investor sentiment on cryptocurrency as a violation of the EMH.

3.2. Investor sentiment

3.2.1 What is investor sentiment

Baker and Wurgler (2006) defined investor sentiment as investors' perceptions of an investment's risk and cash flows that are not validated by fundamental information. The psychology of the investors in the market subsequently reflects in the price movements and their trading activity. Rising asset prices reflect bullish sentiment, and falling prices indicate bearish sentiment (Kurov, 2008). Investor sentiment, therefore, represents the trading behaviour in the market, which is irreconcilable with the fundamental information as outlined by the EMH framework. Investors that are sentiment-driven cause the pricing of the asset to deviate from fundamental values (Stambaugh, Yu and Yuan, 2012). Per Smith et al. (2016), investor sentiment appears to be a significant determinant of asset prices, particularly in the short run, allowing investors to use technical analysis. In addition, Larrabee (2013) explained that the presence of investor sentiment allows for contrarian traders to earn abnormal returns using short-term price predictions of the investors' attitude.

Within a financial market, the mispricing induced by sentiment manifests as noise trading (Antoniou et al., 2013). Noise within a market, according to Black (1986), is contrasted to information and noise traders are a group of investors that make decisions without the use of fundamental information. Further, De Long et al. (1990) described noise traders as investors who believe they have superior information regarding the future pricing of financial assets. While certain investors invest rationally, noise traders in the market misperceive the value and are subject to behavioural biases (Ahmed, 2019). De Long et al. (1990) further pointed out that the noise traders follow trends in the market rather than fundamental information and thus overreact to news in the market, both positive and negative.

3.2.2 Investor sentiment in the cryptocurrency market

The cryptocurrency market currently faces similar issues pertaining to noise traders (Hayes, 2015; Caporale and Plastun, 2019). Due to the complexity of fundamental information, the cryptocurrency market is dominated by noise traders. As a result, two arguments have arisen regarding the impact of noise traders in the market. Dimpfl and Peter (2019) explained that the noise existing in the market constitutes a risk to the traders as they will have less efficient prices due to the uninformative price changes. In contrast to the issues generated by noise traders, Baur and Dimpfl (2018) explained that these traders trade for reasons other than exploiting information and provide liquidity in the cryptocurrency market. Similar to traditional financial markets, Piccoli and Chaudhury (2019) pointed out that among cryptocurrencies, noise traders deviate the cryptocurrency value from its fundamentals creating volatility; thereafter, arbitragers reverse the effects of the noise traders.

The first argument ascribes the efficiency in the market due to the noise traders. Shleifer and Vishny (1997) argued that the actions of noise traders establish risks that inhibit arbitrage, which in turn prevents asset prices from reverting to their fundamental values, as the EMH states. Da et al. (2015) explained that the noise traders thus induce excessive volatility and large price movements, which cannot be justified by the flow of information in the market. Da et al. (2015) further explained that based on a sizable presence of noise traders in the market, their effects would prolong the mispricing of assets in the market. In addition, Scheinkman and Xiong (2003) pointed out that the noise traders create speculative pressures on the asset prices, which leads to larger differences from its fundamental values. According to Palomino (1996), the failure of arbitrageurs to forecast the sentiment of noise traders creates additional volatility, which in turn becomes more extreme. As a result, De Long et al. (1990) explained that rational traders avoid assets that are prone to noise trading, resulting in high returns in these assets.

The second argument of noise traders pertains to the increase in the liquidity of the market. The substantial amounts of noise trading on markets stimulate aggressive trading from rational traders using fundamental information (Tetlock, 2007). Based on the distortion in prices due to the market's noise, trading in return becomes more profitable (Clunie, 2010). Black (1986:528) findings thus show “that noise trading is essential to the existence of liquid markets.” Despite the opposing views of noise trading, these investors' irrational trades are considered contrarian to those of rational traders. Berkman and Eleswarapu (1997) found in their study that noise traders within a stock market enhance the liquidity from their trades. Further, it was found that short term trades increase trading noise. Harris and Schultz (1998) found a similar result where noise traders enhanced liquidity in derivative assets and index funds.

As noise traders do not trade based on fundamental information, their trades are then dependent on the recent performance of the assets, which becomes a key driver for their decision making. Piccoli and Chaudhury (2019) outlined strong evidence of traders following a trend in the cryptocurrency market. The study further explained that, for instance, in 2016-2017, the Bitcoin market drew the attention of many traders. As expected, noise traders were desperate for public information and opinions regarding the new financial asset. There was a positive correlation between the number of online searches pertaining to cryptocurrencies and the increasing prices of the financial asset. This contributed to further buying demand and escalating the prices in the market. However, the markets thereafter contained rational traders, which caused prices to decrease. As a result, noise traders and rational investors create excessive volatility by means of escalating prices exponentially and thereafter causing the prices to crash, resulting in a bubble within the market.

As a repercussion of the noise traders, studies have found the cryptocurrency market to contain several price bubbles (Fry, 2018; Chen and Hafner, 2019; Keilbar and Zhang, 2021). Financial price bubbles are defined as a period of systematic deviation of an assets market value from its fundamental value (Kyriazis et al., 2020). While Kindleberger and Aliber (2011) explained that bubbles are rapid increases in market value that triggers expectations of a series of price enlargements. This, in turn, feeds elevated interest regarding a particular asset and creates higher demand, which Shiller (2000) stated causes' irrational exuberance' in the investor's behaviour. Per Kyriazis et al. (2020), the authors explained that cryptocurrencies were subject to the standard pricing patterns of new investment assets. The study further elaborated that as a new form of liquidity is developed, the first few coins are sold at a very high price which is occurring presently. However, the supply of a cryptocurrency, for example, Bitcoin with a limited supply of 21 million coins with large demand, has to be considered for the significant price increases and a factor for the price bubbles that occur.

Relating to the EMH, Seidens (2018:1) stated that financial bubbles are theoretically possible within the EMH framework. However, empirical evidence does not support this, and consequently, rational bubbles can be ruled out as the investors' behaviour fuels them. Malkiel (2010) demonstrated that the mechanisms of the EMH could not 'prick' the bubble as they continue to inflate. For instance, based on the internet bubble, the prices of many stocks were too high, which made arbitraging very difficult and risky, leading to the ‘limits of arbitrage.’ In addition, the arbitrage was too risky in a sense where no investor could predict when the bubble would burst, where hedge fund managers stated "markets can remain irrational much longer than we can remain solvent" (Malkiel (2010:5). As a result, bubbles form within the markets and oppose the EMH framework.

While the cryptocurrency market experiences bubble behaviour, it is essential to note the classification of the bubble. The bubbles which occur are classified as speculative bubbles (Abolafia and Kilduff, 1988). These bubbles are then characterised as rational or irrational (Dale et al., 2005), where Rational bubbles are intrinsic or extrinsic. Intrinsic bubbles occur due to errors in valuing fundamentals, affecting asset price movements (Dale et al., 2005). While Abolafia and Kilduff (1988) explained that speculative extrinsic bubbles result from spikes in a particular market where the pricing increases to unsubstantiated levels, which are fuelled by irrational, speculative actions. Studies such as Fry and Cheah (2016), Fry (2018) and Chen and Hafner (2019) have documented evidence of speculative extrinsic bubbles in the cryptocurrency market. Interestingly, bubble behaviour is present in the largest cryptocurrencies such as Bitcoin and smaller ones such as Ethereum (Fry, 2018) and Ripple (Gronwald, 2021). Among other issues, a prominent aspect that causes bubbles within the cryptocurrency market is linked to behavioural biases among investors (Hidajat, 2019).

3.2.3 Investor sentiment literature

Multiple studies have been done to analyse the investor sentiment in the market due to the pricing patterns among cryptocurrencies. Bukovina and Marticek (2016) reviewed the sentiment of investors as a driver of Bitcoin volatility. The findings of the paper showed the marginal presence of sentiment during the overall studied period. Sentiment only explained a minor part of total volatility. However, during periods of excessive volatility, an explanatory value of sentiment increases, especially for positive sentiment. Bleher and Dimpfl (2018) reviewed 12 cryptocurrencies based on Google search volumes to determine the sentiment over five years. The analysis was based upon the Granger Causality and Vector autoregression

(VAR) models. The study found that returns could not be predicted using sentiment, whilst volatility could be indicated. The results of unpredictable returns hold on higher frequencies such as hourly, while lower on weekly frequencies. In contrast, volatility is predictable with the sentiment on all frequencies.

Abraham et al. (2018) sought to predict price movements of Bitcoin and Ether by using data from Google Trends and Twitter posts. The data was used to create a search volume index and found that the index had a high correlation with cryptocurrency prices in rising and falling prices. The study further found that the volume of Tweets influenced the prediction of cryptocurrency prices. Using a linear model to combine the Google Trends data and input Tweets, it was discovered that they could predict the direction of price movements and their volatility accurately. Nasir et al. (2019) used Google search volumes to determine sentiment effects on Bitcoin and contrarily found that Bitcoins returns were predictable in the short run. This was explained by the fact that Google searches were used for informational purposes prior to purchasing Bitcoin. Therefore, as searches increased, the returns became predictable. This result, however, may only be subject to Bitcoin rather than other cryptocurrencies, as found by Bleher and Dimpfl (2018).

Chen and Hafner (2019) tested for speculative bubbles using posts found on Stocktwits and compared them against the CRIX. The study identified multiple bubble periods. They further found that volatility increased as the sentiment decreases based on the leverage effect. The authors stated the leverage effect is similar to that found in classical financial markets, where bad news have a more substantial impact on volatility than good news. The findings were driven by the sentiment index and the EGARCH model. In a similar study, Chen et al. (2019) used Stocktwits and Reddit data to compare against CRIX to determine the impact of investor sentiment and conditional on bubble regimes on cryptocurrencies aggregate return prediction. The results found that during a bubble, sentiment-driven prices increase. However, during the post-bubble phase, the results depicted a price reversal, which resulted from the price correction for a behavioural overreaction. The study further found that investor sentiment helped forecast future cryptocurrency returns.

3.3 Conclusion

The chapter has examined investor sentiment and its effects on the cryptocurrency market. The chapter consisted of reviewing the theoretical framework of the financial market, that is, the

EMH and the impact of behavioural finance and biases which opposes the framework. The latter part of the chapter reviewed the empirical literature on investor sentiment and cryptocurrencies. Evidently, the EMH has been found to be flawed to reflect the investors' rationality within the financial market, with further irrationality on the cryptocurrency market. Subsequently, behavioural finance has then been found to be the dominant explanation of the investors' characteristics. By examining the literature, it was found that investors were prone to multiple behavioural biases which influenced their trading patterns. Further, it was found that investor sentiment was evident in the cryptocurrency market based on the sentiment found online. The following chapter will then discuss the methodology of this study, with a discussion on the data used and the models used to examine the cryptocurrency volatility, volatility spillovers and the effects of investor sentiment.

Chapter 4: Methodology

4.1 Introduction

As indicated in the preceding chapters, cryptocurrencies exhibit extreme volatility in their prices and returns. The volatility can be attributed to pump and dump schemes, financial market volatility, speculation and irrational investing behaviour. Further, there are volatility linkages among cryptocurrencies. There is a possibility that the extreme volatility patterns and volatility linkages can be attributed to investor sentiment. This chapter describes the data used in the study, such as the cryptocurrencies and investor sentiment measures, and the empirical methodologies used to achieve the study's objectives. That is, examining the nature of volatility, the nature of volatility spillovers and determining whether global investor sentiment influences the nature of volatility and volatility spillovers amongst cryptocurrencies.

4.2 Dataset

The cryptocurrency price data was taken from the Bloomberg terminal for each of the three cryptocurrencies – Bitcoin, Ethereum and Ripple. As each cryptocurrency was originally issued at different dates, the study's starting date was required to be the earliest common date amongst all three cryptocurrencies. The common starting date enabled the study to analyse the cryptocurrencies equally based on the same period. This then determined whether all cryptocurrencies faced similar volatility within the same period. Hence, the study period began on 2 February 2018, until 24 August 2021. The data period chosen was deemed sufficient to capture significant patterns exhibited by Bitcoin, Ethereum and Ripple. Further, daily data frequency was employed. This is because cryptocurrencies experience significant fluctuations daily (Stosic et al., 2019; Liew et al., 2019). The daily data was found more beneficial as the cryptocurrency volatility could be analysed thoroughly in contrast to a weekly or monthly frequency where some of the volatility spikes could be missed.

4.2.1 Cryptocurrency data

There are quite a large number of cryptocurrencies that continue to be issued in the world. These alternative cryptocurrencies are being brought about due to improvements on the current cryptocurrencies (Bitcoin, 2020). However, in this study, only Bitcoin, Ethereum and Ripple were considered as their market capitalisation, which is their total value in the market, is significantly higher than other cryptocurrencies. Bitcoin’s market capitalisation was around

61%, Ethereum's market capitalisation was at 12.39% and Ripple's market capitalisation was at 3.26%, a market capitalisation of 76.65%.

4.2.1.1 Bitcoin

Bitcoin was the first peer-to-peer currency made public in January 2009. It is the most popular cryptocurrency in the market due to its 'first mover advantage' (Andolfatto and Spewak, 2019). In addition, Bitcoin was the first to offer decentralisation, anonymity and, importantly, stability, which also increased its popularity (Wang and Li, 2015). Per Bornholdt and Sneppen (2014), Bitcoin gained a competitive advantage by having a better reputation, higher price stability, more media coverage, higher liquidity and large market capitalisation. It is not surprising that Bitcoin continues to hold the attention of all market participants due to its ever-increasing adoption by companies, institutional investors, and most recently, by countries such as El Salvador (BBC, 2021). In addition, Bitcoin has a limited supply; thus, the purchasing power of a single Bitcoin increases exponentially based on its demand in the market.

4.2.1.2 Ethereum

Despite its significant popularity, some of Bitcoin's deficiencies led to the development of altcoins (DeVries, 2016; Gandal & Halaburda, 2016). In this regard, Ethereum is second to Bitcoin in the cryptocurrency market and increased significantly in popularity due to its underlying technology. According to Ethereum (2021), it offers DeFi (Decentralised Finance), which is an open financial system that does not have centralised authorities. This provides multiple benefits compared to traditional finance. For instance, customers can personally hold their money in the form of cryptocurrency rather than companies such as banks, transactions are pseudonymous, DeFi is open to anyone, and it is built on transparency (Ethereum, 2021). As a result, multiple cryptocurrencies have been formed using Ethereum technology, providing unique features for companies and investors to benefit from (Lansky, 2020).

4.2.1.3 Ripple

Ripple is the third-largest cryptocurrency, which Ripple Labs created in 2012 (Chen et al., 2017). According to Wang and Vergne (2017), Ripple was developed with an authentication process that could attain consensus without the need for a conventional mining process such as that of Bitcoin. Brown (2013) stated that Ripple is both a network and a virtual currency that facilitates payments without time and cost barriers related to either third-party verification systems or currency exchanges. Ripple mainly serves as a remittance platform and a digital currency exchange (Wang and Vergne, 2017). Via the Ripple platform, banks may transact directly with each other globally without the need for a central intermediary (Chen et al., 2017). In addition, Ji et al. (2019) found Ripple to have returns up to 36000%, thus indicating the popularity of the cryptocurrency based on its tremendous growth.

Before the analysis, log returns were computed for each cryptocurrency series. According to Quantivity (2011), log-returns provide the benefit of normalisation, to which all variables of different price levels can be compared. The normalisation is imperative as cryptocurrency prices vary drastically. Additionally, log-returns use helps to deal with the problem of heteroskedasticity in the data (Boostedml, 2019). Equation 1 shows how the returns were computed:

$$\boldsymbol{R_t = In\ (p_t/p_{t-1})} \tag{1}$$

Where: the log returns, lnR_t, were computed from p_t, the closing price on day t, and p_{t-1}, the previous day closing price using the log transformation.

4.2.2 Investor sentiment data

Per Baker and Wurgler (2007), investor sentiment has no agreed-upon measure. As mentioned in the previous chapter, traditional finance does not account for investor sentiment and behavioural biases. Instead, the EMH stated that all deviations are random rather than systematic. As previously discussed, studies such as Nasir et al. (2019, Bouri et al. (2019) and Chen et al. (2019) found that there is a general consensus that investor sentiment has a pervasive effect on cryptocurrencies. However, investor sentiment lacks a consensus as to how it is measured. Baker and Wurgler (2006) confirmed this by explaining that testing the effects of sentiment is simpler than measuring the phenomenon. Investor sentiment does not have a universal measure as it can be separated into three categories – direct, indirect and meta measures (Panday and Sehgal, 2019). As a result, investor sentiment can be measured in different ways, which are dependent on the study.

Thus, prior studies have used multiple methods to examine the effects of investor sentiment, such as surveys, lexicons and proxies. A survey was defined by Ponto (2015:1) as "a collection of information that is attained from a sample of individuals through their responses to questions." Per Beer and Zouaoui (2011), the survey approach provides an opportunity to examine and analyse an investor's mindset without the need for an affirming financial theory. Further, according to Baker and Wurgler (2007), surveys are appropriate for gathering a vast array of information that shape investor expectations. Some of the most popular surveys include the Investor Intelligence (II) and the American Association of Individual Investors (AAII) surveys. However, surveys may be disadvantageous as the participants may provide inaccurate answers due to dishonesty and misunderstanding (Finter, Niessen and Ruenzi, 2008). Herein, surveys were not used as they are more country-specific, not global, as this study required.

The lexicon method involves determining the orientation of articles using opinion words (Rajput et al., 2016). According to Oliveira, Cortez and Areal (2014), this method comprises developing a scoring system that establishes if an article is of a positive, a neutral or a negative tone regarding the investment outlook or any financial or economic aspect. Jijkoun, de Rijke, and Weerkamp (2010) explained that this approach can be executed automatically or manually and centers around identifying seed words that reflect the sentiment of the writers of the article. They are, however, very subjective and may be inconsistent (Jijkoun et al., 2010). Ding, Liu, and Yu (2008) found that the lexicon approach produced inaccurate results as it failed to detect conflicting opinion words. Also, Rajput, Haider, and Ghani (2016) found that lexicons could not detect a domain and opinion words that are context-specific to interpret the appropriate meaning of a sentence.

Due to both surveys and lexicons' disadvantages, a preferred and vastly used alternative is investor sentiment proxies. These are macroeconomic factors, either quantitative or qualitative, that indirectly reflect the prevailing investor sentiment (Panday and Sehgal, 2019). A wide range of proxies was employed in various studies that investigated sentiment effects on financial markets. These include first-day returns on IPO’s, dividend premiums, share turnover, closed-end fund discounts, Bloomberg commodity index, the VIX, the S&P 500 index, the MSCI emerging market index, the Gold spot price and the equity issue ratio (Baker and Wurgler, 2006; Uygur and Tas, 2014; Han and Li, 2017; Liew et al., 2019) Additional proxies include the advance/decline ratio, the term structure of interest rates and the US Dollar index (Muguto et al., 2019; Rupande et al., 2019). The studies found that proxies were successful in measuring the sentiment on financial markets.

However, proxies are not without their shortcomings. Per Baker and Wurgler (2006), one such drawback is that proxies contain both a sentiment component and an idiosyncratic, non-sentiment related component. These may be difficult to separate. A possible method to amend this issue is to construct a composite index using various proxies. Multiple studies such as Brown and Cliff (2005), Baker and Wurgler (2006), Nor et al. (2013), Khan and Ahmed (2018), Liew et al. (2019), Muguto et al. (2019) and Rupande et al. (2019) have found that a composite index outperforms individual proxies in measuring sentiment and its fluctuations. This is the case of a method that separates the sentiment and the non-sentiment component in a proxy and has been used to construct the index. As such, this study took a similar approach to determine global investor sentiment. A total of five proxies, as described below, was used, with data for each accessed from the Bloomberg database:

1. Global price of gold

Gold is considered a haven from losses in financial markets and investors tend to reallocate their investment portfolio following a shock in another market by including gold as a safety asset (Wen and Cheng, 2018; Akhtaruzzaman et al., 2020). Further, gold can act as a high-quality asset in the flight to quality phenomenon (Padungsaksawasdi, 2019). In addition, the increased level of financial market integration means that security prices in other markets and gold markets are largely based on the same set of information. This explains the simultaneous changes in prices in the gold and stock markets, especially following a market crash (Hossenidoust et al., 2013; Mensi et al., 2013). However, only few studies have employed its price and price changes as proxies to measure investor sentiment. These include studies by Padungsaksawasdi (2019) in Thailand, Reis and Pinho (2020) in Europe and Muguto et al. (2021) in South Africa.

2. Global price of oil

Economic activity, which is highly dependent on energy, affects oil prices (Olayeni et al., 2020). Further, there has been increased financialization of oil futures markets (Du and Zhao, 2017) which, according to Fattouh et al. (2013), has allowed speculation among retail investors to become a major determinant of the spot price of oil. The same retail investors – usually unsophisticated noise-driven speculators – operate on cryptocurrency markets. Various studies have linked oil prices to investor sentiment. For instance, Qadan and Nama (2018) and Apergis et al. (2020) found that unanticipated shocks to oil prices have a significant effect on US investor sentiment. He (2020) and Ye et al. (2020) found a leading position of crude oil prices in the co-movement relationship with investor sentiment. Huang and Zheng (2020) also reported a significant relationship between sentiment and crude oil futures in China, increased following the Covid-19 pandemic.

3. US dollar index

The US dollar index is a calculation of six currencies – the French franc, Japanese yen, British pound, Canadian dollar, Swedish krona and Swiss franc – that are averaged against the US dollar (Sun et al., 2017). The choice of the index was based on its growing significance due to financial market liberalisation policies. These policies have allowed cross-border investments to increase with investors in search of higher returns and portfolio diversification opportunities (Gupta, 2020; Roy and Shijin, 2020). Accordingly, a movement in the exchange rates is likely to be of concern to investors (Mahapatra and Bhaduri, 2019) and, therefore, influence their sentiment. Many studies employed different exchange rates as proxies for investor sentiment. These include Rupande et al. (2019) and Muguto et al. (2019; 2021) in South Africa. Some other studies showed that there is a relationship between exchange rates and sentiment (Heiden et al., 2013; Škrinjarić et al., 2020; Vurur, 2020; Shahzad et al., 2021; Chakraborty, 2021).

4. Bloomberg commodity index

This is a financial benchmark index designed to provide liquid and diversified exposure to physical commodities via futures contracts (Bloomberg Professional Services, 2021).The way it is constructed makes it attractive as a sentiment proxy; it is calculated on an excess return basis and reflects commodity futures price movements. With the increasing cointegration of other markets and commodity markets, its price movements, just as in the case of gold and oil, can reveal the expectations and sentiments of investors on stock markets. While no studies have employed this index specifically to measure sentiment, various studies provided the link between sentiment and commodities. For instance, Gao and Süss (2015) found that sentiment explained comovements among eight groups of commodity futures. Deeney et al. (2015), Qadan and Nama (2018), Ji et al. (2019) and Zhang and Li (2019) reported an association between investor sentiment and crude oil, which makes up 15 percent of the index. Maghyereh and Abdoh (2020) found significant dependence between commodity returns and sentiment.

5. Volatility index

The volatility index (VIX) is considered one of the most common barometers of market sentiment. It is a real-time volatility index created by the Chicago Board Options Exchange that quantifies market expectations of volatility. However, it is a forward-looking index, which means that it only shows the implied volatility of the S&P 500 for the next 30 days. The VIX is also known as the fear index, as it measures the level of market fear and stress. Many studies have employed the VIX as a sentiment measure. For instance, Lei et al. (2012) and So and Lei (2015) employed the VIX to examine the relationship between investor sentiment and US trading volume. Ghorbel et al. (2014) used the VIX to examine the impact of investor sentiment on conventional Islamic indices. Chau et al. (2016) used the VIX to determine the role of investor sentiment on trading behaviour on the US market based on its ability to capture investors' forward-looking expectations of market volatility whereas Mbanga et al. (2019) employed the VIX to examine the role of investor attention on the US market.

In constructing the composite index, the principal component analysis (PCA) method was used, which, according to Brooks (2014), is appropriate when the variables are closely related. It also removes redundant data, which is non-beneficial to the index as it exists in multiple places and reduces noise sensitivity, where random fluctuations from the mean do not result in a deviation from the trend. This, in turn, helps prevent information loss and increases interpretability in determining the influence of investor sentiment on returns and volatility (Rupande et al., 2019). According to Karamizadeh et al. (2013), the reduction of noise sensitivity is increased as the maximum basis of variance is chosen and small variations in the data are automatically ignored. Within the data, possible correlated variables are converted into linearly uncorrelated variables known as principal components (Vyas and Kumaranayake, 2006).

This conversion is based upon the orthogonal transformation. The method assigns weights to the proxies based on their sensitivity to sentiment to the common component they measure – investor sentiment. If the original explanatory variables are $x_1, x_2 \ldots, x_k$, the principal components $p_1, p_2 \ldots, p_k$, can be denoted as:

$$\begin{aligned}
\boldsymbol{p_1} &= \boldsymbol{\alpha_{11}x_1} + \boldsymbol{\alpha_{12}x_2} + \ldots\ldots + \boldsymbol{\alpha_{1k}x_k} \\
\boldsymbol{p_2} &= \boldsymbol{\alpha_{21}x_1} + \boldsymbol{\alpha_{22}x_2} + \ldots\ldots + \boldsymbol{\alpha_{2k}x_k} \\
\ldots \quad & \ldots \quad \ldots \quad \ldots. \\
\boldsymbol{p_k} &= \boldsymbol{\alpha_{k1}x_1} + \boldsymbol{\alpha_{k2}x_2} + \ldots\ldots + \boldsymbol{\alpha_{kk}x_k}
\end{aligned} \tag{2}$$

Where "α_{ij} are the coefficients on the *j*th explanatory variable in the *i*th principal component. Thereafter, the principal components are developed in descending order of importance" (Brooks, 2014:170). The order of importance contains higher related variables initially, thereafter, decreasing in relation. Subsequently, the eigenvalues are calculated and the eigenvector with its covariance matrix (Chen, Chong and She, 2014). Finally, the principal component index in general form is specified as:

$$\boldsymbol{y_t = y_0 + y_1 p_{1t} + \ldots + y_r p_{rt} + u_t} \quad \textbf{(3)}$$

Where: y_t is the principal component index, y_r is the weighting of each component and p_{rt} is the proxy within the index. The composite sentiment index equation of the study is:

$$\boldsymbol{Sentiment_t = \sigma_1 Gld_t + \sigma_2 Oil_t + \sigma_3 Udi_t + \sigma_4 Bci_t + \sigma_5 Vix_t} \quad \textbf{(4)}$$

Where: σ is the weighting of the component, *Gld* represents the Gold spot prices, *oil* represents oil spot price, *Udi* represents the US dollar index, *Bci* represents the Bloomberg commodity index, and *Vix* represents the VIX index. The five variables in the principal component analysis shared a common trait of daily values. Therefore, there was no need to convert the data to a standardised data frequency. Initially, the five variables were standardised to ensure all contribute equally to the analysis. According to Jolliffe and Cadima (2016), although there is nothing wrong from a mathematical perspective, the fact that the analysis is defined by variance, which depends on units of measurement, principal components based on the covariance matrix will change if the units of the variables of measurement are vastly different.

4.3 Methods of analysis

GARCH models are the most suitable for determining volatility and return volatility (Brooks, 2014). As such, section 4.3.4 outlines the requirements to enable GARCH modelling, while discussing the chosen GARCH models to examine the effects of investor sentiment on cryptocurrencies. Thereafter, section 4.3.5 explains the ADCC-GARCH model, which examines volatility spillovers. In addition, section 4.3.8 discusses the Toda-Yamamoto model, which analyses the causality.

4.3.1 Preliminary tests

4.3.1.1 Tests for unit roots and stationarity

Many time series have been documented as non-stationary, which implies that it may behave as a random walk process that deviates from the long-term mean (Lamba and Otchere, 2001). Brooks (2014:690) stated that "non-stationarity is due to time series data not having a constant mean, constant variance and a constant autocovariance structure". According to Brooks (2014), using non-stationary data results in spurious regression outputs with a very high R-squared value. Despite the high R-squared value and highly significant t-ratios, the spurious regression will indicate a relationship; however, there is no relationship between the variables in reality. Prior to estimations, unit root testing and stationarity testing were done using the Augmented Dickey-Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests, respectively.

The ADF test was created by Dickey and Fuller (1979) and is an autoregressive test that determines whether a shock to the series dissipates over time as it should for a stationary process, or the effects remain without dying away as in the case of a non-stationary variable. The ADF test was conducted using the intercept and the trend and intercept specifications methods to test the data for unit roots. The ADF test was carried out by estimating the following regression:

$$\Delta \boldsymbol{y_t} = \boldsymbol{\mu}\, \boldsymbol{y_{t-1}} + \sum_{i=1}^{p} \boldsymbol{a_i} \Delta \boldsymbol{y_{t-i}} + \boldsymbol{u_t} \qquad \textbf{(5)}$$

Where: "μ is white noise, u_t is assumed not to be autocorrelated and y_t is the time series data. The null hypothesis states H_0: Series has a unit root, and the alternative hypothesis states H_1: Series is stationary. If test statistic y_t is found more negative than its critical value, reject the null hypothesis; therefore, concluding there are no unit roots in the data" (Brooks, 2014:363).

A drawback of the ADF test is that it commonly fails to distinguish a highly persistent but stationary process from a non-stationary process (Brooks, 2014). Therefore, the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test of Kwiatkowski et al. (1992) was used to test stationarity to confirm the result. The KPSS test followed the ADF test, where the intercept and the trend and intercept were examined. The KPSS was specified as follows:

$$\boldsymbol{x_t} = \boldsymbol{r_t} + \boldsymbol{\beta_t} + \boldsymbol{\varepsilon_1} \qquad \textbf{(6)}$$

Where: "β_t is the deterministic trend, $\varepsilon_1$is the stationary error term and r_t is the random walk. The null hypothesis states that the process is trend stationary. Therefore, rejecting the null hypothesis if the test statistic is higher than its critical value means the series is not stationary. The results from both the ADF and KPSS are compared; if both tests depicted the same results, the results are deemed robust. However, in the case of different conclusions occurring, the KPSS test was used as the ADF tends to be biased towards rejecting the null hypothesis" (Brooks, 2014:365).

4.3.1.2 Tests for serial correlation

The Ljung-Box test (1978) was used to determine whether the cryptocurrency returns exhibited a significant serial correlation. For the test, specifying the number of lags are necessary to examine the patterns of autocorrelation. According to McQuarrie and Tsai (1998), there is no universally agreed number of lags to be used for time-series data. As daily data was used in this study, the returns may potentially be correlated over numerous periods. Therefore, 12 lags were used to compute the LB test. The LB test was calculated as follows:

$$\boldsymbol{Q^* = T(T+2)\sum_{k=1}^{m}\frac{\tau_k^2}{T-k} \sim \chi_m^2} \tag{7}$$

Where: T is the number of observations, Q is χ^2distributed with *j* degrees of freedom and τ_j is the k^{th} order autocorrelation.

4.3.1.3 ARCH model

Prior to estimating the GARCH models, the ARCH effects were tested for initially. The ARCH test is essential for discovering time dynamics of conditional variance such as volatility clustering. That is, a phenomenon that occurs within financial markets whereby phases of higher volatility often follow phases of high volatility, and phases of low volatility are followed by phases of lower volatility (Brooks, 2014). The ARCH test was done to verify the suitability of GARCH modelling. When testing for ARCH effects, Brooks (2014:426) explained that autocorrelation found within volatility was modelled by allowing σ_t^2, that is the "conditional variance of the error term, to depend on the immediate previous value of the squared error" as:

$$\boldsymbol{\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2} \tag{8}$$

As stated in Brooks (2014:426), "The null and alternative hypotheses are H_0: $\gamma_1 = 0$ and $\gamma_2 = 0$ and $\gamma_3 = 0$ and ... and $\gamma_q = 0$. H_1: $\gamma_1 \neq 0$ or $\gamma_2 \neq 0$ or $\gamma_3 \neq 0$ or ... or $\gamma_q \neq 0$. If the test statistic value is higher than the critical value found in the χ^2 distribution, the null hypothesis will be rejected." Once the ARCH effects were found in the data, the GARCH models were then utilised.

4.3.2 Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model

4.3.2.1 GARCH type models

Based on the confirmation of ARCH effects, GARCH models were estimated using the returns that were calculated using equation 1. The GARCH model was developed by Bollerslev and Tylor (1986) to model volatility in financial markets. The GARCH model consists of two equations: the mean equation and the variance equation (Katze and Garbers, 2016). The mean equation models the evolution of returns based on the input data and an error term. On the other hand, the variance equation models the error term's conditional variance from its mean with the variance examined as a function of lagged errors and past conditional variance. As the study is based upon determining the effects of investor sentiment on cryptocurrencies, an additional term was added to account for the sentiment. In modelling cryptocurrency volatility, certain aspects of the phenomenon are examined to understand its nature. This includes the risk-return relationship, volatility clustering, persistence, mean reversion and asymmetry. Thus, the first volatility models considered are three GARCH models: GARCH (1,1), GJR-GARCH (1,1) and the EGARCH (1,1). All these models have the same mean equation specified as:

$$\boldsymbol{y_t} = \boldsymbol{\mu} + \theta y_{t-1} + \nu\varepsilon_{t-1} + \boldsymbol{\delta y_{t-1}} + \boldsymbol{\varepsilon_t} \quad \textbf{(9)}$$

$$\boldsymbol{y_t} = \boldsymbol{\mu} + \theta y_{t-1} + \nu\varepsilon_{t-1} + \boldsymbol{\delta y_{t-1}} + \boldsymbol{\emptyset_t Sent_t} + \boldsymbol{\varepsilon_t} \quad \textbf{(10)}$$

Where: "δ represents cryptocurrency risk premium, θ captures the effect of past returns, ν captures the effect of past shocks, ε_t being the error term and $\emptyset_t Sent_t$ is the sentiment index. Coefficient δ is expected to be significant and positive, indicating that the increase in risk, given by the increase in the conditional variance, leads to a rise in mean returns, implying a risk premium among cryptocurrencies" (Brooks, 2014:445). The $\emptyset_t Sent_t$ coefficient is of importance as it indicates whether investor sentiment affects the returns of cryptocurrencies. The coefficient was expected to be significant and negative, proving that higher returns in the cryptocurrency market are due to investor sentiment.

The ARMA (1,1) model was applied to the cryptocurrency returns mean equation. The ARMA (1,1) model are made up of two components, namely the AR(1) and MA(1). The AR(1) parameter signified whether the returns series' current value is fitted with its previous values, which is the autoregressive. If the AR(1) parameter is positive, it indicates a positive serial correlation, with values closer to 1 having an extreme positive serial correlation. However, if the parameter is negative, it means a negative serial correlation, with values closer to -1 having extreme negative serial correlation (Solibakke, 2001). The MA(1) parameter shows the moving average of returns based on the error term's current and previous values. If the value is found positive, it shows positive autocorrelation in the return's series. If the value is negative, it implies negative autocorrelation (Solibakke, 2001).

The first GARCH model that was chosen for examination was the GARCH (1,1) model. The GARCH (1,1) is identified as the most robust and most straightforward GARCH model (Engle, 2001). The GARCH (1,1) embodies parsimonious qualities; therefore, it was chosen to estimate the implied volatility. According to Choudhry et al. (2015), the GARCH (1,1) avoids overfitting and allows for an infinite number of past squared errors, thereby influencing the current conditional variance. In estimating the GARCH (1,1) model, the conditional variance of cryptocurrency returns was allowed to be dependent on its own past values of the squared errors and on the past conditional variance (Brooks, 2014). This allowed the model to capture volatility clustering. The GARCH (1,1) model expects the coefficients α and β to be significant and positive, indicating the presence of volatility clustering. If: $\alpha_1 + \beta \geq 1$, it is termed non-stationarity in variance. If: $\alpha_1 + \beta = 1$ it is a unit root in variance. The stationarity constraint should be that for both $\alpha_1 + \beta$ should sum less than 1. The sum of $\alpha_1 + \beta$ indicates volatility persistence, with higher values showing more substantial volatility persistence in the returns (Rupande et al., 2019). In addition, the persistence in volatility should be less than 1 if volatility is mean-reverting.

With the GARCH (1,1) model, leverage effects in the market cannot be accounted for, and there may still be a violation of non-negativity constraints. The leverage effect, commonly known as asymmetric volatility, is described as the negative relationship between asset value and volatility. Black (1976) describes it as negative shocks increasing volatility more than positive shocks of equal magnitude. Nelson (1991) proposed the EGARCH (1,1) to deal with the issue, which was also used to estimate cryptocurrency volatility and return volatility. Logged conditional variance is used in the model to ease the non-negativity constraint (Tsay, 2010). The EGARCH (1,1) contains a leverage term explained as γ. To prove the asymmetry within returns and the presence of leverage effects, the coefficient γ was expected statistically significant and negative. Brooks (2014) stated the stationarity constraint for investor sentiment and volatility is expected to be (α_1+ β + γ) less than 1. If the model with the sentiment index contained a leverage term that was more negative than the model without the sentiment index, it, therefore, meant that investor sentiment increased volatility and the leverage effect.

The third model considered was the GJR-GARCH (1,1). Glosten, Jagannathan, and Runkle (1993) created the GJR-GARCH (1,1) as an extension of the GARCH in which a term was added that accounts for asymmetry (Brookes, 2014). The GJR-GARCH (1,1) is akin to the T-GARCH, where it differentiates with the use of variance rather than the standard deviation. The GJR-GARCH (1,1) contained an advantage over the EGARCH (1,1). The variance is directly modelled and does not use a natural logarithm; therefore, making it simpler to implement and use. The model was created as an indicator function to explain the volatility shocks that are positive and negative. The model assumes a zero-conditional mean. For a leverage effect, it will be shown as $\gamma > 0$. For non-negativity, it is required that $\alpha_1 + \gamma \geq 0$ and $\alpha_1 \geq 0$. According to Brooks (2014), the leverage term should be found positive and statistically significant to indicate the presence of asymmetry and leverage effects. Similarly, if the model with the sentiment index was found to be greater than the model without the sentiment index, the leverage effect is found to be higher with investor sentiment.

While the mean equation was common among the GARCH models to examine the returns, the four other aspects pertaining to volatility – persistence, clustering, mean reversion and leverage effects - were examined in the variance equations of the three models. The three GARCH models, As shown in Equations 11, 12 and 13, fulfil examining objectives one and three of the study. That is, examining the nature of volatility to explain the large variation in returns. Further, Equation 14, 15 and 16 addressed objective three, which is the effect of investor sentiment on cryptocurrency volatility. The GARCH models were parameterised as:

$$\boldsymbol{\sigma_t^2 = \omega + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 + \epsilon_t} \tag{11}$$

$$\boldsymbol{In(\sigma_t^2) = \omega + \beta\, In(\sigma_{t-1}^2) + \gamma\, \frac{U_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha\left[\frac{U_{t-1}}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{n}}\right] + \epsilon_t} \tag{12}$$

$$\boldsymbol{\sigma_t^2 = \omega + \alpha_1 u_{t-n}^2 + \beta\sigma_{t-n}^2 + \gamma u_{t-n}^2 + l_{t-n} + \epsilon_t} \tag{13}$$

Where: Equations 11, 12 and 13 are the equations of the GARCH (1,1), E-GARCH (1,1) and GJR-GARCH (1,1), respectively. "σ_t^2 is the conditional variance since it is one period ahead estimate or the variance based on any past information thought relevant, ω is a constant, u_{t-1}^2 measures the shock in volatility and σ_{t-1}^2 is the forecasted past variance" (Brooks, 2014:430). In Equation 12, "ω is the variance intercept, β is the coefficient of the logged GARCH term, $In(\sigma_{t-1}^2)$ is the logged GARCH term, γ is the scale of asymmetric volatility, γ $\frac{U_{t-1}}{\sqrt{\sigma_{t-1}^2}}$ is the last periods' shock, $\left[\frac{U_{t-1}}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{n}}\right]$ is the parameter that takes into account the absolute value of the last periods' volatility shock" (Brooks, 2014:441). While in Equation 13, "α_0 is the intercept for the variance, $\alpha_1 u_{t-n}^2$ is the variance that depends on the previous lag error terms, β is the coefficient for previously forecasted variance, γ is the scale of asymmetric volatility and l_{t-n} is a dummy variable" (Brooks, 2014:440).

Equations 11 to 13 were used to examine the effects of the volatility on cryptocurrencies. However, to determine whether investor sentiment has an effect on the volatility, a term was required to be added to the equations, which is the composite sentiment index. The GARCH (1,1), E-GARCH (1,1) and GJR-GARCH (1,1) with the sentiment index included are shown in equations 14 to 16, respectively. The models were depicted as:

$$\boldsymbol{\sigma_t^2 = \omega + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 + \varphi_t Sent_t + \epsilon_t} \qquad \textbf{(14)}$$

$$\boldsymbol{In(\sigma_t^2) = \omega + \beta\, In(\sigma_{t-1}^2) + \gamma \frac{U_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha\left[\frac{U_{t-1}}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{n}}\right] + \varphi_t Sent_t + \epsilon_t} \qquad \textbf{(15)}$$

$$\boldsymbol{\sigma_t^2 = \omega + \alpha_1 u_{t-n}^2 + \beta\sigma_{t-n}^2 + \gamma u_{t-n}^2 + l_{t-n} + \varphi_t Sent_t + \epsilon_t} \qquad \textbf{(16)}$$

Where: $\varphi_t Sent_t$ represents the composite sentiment index included in the GARCH models. As previously mentioned, to determine the effects of investor sentiment, the GARCH models would be run initially and examined. Thereafter, the GARCH model with the sentiment index would be examined and compared against the unaugmented GARCH model. If the sentiment augmented models have shown that volatility has increased, it is evident that investor sentiment affects the cryptocurrency volatility.

4.3.2.2 Model specification selection

Information criteria are used to find the optimal GARCH specification to model return volatility and volatility found in cryptocurrencies. These include the Schwarz's Bayesian Information Criterion (SBIC), Akaike's Information Criterion (AIC), and the Hannan–Quinn Information Criterion (HQIC). The SBIC incorporates a stricter penalty term compared to the AIC while the HQIC is somewhere in between. “The SBIC is strongly consistent, although inefficient, while the AIC is inconsistent but more efficient” (Brooks, 2014:278). According to Kumar et al. (2017), the SBIC delivers the correct model order, while the AIC will depict a too large model. Within the study, the SBIC model was chosen and used as it contains superior large sample properties. Further, it is unbiased and consistent in large samples. According to Ivanov and Killian (2001), the SBIC model is more accurate on a 120 or more sample size. Therefore, the SBIC was found apt as the study contained a total of 435 observations. The SBIC model was depicted as:

$$\boldsymbol{SBIC = In(\sigma^2) + \frac{2k}{T}\, In\, T} \qquad \textbf{(17)}$$

Where: residual variance is σ^2, the total parameters estimated are k=p+q+1, and T is the sample size. The SBIC values can take the form of both positive or negative. However, upon analysing the various GARCH specifications, the optimal model was based upon choosing the smallest SBIC value.

4.3.2.3 Model distribution

The augmented and unaugmented GARCH models were all estimated with three distribution assumptions – the normal distribution, the student's t and the generalised error distribution (GED). The normal distribution is based on bell curve distribution, where the curve is symmetric at the centre, and the mean, median and mode are all equal (StatisticsHowTo, 2021). The Student t distribution is similar to the normal distribution; however, it is more useful for smaller sample sizes and when the sample standard deviation is unknown (JMP, 2021). The GED differs from the other distributions mentioned. The GED is useful when the errors around the mean are of particular interest (StatisticsHowTo, 2021). The mean determines the distribution's peak; the standard deviation determines the dispersion, and the shape is determined by the kurtosis value, as kurtosis indicates the data found in the tails (StatisticsHowTo, 2021). The model with the best specification was subsequently was chosen by using the SBIC. Per Belhoula and Naoni (2011), the GARCH models' residuals have generally been found to be leptokurtic. This means that it was likely that the student's t and the generalised error distribution specifications would be chosen as the two distributions assume thick tails, which allows to better capture the leptokurtic pattern (Gregory et al., 2013).

4.3.3 Asymmetric Dynamic Conditional Correlation (ADCC) - GARCH Model

4.3.3.1 Constant Conditional Correlation GARCH (CCC-GARCH)

Sections 4.3.2 outlined the three commonly used GARCH models – GARCH (1.1), EGARCH (1,1) and GJR-GARCH (1,1). These models can be used to examine aspects of volatility such as the heteroscedasticity and asymmetry in volatility, for instance, the volatility clustering, volatility persistence, mean reversion and asymmetries. However, the aforementioned GARCH models do not account for the correlation amongst the data tested, as the explanatory variables cannot test for the correlation. To resolve this, Bollerslev (1990) initially created the constant conditional correlation GARCH (CCC-GARCH) to account for the correlations of exchange rates in the financial market between the pre and post periods of the European Monetary System. The estimation followed a two-step process. The first step entailed estimating GARCH models for all return series. In the second step, the estimated residuals from the first step were then used to calculate the dynamic correlation parameters. These were used to analyse co-movements (Gilmore et al., 2009).

The first step, according to Bollerslev (1990), was to estimate the GARCH model. The GARCH (1,1) model of Bollerslev (1986) was used, with the mean equation as follows:

$$\boldsymbol{y_t = \mu + \delta y_{t-1} + \varepsilon_t} \quad \textbf{(18)}$$

$$\boldsymbol{y_t = \mu + \delta y_{t-1} + \emptyset Sent_t + \varepsilon_t} \quad \textbf{(19)}$$

Where: "y_t represents cryptocurrency returns, θ captures the effect of past cryptocurrency returns, ε_t is the error term, and φ is the parameter that captures the effects of sentiment on returns" (Brooks, 2014:430). The variance equation of the GARCH (1,1) was as follows:

$$\boldsymbol{\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \epsilon_t} \quad \textbf{(20)}$$

$$\boldsymbol{\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \varphi Sent_t + \epsilon_t} \quad \textbf{(21)}$$

Where: σ_t^2 is the conditional variance, ω is a constant and long-term average value of the conditional variance, α measures the impact of past shocks on volatility and β captures the effects of past volatility on current volatility.

In the second step, the standardised residuals were used to estimate the conditional correlations, defined as:

$$\boldsymbol{H_t = D_t R D_t} \tag{22}$$

$$\textbf{Where: } \boldsymbol{D_t} = \begin{bmatrix} \sqrt{\boldsymbol{h_{o,t}^2}} & \mathbf{0} \\ \mathbf{0} & \sqrt{\boldsymbol{h_{s,t}^2}} \end{bmatrix} \tag{23}$$

4.3.3.2 Dynamic Conditional Correlation GARCH (DCC-GARCH)

Based on the limitations of the CCC-GARCH, Engel (2002) developed the DCC-GARCH, which has the flexibility of univariate GARCH. The advantage is the number of parameters estimated in the correlation does not depend on the number of series to be correlated. The DCC-GARCH is an extension of the CCC-GARCH and assumes the conditional correlation matrix is time-dependent (Bonga-Bonga & Nleya, 2016). The variance-covariance matrix of the DCC model was expressed as:

$$\boldsymbol{H_t = D_t R_t D_t} \tag{24}$$

Where: "$\mathrm{H_t}$ is a N x N covariance matrix, $D_t = diag\left(\sqrt{h_{it}}\right)$ defines the conditional correlation model and R_t represents a time-varying N x N correlation matrix where the diagonal elements are equal to one" (Katzke, 2013:11) and specified as:

$$\boldsymbol{R_t = (Q_t^*)^{-1} Q_t (Q_t^*)^{-1}} \tag{25}$$

Where: "$Q_t^* = diag(Q_t)^{\frac{1}{2}}$, a diagonal matrix where Q_t is the $(N \times N)$ symmetric positive definite matrix" (Katzke, 2013:12). Per Kocaarslan et al. (2017:46), "when Q_t is positive, Q_t^* ensures that R_t represents with ones on the diagonal and all other elements in the matrix have an absolute value less than 1. $Q_t = \{q_{ij,t}\}$ is a covariance matrix." The dynamic correlation relationship followed the equation:

$$\boldsymbol{Q_t = (1 - \theta_1 - \theta_2)\overline{Q_t} + \theta_1 u_{t-1} u_{t-1}' + \theta_2 Q_{t-1}} \tag{26}$$

Where "Q_t is the unconditional variance, $\bar{Q} = E[u_t u_t']$ is the unconditional covariance and θ_1 and θ_2 depict scalars that are non-negative and satisfy the stability condition when $\theta_1 + \theta_2 < 1$" (Katzke, 2013:12). The parameters θ_1 and θ_2 were estimated by maximising the log-likelihood function. The correlation estimator was as follows:

$$\boldsymbol{\rho_{ij,t} = q_{ij,t} / \sqrt{q_{ii,t} q_{jj,t}}} \tag{27}$$

4.3.3.3 Asymmetric Dynamic Conditional Correlation GARCH (ADCC-GARCH)

To account for asymmetries, Cappiello et al. (2006) added a term that allows for leverage effects. The ADCC-GARCH was used to model conditional volatilities and correlations for asset pairs, which was used within this study. The model allowed for identifying the volatility linkages within the cryptocurrency market, together with the impact that global investor sentiment has on the volatility linkages. In addition, the model accounts for the asymmetric response of conditional variance and correlation during periods of shocks (Chkili, 2016); that is, the leverage effects are taken into account as an explanation for volatility linkages. The model was specified as:

$$\boldsymbol{h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + d_i \varepsilon_{i,t-1}^2 I(\varepsilon_{i,t-1})} \tag{28}$$

$$\boldsymbol{h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + d_i \varepsilon_{i,t-1}^2 I(\varepsilon_{i,t-1}) + \varphi_t Sent_t} \tag{29}$$

Where: If $\varepsilon_{i,t-1} < 0$, its indicator function is I ($\varepsilon_{i,t-1}$) = 1. ω is the intercept for the variance, and α and β are the coefficients. A positive d will imply that negative residuals increase the variance more than positive residuals of equal magnitude in the model. Further, Cappielo et al. (2006) incorporated the asymmetric effect and the asset-specific news as follows:

$$\boldsymbol{Q_t = \left(\overline{Q} - A'\overline{Q}A - B'^{\overline{Q}}B - G'\overline{Q}^{\,*}G\right) + A'z_{t-1}z'_{t-1}A + B'Q_{t-1}B + G'^{z_t^- z_t'^-}G} \tag{30}$$

Where: z_t, z_t^-. z'^-_t are zero-threshold standardised errors = z_t when < 0, $\bar{Q}$ and $\bar{Q}^*$ are unconditional matrices, and the parameter matrices are A, B and G. Q_t is assumed to be positive, A+B+G < 1.

By implementing the ADCC-GARCH, two objectives were addressed. The first was objective two, which determined whether volatility transmission occurs among cryptocurrencies based on shocks in the market that are both positive and negative. The second objective addressed was objective three, which determines whether investor sentiment influences volatility spillovers amongst cryptocurrencies. Therefore, using the ADCC-GARCH model will identify the spillovers within the cryptocurrency market, together with the impact investor sentiment has on volatility and spillovers by determining the co-movement of cryptocurrencies in the market.

mean vector, no autocorrelations, constant variance, and normal distribution (Malek, 2018).

4.3.4 Diebold and Yilmaz volatility spillover index

To examine spillovers in the volatility of the cryptocurrencies, the generalized version of the spillover index in Diebold and Yilmaz (2012, 2014, 2015) was employed. This generalized version of the spillover index measures volatility spillover grounded on the forecast error variance decompositions from vector autoregressions. Thus, it can be used to measure the spillovers in any return characteristic of interest across the individual assets, asset portfolios and asset markets (Fasanya et al. 2020). This approach builds on the seminal work on VAR models by Sims (1980) and the notion of variance decompositions, which allows for examining how much of each cryptocurrency's forecast error variance can be explained by exogenous shocks to the cryptocurrencies. Following Diebold and Yilmaz (2012, 2014, 2015), the analysis first constructed a VAR with N variables and following the K^{th} order as:

$$\mathbf{y_t} = \sum_{\mathbf{k=1}}^{\mathbf{K}} \mathbf{\Theta_k}\, \mathbf{y_{t-k}} + \boldsymbol{\varepsilon}_\mathbf{t} \tag{31}$$

where $y_t = (y_{1t}, y_{2t}, \ldots, y_{Nt})$ is a vector of endogenous variables, comprising n = 1,…, N(12) observations on the volatility of the cryptocurrencies at day t; Θ_k, k = 1, …; K, are N x N parameter matrices; and $\varepsilon_t \sim (0, \Sigma)$ is a vector of disturbances that are assumed to be independently (though not necessarily identically) distributed over time. Key to the dynamics of the system is the moving average representation of Equation 31, which is given by:

$$\mathbf{y_t} = \sum_{\mathbf{p=0}}^{\infty} \mathbf{A_p}\, \boldsymbol{\varepsilon}_\mathbf{t-p} \tag{32}$$

where the N x N coefficient matrices of A_p are recursively defined as follows:

$$\mathbf{A_p} = \mathbf{\Theta_1 A_{p-1}} + \mathbf{\Theta_2 A_{p-2}} + \cdots + \mathbf{\Theta_p A_{p-l}} \tag{33}$$

where A_0 is the N x N identity matrix and $A_p = 0$ for $p < 0$. The variance decomposition transformation of the moving average coefficients from Equation 31 helps understand the system's dynamics. Such dynamics depend on the identification scheme applied and whether VAR innovations are contemporaneously correlated. Since VAR innovations are generally contemporaneously correlated, identification schemes based on Cholesky factorization achieve orthogonality, but variance decomposition results depend on variable ordering. Therefore, the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998) was used to overcome this shortcoming. This generalized VAR framework produces variance decompositions invariant to the variable ordering (Diebold and Yilmaz, 2012; 2014; 2015). In the generalized VAR framework, the H-step-ahead forecast error variance decomposition is:

$$\boldsymbol{\emptyset_{ij}(H) = \sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma_{ej})^2 / \sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \quad \textbf{(34)}$$

where Σ is the (estimated) variance matrix of the error vector ε, σ_{jj} is the (estimated) standard deviation of the error term for the volatility of cryptocurrency j, and e_i is a selection vector with 1 as the i^{th} element and zeros otherwise. This yields a 12 x 12 matrix $\phi(H) = [\phi_{ij}(H)]_{i, j=1,12}$, where each entry gives the contribution of cryptocurrency j to the forecast error variance of cryptocurrency i's volatility. The main diagonal elements contain the own contributions of volatility shocks to cryptocurrency i to its own forecast error variance. The off-diagonal elements represent cross-cryptocurrency volatility spillovers, defined here as contributions of other cryptocurrencies j to the forecast error variance of cryptocurrency i. Since own and cross-cryptocurrency variance contribution shares do not sum to 1 under the generalized decomposition, i.e., $\Sigma_{j=1}^{N} \phi_{ij}(H) \neq 1$, its row sum normalizes each entry of the variance decomposition matrix, such that

$$\boldsymbol{\widetilde{\phi}ij(H) = \phi_{ij}(H) / \sum_{j=1}^{N} \phi_{ij}(H)} \quad \textbf{(35)}$$

with $\sum_{j=1}^{N} \widetilde{\phi}_{ij}(H) = 1$ and $\sum_{i,j=1}^{N} \widetilde{\phi}_{ij}(H) = N$ by construction. From this expression in Equation 35, the total spillover index was constructed as:

$$\boldsymbol{T(S)H = \sum_{i,j=1, i \neq j}^{N} \widetilde{\phi}_{ij}(H) / \sum_{i,j=1,}^{N} \widetilde{\phi}_{ij}(H) \times 100 = \sum_{i,j=1, i \neq j}^{N} \widetilde{\phi}_{ij}(H) / N \times 100} \quad \textbf{(36)}$$

On average, Equation 36 measures and determines the contribution of volatility spillover shocks across all cryptocurrencies to the total forecast error variance. This approach is quite flexible and allows for obtaining a more differentiated picture by considering directional volatility spillovers. As such, the directional volatility spillovers received by cryptocurrency i from all other cryptocurrencies j and the directional volatility spillovers transmitted by cryptocurrency i to all other cryptocurrencies j are defined respectively as:

$$\mathbf{DS_{i\leftarrow j}} = \sum_{j=1,j\neq i}^{N} \tilde{\boldsymbol{\Phi}}_{ij}(\mathbf{H}) / \sum_{i,j=1,}^{N} \tilde{\boldsymbol{\Phi}}_{ij}(\mathbf{H}) \times \mathbf{100} = \sum_{j=1,j\neq i}^{N} \tilde{\boldsymbol{\Phi}}_{ij}(\mathbf{H}) / \mathbf{N} \times \mathbf{100} \qquad \textbf{(37)}$$

$$\mathbf{DS_{i\rightarrow j}} = \sum_{j=1,j\neq i}^{N} \tilde{\boldsymbol{\Phi}}_{ji}(\mathbf{H}) / \sum_{i,j=1,}^{N} \tilde{\boldsymbol{\Phi}}_{ji}(\mathbf{H}) \times \mathbf{100} = \sum_{j=1,j\neq i}^{N} \tilde{\boldsymbol{\Phi}}_{ji}(\mathbf{H}) / \mathbf{N} \times \mathbf{100} \qquad \textbf{(38)}$$

Note that the set of directional volatility spillovers decomposes total volatility spillovers into those coming from (or to) a particular cryptocurrency. By subtracting Equation 37 from equation 38, the net volatility spillovers from cryptocurrency i to all other cryptocurrencies j are obtained as:

$$\mathbf{NS_i}(\mathbf{H}) = \mathbf{DS_{i\rightarrow j}}(\mathbf{H}) - \mathbf{DS_{i\leftarrow j}}(\mathbf{H}) \qquad \textbf{(39)}$$

Equation 39 provides information on whether a cryptocurrency was a receiver or transmitter of volatility shocks in net terms. Put differently, Equation 39 provides summary information about how much each cryptocurrency's volatility contributes to the volatility in the other cryptocurrencies in net terms. Finally, the net pairwise volatility spillovers can be calculated as:

$$\mathbf{NPS_{ij}}(\mathbf{H}) = (\left(\frac{\tilde{\boldsymbol{\Phi}}_{ji}(\mathbf{H})}{\sum_{i,m=1,}^{N} \tilde{\boldsymbol{\Phi}}_{im}(\mathbf{H})} - \frac{\tilde{\boldsymbol{\Phi}}_{ij}(\mathbf{H})}{\sum_{j,m=1,}^{N} \tilde{\boldsymbol{\Phi}}_{jm}(\mathbf{H})}\right) \times \mathbf{100} = \frac{\tilde{\boldsymbol{\Phi}}_{ji}(\mathbf{H}) - \tilde{\boldsymbol{\Phi}}_{ij}(\mathbf{H})}{\mathbf{N}} \times \mathbf{100} \qquad \textbf{(40)}$$

The net pairwise volatility spillovers are simply the difference between the gross volatility shocks transmitted from cryptocurrency i to cryptocurrency j and those transmitted from cryptocurrency j to cryptocurrency i. Overall, four different spillover types can be generated using the Diebold and Yilmaz (2012, 2014, 2015) spillover index, and they are the total spillovers, directional spillovers, net spillovers and net pairwise spillovers. This index presents a method of analysing the connectedness between all the cryptocurrencies simultaneously.

4.3.5 Toda-Yamamoto model

To analyse the cryptocurrency market thoroughly, the GARCH models explained previously analyses the volatility and return volatility based on investor sentiment, while the ADCC-GARCH analyses the spillovers among cryptocurrencies. To investigate further, a causality model was found beneficial to determine the causality between each cryptocurrency and the sentiment index in both low and high sentiment periods. The Granger causality model can be used to examine short term causality between variables. The model was used in multiple studies such as Trabelsi (2018), Huynh (2018), Bouri et al. (2019) and Sojka et al. (2019). Despite the models use in multiple studies, the Granger causality model was found to consist of many issues. For instance, the model was found to produce spurious regressions (Aziz, Habibullah, Azman-Saini and Azali, 2000; Shakya 2015), and the model ignores critical components of a systems dynamics (Stokes and Purdon, 2017).

Toda and Yamamoto (1995) and Dolado and Lutkepohl (1996) developed an alternate short-run causality test due to the shortcomings of the Granger causality model. The Toda-Yamamoto model allows for the examination of causality dynamics regardless of the variables' order of integration. It is based on the VAR model, for which the appropriate lag length is determined based on the information criteria (Bedowska-Sojka and Kliber, 2018). “The VAR undergoes specification testing, and after that, the number of lags is added to the maximum order of integration, and the augmented VAR is set up” (Bedowska-Sojka and Kliber, 2018:6). Finally, a WALD test is run for the first p variables (Wolde-Rufael, 2005). The Toda-Yamamoto model is thus based on the VAR specified as:

$$\boldsymbol{Y_t = \alpha_x + \sum_{i=1}^{k+d} \theta_{x,i} X_{t-i} + \sum_{i=1}^{k+d} \theta_{x,i} Y_{t-i} + \varepsilon_{x,t}} \quad \textbf{(41)}$$

$$\boldsymbol{X_t = \alpha_y + \sum_{i=1}^{k+d} \theta_{y,i} X_{t-i} + \sum_{i=1}^{k+d} \theta_{y,i} Y_{t-i} + \varepsilon_{y,t}} \quad \textbf{(42)}$$

“K is the optimal lag length of X_t and Y_t, d is the maximal order of integration of the series in the system and error terms $\varepsilon_{y,t}$ and $\varepsilon_{x,t}$ are assumed to be white noise with zero mean, constant variance and no autocorrelation” (Amiri and Ventelou, 2012:542). To apply the model, the maximum order of integration of the series was determined. Thereafter, the SBIC model was used to determine the optimal lag of the VAR model. The third step consisted of estimating the (k+d) max order. The model tests the hypothesis that the coefficients of the first p lagged values of Y are zero in the X equation, and that of X is zero in the Y equation, based on the Wald test. If the null hypothesis is rejected, this indicates there is a causal relationship between cryptocurrencies and investor sentiment. By using the Toda-Yamamoto model, this addresses objective three – which is the influence of investor sentiment on cryptocurrencies.

4.4 Chapter summary

This chapter outlined the methodology used to analyse investor sentiment's effects on the volatility, return volatility and volatility spillovers in the cryptocurrency market. The study used three cryptocurrencies, namely, Bitcoin, Ethereum and Ripple and an investor sentiment index constructed using five proxies, namely, gold, oil, the US Dollar index, VIX and the Bloomberg commodity index. Preliminary tests include the stationarity tests using the ADF and KPSS tests, the Ljung Box test, Breusch-Godfrey LM test, and the Ljung Box squared test. Upon completing the preliminary tests, the ARCH model was employed to test for ARCH effects and allow the use of the GARCH models. The study used the GARCH (1,1), EGARCH (1,1) and GJR-GARCH models to examine cryptocurrency return volatility and the ADCC-GARCH model and the Diebold and Yilmaz volatility spillover index to examine spillovers in the market. A further test was done using the Toda-Yamamoto model to examine the causality between the investor sentiment index and cryptocurrency returns. The following chapter presents the results from the analysis and reviews the findings of the study.

CHAPTER 5: RESULTS AND ANALYSIS

5.1 Introduction

In the preceding chapter, the data and methodology of the study were illustrated. This chapter presents the results from the tests conducted on cryptocurrencies and investor sentiment in examining the nature of volatility, the nature of volatility spillovers and whether global investor sentiment has an influence. The results are based on the methods outlined in the previous chapter and relate the findings to prior studies on cryptocurrencies. The chapter begins with the examination of the Principal component analysis and its results. Thereafter, analysing Bitcoin, Ethereum and Ripple based on the descriptive statistics and preliminary tests. The subsequent section contains the tests using the chosen GARCH model for volatility, the ADCC-GARCH and Diebold and Yilmaz volatility spillover index for spillovers and the Toda-Yamamoto model for causality.

5.2 Investor sentiment index

5.2.1 Standardisation and orthogonalisation

To analyse the investor sentiment in the market, the Principal component analysis approach was used. Table 5.1 below reports the correlation results of the principal component analysis of the five proxies used to create the sentiment index. Initially, the five variables were standardised to ensure all contributed equally to the analysis. Following Kassambara (2017), this was achieved by taking the value minus the mean and thereafter dividing by the standard deviation. According to Jolliffe and Cadima (2016), there is nothing wrong from a mathematical perspective as the analysis is defined by variance, which depends on units of measurement. If there are large differences between the ranges of the initial variables, those larger range variables will dominate those with smaller ranges, resulting in biased results. Therefore, standardising the data to comparable scales prevents this problem. Accordingly, principal components based on the covariance matrix will change if the units of the variables of measurement are vastly different.

As mentioned in section 4.2.2, the study used the orthogonal transformation on the proxies. This method was used to assign weights to the proxies based on their sensitivity to sentiment to the common component they measure, which is investor sentiment. In Table 5.1, there were many instances where the orthogonal proxies' correlation increased than those between the raw proxies. This was consistent with Baker and Wurgler (2006), where they explained that if the raw proxies were driven by common macroeconomic conditions that were not removed through orthogonalisation rather than common investor sentiment, the outcome would have been opposite. This implied that the orthogonalisation of the sentiment proxies created variables that can better measure a common aspect compared to the non-orthogonalised variables.

Table 5. 1 Correlations between sentiment proxies

Panel A: Raw proxies					
	BCI	GLD	OIL	UDI	VIX
BCI	1.0000				
GLD	0.1594	1.0000			
OIL	0.7242	-0.0409	1.0000		
UDI	-0.2147	-0.5313	-0.0338	1.0000	
VIX	-0.3143	0.1539	-0.2954	-0.0234	1.0000
Panel B: Orthogonal proxies					
	BCI	GLD	OIL	UDI	VIX
BCI	1.0000				
GLD	-0.4618	1.0000			
OIL	0.7298	-0.4705	1.0000		
UDI	-0.8081	0.2733	-0.4660	1.0000	
VIX	-0.1117	0.0316	-0.4368	-0.1141	1.0000

Source: Own estimations (2021)

5.2.2 Principal component analysis

Accordingly, using the orthogonalised proxies depicted above, the principal component analysis was executed. Table 5.2 illustrates the results from the principal component analysis procedure. The first principal component accounts for 57.74% of the total variance. The result is higher than the 53% reported by Baker and Wurgler (2006), which indicated that the figure is robust. The variables that correlate the most with the principal component denoted PC 1 is OIL (0.5755), GLD (0.5360), UDI (0.5242) and BCI (0.3070). On the other hand, its correlation with VIX (0.1105) is low. A further examination of the results revealed each proxy yielded its expected correlation. This implied that as optimism in the market increases, it was expected that Gld, Oil and the Udi increases while Vix falls. Surprisingly, the Bci was found to have a lower and negative correlation to the sentiment index similar to Vix. This implied that Bci did not behave similarly to gold, oil and the US dollar index over the same period. Based on the first principal component, the sentiment index was defined by the equation:

$$Sentiment_t = -0.3070Bci_t + 0.5360Gld_t + 0.5755Oil_t + 0.5242Udi_t - 0.1105Vix_t$$

The first principal component is positively correlated with three variables and negatively correlated with the other two variables. Therefore, increasing the values of gold, oil and the US dollar index will increase the value of the first principal component. Conversely, increasing the values of the Bloomberg commodity index and the volatility index will decrease the value of the first principal component. The first two principal components explain 81% of the variation in the data. These two components lie on the steeper slope of the eigenvalue scree plot in Figure 5.2. The inclusion of the following two principal components accounts for 99%, which makes the slope less steep. The first two would have been an acceptable explanation level if the principal component analysis was for descriptive purposes. However, as there were subsequent analyses to be performed on the cryptocurrencies, all five proxies were used to analyse the investor sentiment.

Table 5. 2 Principal component analysis output

Eigenvalues: (Sum = 5, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	2.887057	1.704807	0.5774	2.887057	0.5774
2	1.182250	0.448351	0.2365	4.069307	0.8139
3	0.733899	0.562179	0.1468	4.803207	0.9606
4	0.171721	0.146648	0.0343	4.974927	0.9950
5	0.025073	---	0.0050	5.000000	1.0000

Eigenvectors (loadings):

Variable	PC 1	PC 2	PC 3	PC 4	PC 5
BCI	-0.307091	-0.548927	0.706445	-0.133041	0.295989
GLD	0.536095	0.162433	0.194971	-0.804534	0.030479
OIL	0.575510	-0.058596	-0.020381	0.393769	0.714063
UDI	0.524277	-0.259801	0.358631	0.359860	-0.632077
VIX	-0.110538	0.775477	0.577832	0.224659	0.045331

Ordinary correlations:

	BCM	GLD	OIL	USD	VIX
BCI	1.000000				
GLD	-0.461020	1.000000			
OIL	-0.486477	0.822714	1.000000		
UDI	-0.123193	0.762670	0.896752	1.000000	
VIX	-0.110472	0.029514	-0.230024	-0.240251	1.000000

Source: Own estimations (2021)

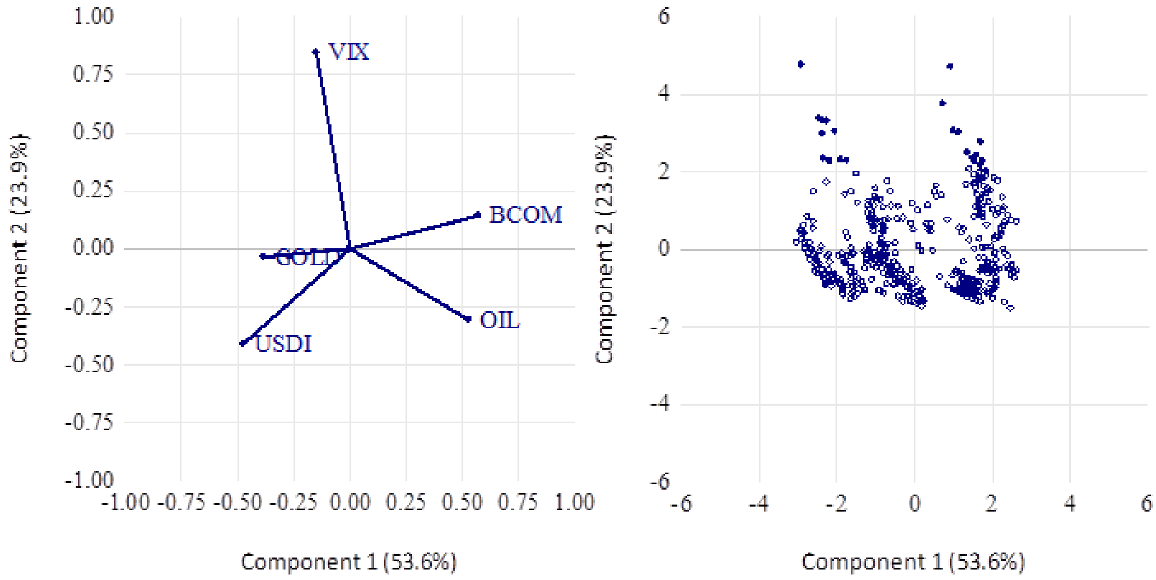

Figure 5.1 Orthonormal loadings and scores

Source: Own depiction (2021)

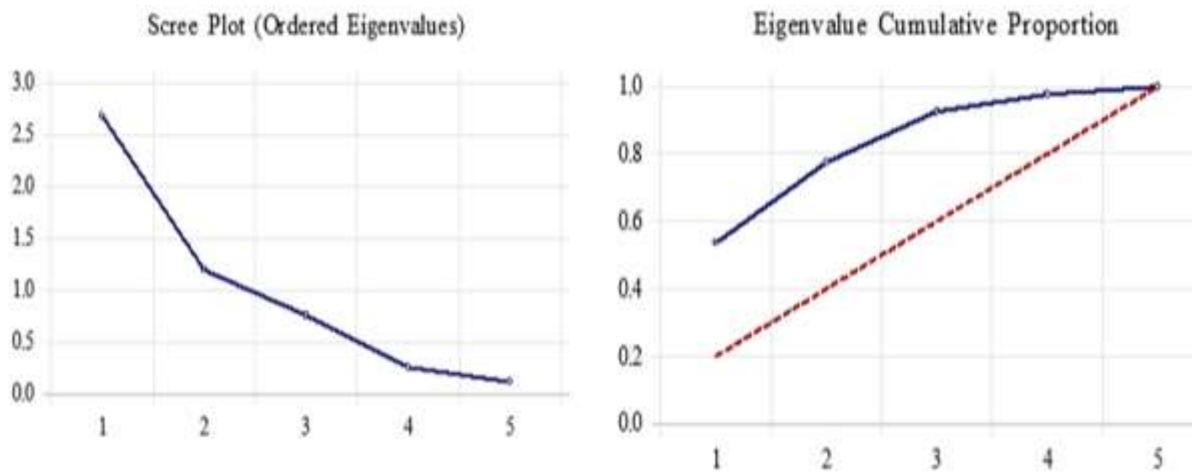

Figure 5.2 Eigenvalues and cumulative proportion plot

Source: Own depiction (2021)

5.3 Descriptive statistics

Kaur et al. (2018:60) stated that "descriptive statistics are used to summarise the data obtained in an organised manner by describing the variables in the dataset to interpret them in a meaningful way." The descriptive statistics of daily returns for cryptocurrencies are presented in Table 5.3 below. All cryptocurrency returns were negative, with Ethereum displaying the lowest average daily return (-0.3809%), followed by Ripple and Bitcoin (-0.2739% and -

0.0202%, respectively). The negative result was related to the bearish market in the study's time period. During this period, cryptocurrencies were faced with constant decreases in value, resulting in negative returns (Cleartax, 2021).

One of the contributing factors to Ethereum's low returns was a large sell-off witnessed in 2018, where the price fell temporarily from $319 to 10 cents (CNBC, 2018). The sell-off was due to an investor conducting a 'multimillion dollar' sell trade. The large trade caused the price to fall significantly, resulting in losses. As the sell-off was based on Ethereum, a smaller market capitalised cryptocurrency; the sell-off effects were not experienced in other cryptocurrencies due to its size and position in the market. Contributing to the volatility in Ethereum returns was in 2019 when the Bitcoin bubble supposedly burst, thus causing a spillover effect onto the Ethereum market.

On the other hand, the higher return on Bitcoin could be due to its better stability amongst the three cryptocurrencies, despite large crashes such as the 2019 Bitcoin bubble crash. While the Bitcoin market experiences volatility, the cryptocurrency is significantly more stable due to its larger market capitalisation and reputation in the market due to its continuous adoption. In addition to the stability factor, CNBC (2019) reported that in mid-2019, Bitcoin's value doubled since the beginning of the year. This significant increase in value was a contributing factor that led to the return value shown in Table 5.3. As a result, Bitcoin could provide higher returns compared to Ethereum and Ripple, as shown by the highest return figure.

Ethereum had the highest maximum and lowest minimum returns amongst the three cryptocurrencies. This result was possibly due to the sell-off crash. As stated in the report by CNBC (2018), the price rebounded promptly, resulting in sudden high returns. Ripple followed with the second-highest maximum return but had a lower minimum than Ripple. Correspondingly, Ethereum had the highest standard deviation (5.81%), followed by Ripple (5.73%) and Bitcoin (4.49%). Ethereum seems to have been significantly affected by issues in the market, such as large sell-offs and spillovers from other cryptocurrencies. Despite Ethereum holding the second position in market capitalisation, where it was believed the market is more stable, the cryptocurrency is prone to volatile price movements due to investors' trading. This was illustrated by CNBC (2018), where the report stated that Ethereum's year-to-date price increase was 4100% regardless of crashes, which depicts the actions of investors.

While Ripple is the least stable cryptocurrency among the three, there was not as much volatility in the Ripple market during the examined period compared to Ethereum. The instability was explained by Forbes (2018), where Ripple took as much as an 18% decrease in price when investors fled the market, which outpaced the losses suffered by other cryptocurrencies. Bitcoin had the lowest standard deviation as it is the largest and more stable cryptocurrency. Therefore, investors seem to correct any large deviations. Caporale and Plastun (2019) explained that this occurred by investors trading on price overreactions in the cryptocurrency market to exploit opportunities, resulting in the correction of large deviations.

The table shows negative skewness of -0.1188 for Bitcoin, while Ethereum and Ripple returns were positively skewed with values of 0.0756 and 0.5287, respectively. Per Mandimika and Chinzara (2012), the negative skewness of Bitcoin is an undesirable property as it indicates that more of the returns were below the mean, while the positive skewness of returns of Ethereum and Ripple were above the mean. This means that during a bearish market, Bitcoin faces lower returns in comparison to the altcoins in the cryptocurrency market.

Based on the kurtosis, Bitcoin, Ethereum, and Ripple had values of 5.2256, 5.2637, and 5.4548, respectively, which indicated that the cryptocurrencies have peaked curves. A similar result was found by Gyamerah (2019), where it was explained that as the cryptocurrencies are leptokurtic, it implied that the returns experienced broader fluctuations, resulting in extreme low and high returns. The Jarque-Bera test was also used to identify whether the cryptocurrencies were normally distributed. It was shown that all three cryptocurrencies were rejected at the 1% significance level, implying that they are not normally distributed. As a result, the GARCH models were likely to follow a student t distribution or the GED rather than the normal distribution.

Table 5. 3 Descriptive statistics

	InBtc	InEth	InXrp
Mean (%)	-0.0202	-0.3809	-0.2739
Maximum	15.1654	27.5110	26.9487
Minimum	-17.5305	-21.4403	-16.6597
Std. Dev (%)	4.4982	5.8127	5.7321
Skewness	-0.1188	0.0756	0.5287
Kurtosis	5.2256	5.2637	5.4548
Jarque-Bera	90.5996***	93.0860***	129.1988***

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively

Source: Own estimations (2021)

Figures 5.3 to 5.5 depict the cryptocurrency returns in relation to the composite sentiment index. From Figure 5.3, Bitcoins' volatility clustering frequently occurred in periods of increasing sentiment periods such as October 2018 and May 2019. The 2018 return volatility was related to the possible regulation of Bitcoin, which was affected by the investor sentiment in the market (CNBC, 2018). Further, between May and June 2019, Figure 5.3 showed evidence of volatility clustering and persistence due to the apparent bubble collapse. As Brooks (2014) explained, volatility clustering is the tendency for the variability of asset returns to occur 'in bunches.' While volatility persistence is when today's return has a large effect on the unconditional variance of many periods in the future (Mendelbrot, 1963).

Ethereum in Figure 5.4, however, displayed evidence of volatility clustering during November 2018, with evidence of increasing sentiment, as shown by the Sentiment index. Ripple, in Figure 5.5, depicted contrary results as the volatility clustering was found in decreasing sentiment periods between July 2018 and October 2018. Interestingly, Ripples' volatility clustering occurred in different phases from Bitcoin and Ethereum. While Ripple experienced volatility clustering in its own periods, Ethereum was found to contain volatility clustering soon after Bitcoin, indicating volatility spillovers. The patterns of the graphs suggested that cryptocurrencies were prone to the effects of investor sentiment as sought to examine based on the aim and objectives of the study.

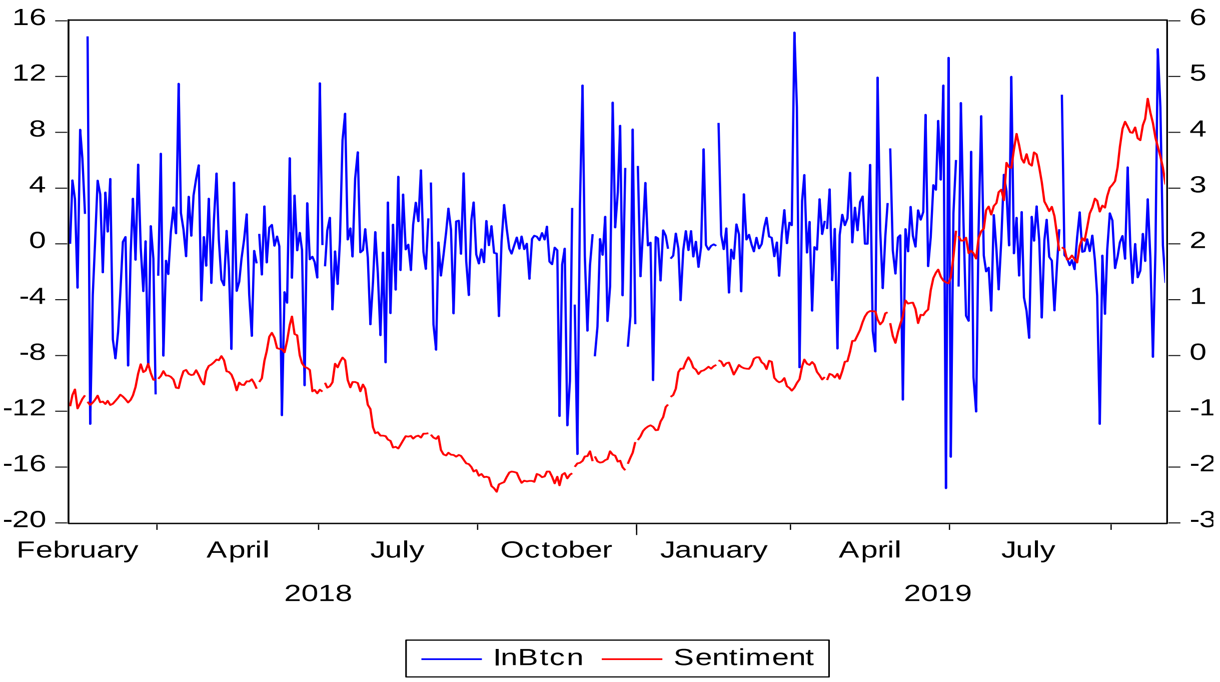

Figure 5.3 Bitcoin vs sentiment

Source: Own depiction (2021)

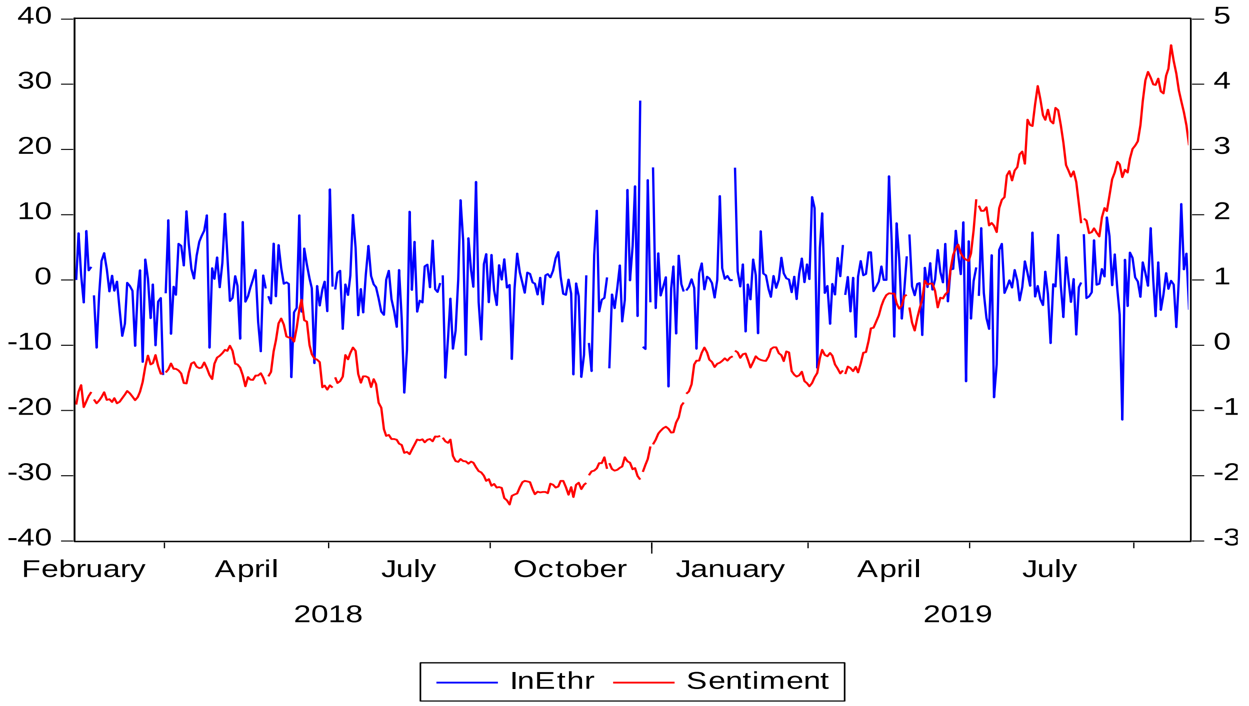

Figure 5.4 Ethereum vs sentiment

Source: Own depiction (2021)

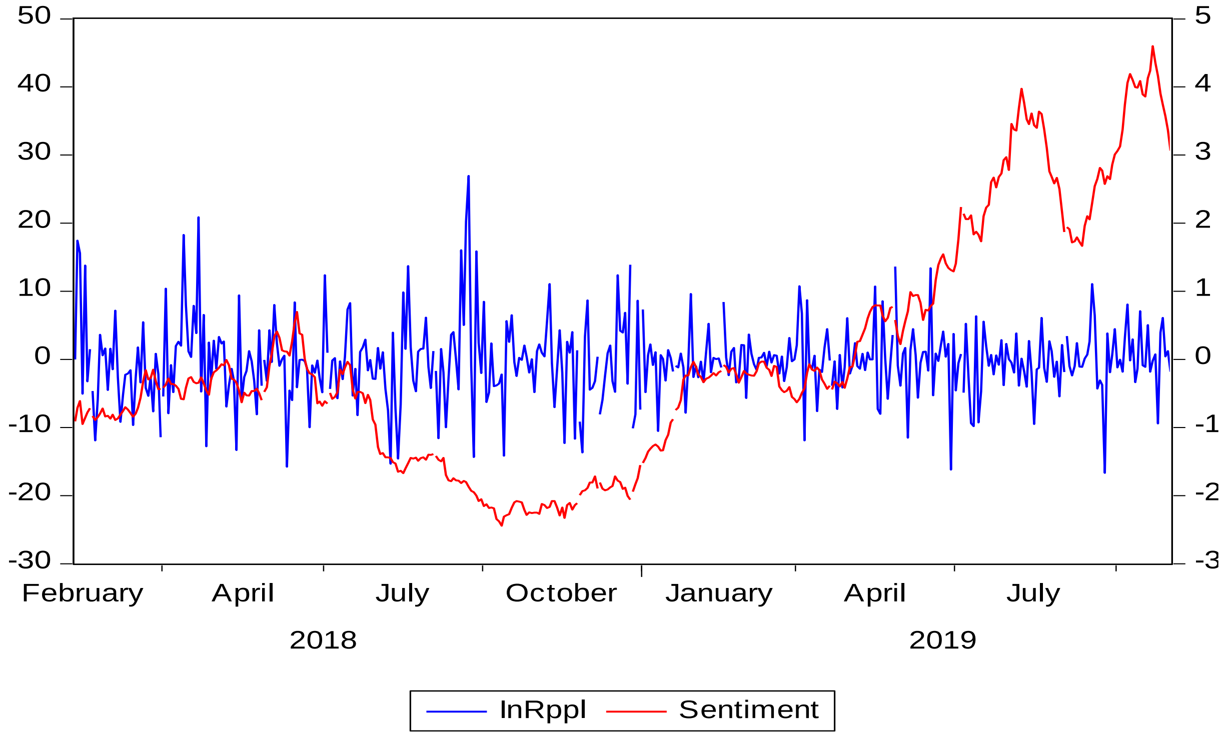

Figure 5.5 Ripple vs sentiment

Source: Own depiction (2021)

5.4 Stationarity tests

Lamba and Otchere (2001:208) explained that "time-series data tends to be non-stationary, implying that it may behave as a random walk process where it deviates from the long term mean without returning to the mean again." The use of non-stationary data yields a spurious relationship, with a high R-squared value (R^2). Table 5.4 displays the stationarity and unit root test statistics. The KPSS test was used to determine whether the series is stationary. This test ensures that the statistical properties of a series do not change over time (TowardsDataScience, 2020). Further, the unit root test, that is, the ADF test, determines whether a shock to the series dissipates over time as it should for a stationary process, or the effects remain in the case of a non-stationary process (Brooks, 2014). As mentioned in section 4.3.1, the ADF and KPSS tests were both completed as the ADF commonly fails to distinguish a highly persistent but stationary process from a non-stationary process. Therefore, the KPSS was used to confirm the results of the ADF.

The ADF test result showed that all cryptocurrencies reject the null hypothesis and indicate there are no unit roots at the intercept and trend and intercept level. The Sentiment index, however, contained a unit root at level. The first difference was then used, which led to the stationarity of the Sentiment index at all significance levels. The KPSS followed the same result as the ADF test, which found a consistent result of stationarity in the cryptocurrency returns at all significance levels. Therefore, based on both stationarity tests, the series was found strongly significant at the 1% level.

Table 5. 4 Unit root and stationarity tests

		InBtcn	**InEthr**	**InRppl**	**InSent**	
		Level	Level	Level	Level	First diff.
ADF	**C**	-21.1401***	-20.8633***	-20.7653***	-0.3735	-16.0595***
	T+C	-21.1484***	-20.8981***	-20.7495***	-1.5476	-16.1029***
KPSS	**C**	0.1561***	0.1755***	0.0286***	1.5601	0.2199***
	T + C	0.0713***	0.0538***	0.0223***	0.5801	0.0621***
Order of integration		I(0)	I(0)	I(0)	I(0)	I(1)

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively

Source: Own estimations (2021)

5.5 ARCH tests

Table 5.5 below displays the ARCH-LM and Ljung-Box test statistics. The ARCH-LM test results indicated the presence of ARCH effects within all three cryptocurrencies at the 1% significance level. This implied that the GARCH model could be used to determine cryptocurrency volatility, as well as the impact of global investor sentiment on cryptocurrency returns. The Ljung-Box statistic squared residuals were significant at the 1% level for Bitcoin and Ripple. However, Ethereum was found significant at lag 2 at the 1% level. The ARCH test thus indicated that the cryptocurrency returns are time-varying, and the GARCH model can be used.

Table 5.5: ARCH-LM test and Ljung-Box test

		InBtcn	InEthr	InRppl
ARCH-LM statistic		10.8835***	5.5322***	13.7700***
LB-statistic	**Lag 1**	23.125***	1.1947	14.329***
	Lag 2	36.718***	8.5919***	21.010***

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively

Source: Own estimations (2021)

5.5 Results and discussion

5.5.1 GARCH models

Tables 5.6 displays the information criteria results based on the SBIC values from the three GARCH specifications estimated without and with a sentiment factor, respectively. The SBIC method was selected as it contains superior large sample properties; further, it is sufficient, unbiased, and consistent (Brooks, 2019). The optimal GARCH specification that minimized the SBIC information criteria was chosen for each cryptocurrency. The GARCH (1.1) model with a student-t distribution was selected as the optimal model for Ethereum and Ripple, for both the no sentiment and with sentiment model scenarios. On the other hand, the E-GARCH (1.1) model was the optimal model for Bitcoin for the no sentiment scenario whereas the GARCH (1.1) with a GED distribution was optimal for the sentiment augmented models. The selection of GED and student-t distributions aligns with the descriptive statistics analysis that rejected normality as shown by high kurtosis values and significant JB statistics. Overall, the best models for the three cryptocurrencies were sentiment – augmented models as they minimised the SBIC information criteria more than the models without sentiment. These were GARCH (1.1) models with a student -t distribution for Ethereum and Ripple and GED for Bitcoin. The selection of these symmetric models suggested that there was no evidence of significant leverage effects.

Table 5. 6 Model selection

Unaugmented				
		BTC	**ETH**	**XRP**
GARCH-M (1.1)	Normal	-3.663786	-3.119734	-3.013823
	T	-3.971749	**-3.330025**	**-3.359649**
	GED	-3.963694	-3.329079	-3.338938
GJR-GARCH (1.1)	Normal	-3.670157	-3.117636	-3.008507
	T	-3.969126	-3.326214	-3.355350
	GED	-3.958835	-3.325011	-3.334045
E-GARCH (1.1)	Normal	-3.670725	-3.111080	-3.016738
	T	**-3.976922**	-3.328659	-3.358414
	GED	-3.885634	-3.326444	-3.336971
Augmented				
		BTC	**ETH**	**XRP**
GARCH-M (1.1)	Normal	-4.109842	-3.535191	-3.314207
	T	-4.197436	**-3.580159**	**-3.638113**
	GED	**-4.201040**	-3.566566	-3.477411
GJR-GARCH (1.1)	Normal	-3.966641	-3.524481	-3.303432
	T	-3.137211	-3.576738	-3.482315
	GED	-4.196679	-3.567586	-3.467780
E-GARCH (1.1)	Normal	-3.870547	-3.291930	-3.322394
	T	-3.998538	-3.399463	-3.449354
	GED	-4.007779	-3.398889	-3.445465

Source: Own estimations (2021)

In the mean equation of the unaugmented models in Table 5.7, the risk premium parameter, δ, was insignificant for all the cryptocurrencies suggesting no evidence of a reward for bearing more risk (Brooks, 2014). Thus, there was no feedback from the conditional variance to the mean return (Hossain, 2011). The autoregressive parameter θ, was statistically significant and negative for Bitcoin and Ethereum suggesting that past negative returns can be used to explain the current returns of these two cryptos. However, this parameter was insignificant for Ripple, which suggested efficiency in its pricing. The moving average parameter υ, was also statistically significant for Bitcoin and Ethereum but insignificant for Ripple. This meant that past shocks had explanatory power on the current returns of Bitcoin and Ethereum.

When sentiment was added, a change in significance of the mean equation parameters was noted as shown in Table 5.8. The intercept and the risk premium became significant for all the cryptos whereas, the ARMA parameters became insignificant. The results now showed evidence of a positive risk premium and efficient pricing of these cryptos as there was no serial correlation in the returns. The parameter that captured the effect of sentiment on returns, $\emptyset$, was statistically significant and positive for all the cryptos suggesting that returns increased with sentiment. This is not surprising given that there are many noise traders who mainly trade based on non-fundamental information.

The GARCH (1,1) specification requires that in the conditional variance equation, the parameters ω, α and β should be positive for a non-negativity condition. The non-negativity conditions were met for all models. The sum of α and β should be less than 1 to secure the covariance stationarity of the conditional variance. Moreover, the sum of $\alpha + \beta$ must be less than or equal to 1 for stability to hold (Bollerslev, 1986). If it is more than 1, an integrated GARCH process has occurred, which means that the conditional variance forecast will tend to infinity as the forecast horizon increases (Brooks, 2014). When examining the GARCH (1,1) results in Table 5.7, only one model satisfied the stationarity condition, as the models for Bitcoin and Ripple were explosive. These higher values of $\alpha + \beta$ indicated higher volatility persistence with even stronger persistence being evidenced for the explosive models (Zhang et al., 2018; Rupande et al., 2019). Given the extremely volatile nature of cryptocurrencies, volatility shocks are common, as indicated in Figures 5.3 to 5.5, where large fluctuations in returns were evident. However, the stationarity condition for all models was met when the models were augmented with a sentiment factor.

Similarly, the sum of $\alpha + \beta$ was used to indicate the presence of mean reversion among cryptocurrencies. Where a value of less than 1 indicates whether the volatility exhibited by the asset will tend to move toward its average level over time (Goudarzi, 2013). Upon analysing the results in Table 5.7, only Ethereum's volatility exhibited mean reversion. According to Poterba and Summers (1988), if the sum of $\alpha + \beta$ is high, which is high volatility persistence, it indicates that the mean reversion to average volatility will occur slowly. However, the results in Table 5.8, with the sentiment augmented models, showed that all cryptocurrencies' volatility mean-reverted. Of note, Bitcoin's volatility had the slowest mean reversion whereas Ethereum's volatility had the fastest mean reversion. Comparing the results in Table 5.7 and 5.8, shows that adjusting for sentiment lowers volatility persistence as all the volatility persistence values dropped when sentiment was added to the models. More so, there were no explosive models in Table 5.8. This shows that sentiment has a significant influence on the volatility persistence of cryptocurrencies.

Based on analysing the variance equation, coefficient ω denoted the long-term average volatility and was used to determine the long-term variance rate (Nilakantan, 2013). The term is expected to be positive, with an increase in the value signifying an increase in the long-term variance rate. The Bitcoin, Bitcoin-sentiment and Ethereum models were found insignificant, illustrating that long-term average volatility effects do not affect current volatility. However, the Ethereum-sentiment model was found to be significant and larger than Ethereum's value, which meant that investor sentiment affects Ethereum's long term average volatility on current volatility, with the variance rate increasing. Ripple and Ripple-sentiment values were found significant. The Ripple-sentiment value was larger than that of Ripple, indicating that investor sentiment increases the long-term variance rate. Notably, the GARCH (1,1) model recognises that the variance tends over time to get pulled back to a long-run average when significant (Nilakantan, 2013). This meant that the Ethereum-sentiment, Ripple and Ripple-sentiment models returned to their long-run average, while Bitcoin, Bitcoin-sentiment and Ethereum deviated from the long-run average.

Consistent with Dyhrberg (2016) and Cheikh et al. (2019), Bitcoin's results indicated that it was affected by past news and shocks in the market represented by α. This meant that prior effects in the Bitcoin market have continued into another period, which could be used to forecast shocks. Bitcoins past shocks were evident as it faced turbulence as an offshoot of Bitcoin, Bitcoin cash, was split into two separate versions, namely Bitcoin ABC and Bitcoin SV, in November 2018 (BBC, 2018). This challenge led to excessive volatility in Bitcoin itself as investors had claimed this move as creating turmoil within the cryptocurrency market. The shock in the market led to Bitcoin's market capitalisation falling by 37%. Further, Bitcoin was shown to have a highly significant GARCH parameter β, which indicated high levels of volatility clustering. The large value indicated by β was substantiated by the excessive volatility incurred in 2018, as there were prolonged periods where volatility was high and other periods where volatility was low.

Interestingly, as Bitcoin is the largest cryptocurrency, it was expected that it would be prone to the effects of investor sentiment in the market. However, the sentiment augmented model contained an insignificant value, thus indicating that volatility in the Bitcoin market cannot be explained by investor sentiment. Despite Figure 5.3 illustrating a close relationship between Bitcoin and the composite sentiment index, global investor sentiment could not be an explanation for the volatility in the Bitcoin market, although it can explain Bitcoins returns. Based on the findings by Baur & Dimpfl (2018), the authors stated that Bitcoin investors might be less prone to herding behaviour and act as contrarians. In addition, Bitcoin is the most mature cryptocurrency, with the additional option of trading Bitcoin futures, thus making it less prone to volatility caused by the effects of global investor sentiment as they are not dominated by uninformed investors (Baur & Dimpfl, 2018).

Upon examining the Ethereum models, similar to the Bitcoin's results, the ARCH coefficient in both Tables 5.7 and 5.8 was significant, revealing that Ethereum's volatility was also affected by past shocks in the market. The GARCH coefficient was highly significant, which indicated there was volatility clustering present. However, based on the sentiment augmented model, the sentiment term φ was insignificant suggesting that Ethereum's volatility was unaffected by investor sentiment unlike the mean equation findings where the returns where affected by investor sentiment.

Over the study period, Ethereum was faced with significant challenges that affected its returns and volatility, with the GARCH models confirming that investor sentiment was an explanation. For instance, in August 2018, Ethereum faced a sell-off which led to an eleven-month low (Business insider, 2018). The cause of the massive sell-off was due to investors who initially raised money via Ethereum, who then cashed in their holdings for their own developing cryptocurrency. The liquidation of their assets led to other investors selling, thereby creating volatility. In contribution to the volatility, a spillover in November 2018 from Bitcoin led to Ethereum's market capitalisation decreasing by 43% (CNBC, 2018). A year later, in August

2019, Ethereum was faced with a further decline in its prices as the co-founder of Ethereum announced that the cost of processing transactions done on Ethereum might get too expensive for some users (Bloomberg, 2019). Based on the news in the market, it was shown that Ethereum's prices fell thereafter. These significant events in the market were large influences on the investor sentiment that was found. The sentiment was directly linked to herding behaviour in the market as large amounts of assets were liquidated, with many investors following the same trend.

Ripple's result was similar to that of Bitcoin and Ethereum. It was found that the ARCH term was significant, implying that past shocks had affected Ripple's volatility. Further, the GARCH term was highly significant, depicting the presence of volatility clustering. Based on the volatility experienced in Bitcoin in November 2018, a spillover affected Ripple, which decreased its market capitalisation by 18%. In addition to the volatility in the Ripple market, according to a report in Bloomberg (2019), Ripple's returns decreased to low levels in August 2019 due to an increase in selling. This increase led to downward pressure in prices, which signified the dumping of the cryptocurrency. Akin to Bitcoin, the composite sentiment index was found not to impact the volatility of Ripple. Unlike the variance equation results, Ripple's returns were affected by global investor sentiment.

Table 5. 7 Selected model outputs for the unaugmented models

	BTC	ETH	XRP
Selected model	E-GARCH-M t dist.	GARCH-M t-dist.	GARCH-M t-dist.
Parameters	**CONDITIONAL MEAN EQUATION**		
μ	-0.0002	-0.0046	-0.0019
δ	0.0398	0.1207	0.0148
θ	-0.4734**	-0.4836***	-0.0972
υ	0.4035*	0.3962**	-0.0346
	CONDITIONAL VARIANCE EQUATION		
ω	-0.1713***	0.0001***	0.0001**
α	0.2229***	0.1411***	0.3010***
β	0.9937***	0.8333***	0.8225***
γ	0.0184	-	-
α + β	1.2166	0.9744	1.1235

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. All mean equations were modelled as ARMA (1.1) processes.

Source: Own estimations (2021)

Table 5. 8 Selected model outputs for the sentiment augmented models

	BTC	ETH	XRP
Selected model	GARCH-M GED	GARCH-M t-dist.	GARCH-M t-dist.
Parameters	**CONDITIONAL MEAN EQUATION**		
μ	-3.4244***	-7.9167***	-3.8922**
δ	0.2030***	0.4781***	0.2578***
θ	-0.0476	-0.0476	-0.1036
υ	-0.0386	-0.0291	-0.0052
∅	4.64E-06***	1.07E-05***	5.26E-06**
	CONDITIONAL VARIANCE EQUATION		
ω	0.0014	0.0025	0.0039
α	0.0881***	0.1801***	0.3086***
β	0.8956***	0.6134***	0.6600***
γ	-	-	-
φ	-1.90E-09	-2.53E-09	-4.82E-09
α + β	0.9837	0.7935	0.9686

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. All mean equations were modelled as ARMA (1.1) processes.

Source: Own estimations (2021)

Based on the results depicted in Table 5.8, coefficients α and β showed the levels of volatility amongst the three cryptocurrencies. It was evident by the sum of α and β that Bitcoin experienced the highest volatility, with Ripple after Bitcoin and Ethereum having the lowest volatility among the three. The result was found consistent with Hawaldar et al. (2019), who stated that more popular cryptocurrencies exhibited higher volatility than smaller cryptocurrencies, especially regarding their daily prices. However, the results within this study contradicted Cheikh et al. (2019), who argued that alternative cryptocurrencies (altcoins) fluctuated wider than Bitcoin, which is the dominant cryptocurrency. Furthermore, it was stated that the size of market capitalisation influenced volatility. However, the results of Cheikh et al. (2019) was inconsistent with the results of this study as Bitcoin was the most volatile, and Ethereum, which is the second-largest cryptocurrency, was found least volatile amongst the three.

The analysis results concluded all the cryptocurrencies' returns were influenced by global investor sentiment. However, the volatilities of these three cryptocurrencies were unaffected by sentiment. Pertaining to the effect of global investor sentiment, the lack of an official intrinsic value of cryptocurrencies leads to speculation in the market. Depending on the behaviour of the market price and new information, investors tend to overvalue and undervalue cryptocurrencies, which in turn further influences their pricing. The speculative behaviour of cryptocurrencies was proven in a study by Bhosale and Mavale (2018), which found Ethereum subject to speculation, news and hype. Thereby proving the findings of this paper in which global investor sentiment affected the cryptocurrencies'returns.

It is worth noting that a significant contributor to the effects of global investor sentiment was uninformed investors using noise trading on their decision making. According to Hellwig (1980) and Wang (1993), this implied that trading of uninformed investors leads to a rise in volatility, while informed trading reduces it. Price changes due to uninformed investors will be reversed, which then increases volatility by more than price changes due to informed investors (Avramov et al., 2006). The effect is also consistent with the disposition effect in the absence of informed investors. If uninformed investors are more likely to sell in rising markets than in falling markets, it implies a reversal, and thus creating higher volatility in rising markets. Therefore, there will be no reversal and lower volatility in a falling market.

5.5.2 Volatility co-movements among cryptocurrencies

In this section, the evolution of cryptocurrency conditional volatilities, as well as the volatility correlations among the cryptocurrencies, are examined to shed more light on their volatility associations.

5.5.2.1 Evolution of conditional volatilities

The evolutions of the conditional volatilities for each cryptocurrency over time are plotted in Figures 5.6 to 5.8 – based on the unaugmented and sentiment-augmented GARCH models. Similar patterns emerge across all markets, particularly the spikes in periods coinciding with certain events such as the COVID-19 global pandemic. Shocks regarding regulation announcements, raised environmental concerns of mining currency, stablecoin scrutiny and meme coins and scams seem to have been affecting all these cryptocurrencies similarly (Browne, 2021). This shows these events represent systemic shocks that affected all these cryptocurrencies, and the similar reaction to the shocks suggests volatility co-movements in these markets. Generally, the sentiment-augmented model residuals are lower than the unaugmented model residuals. This is indicative of the significant impact of investor sentiment on the conditional volatilities of the cryptocurrencies.

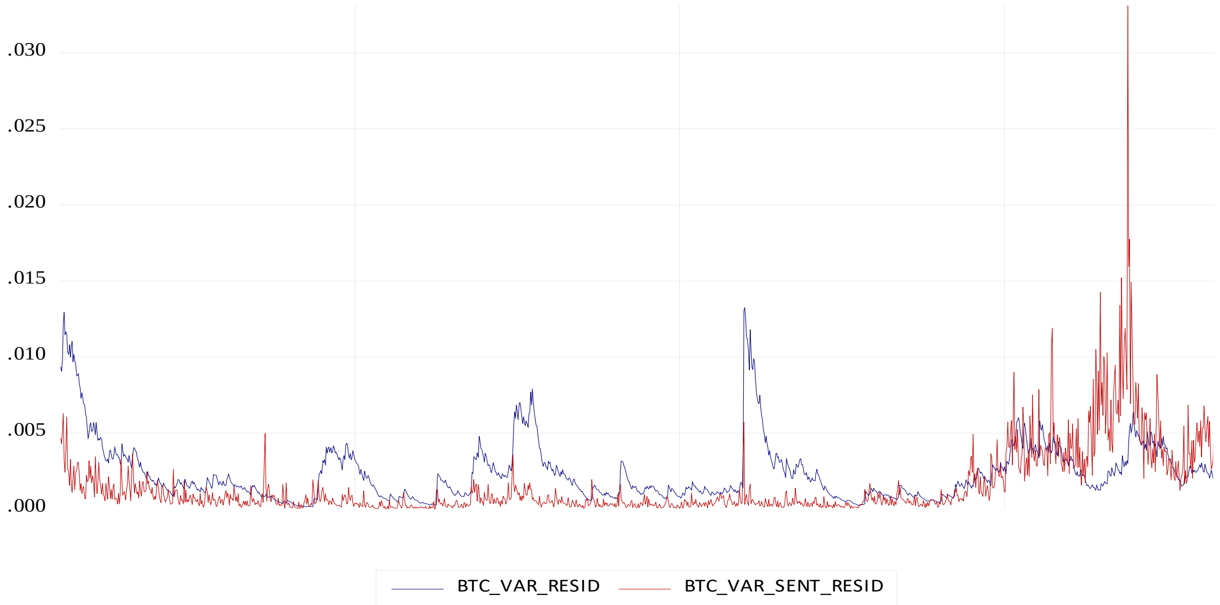

Figure 5.6 Conditional volatility plot: Bitcoin

Source: Own depiction (2021)

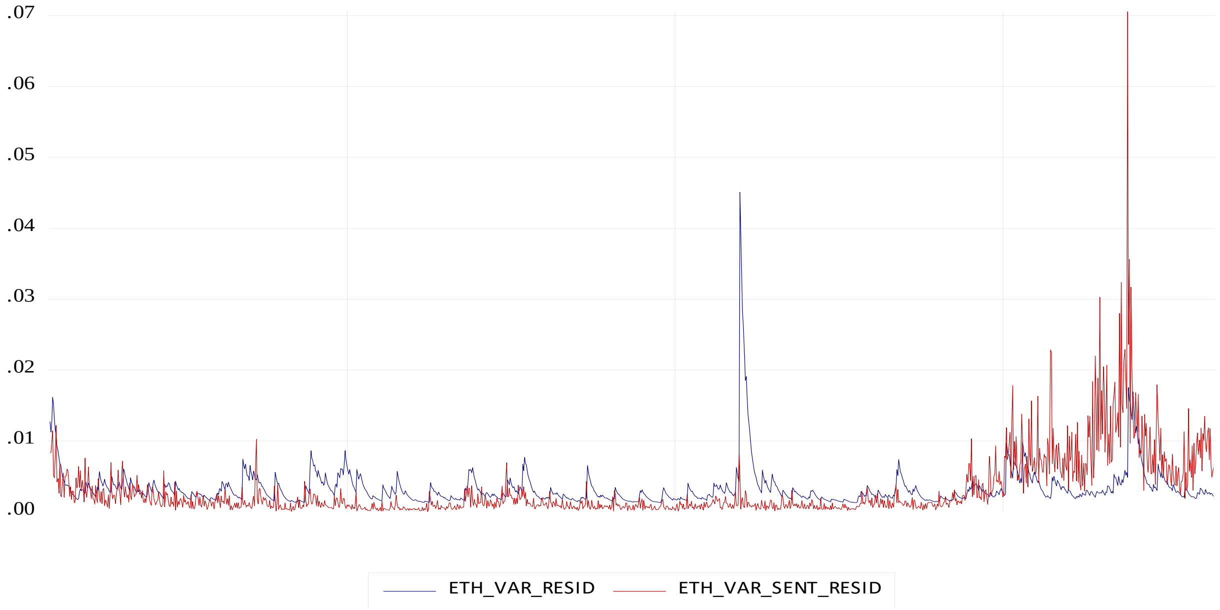

Figure 5.7 Conditional volatility plot: Ethereum

Source: Own depiction (2021)

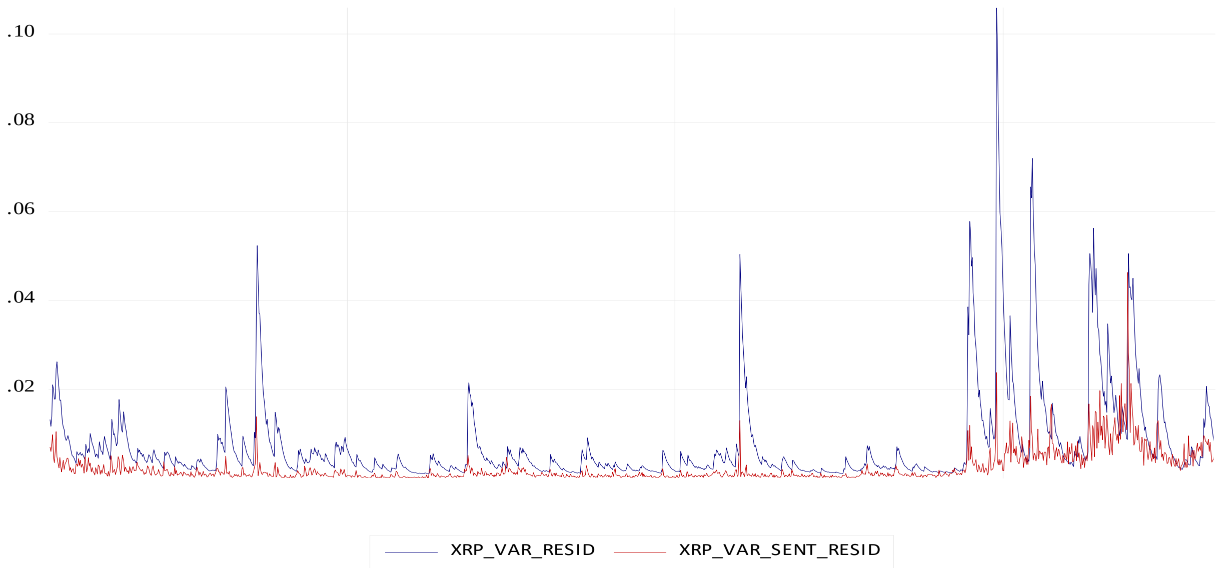

Figure 5.8 Conditional volatility plot: Ripple

Source: Own depiction (2021)

5.5.2.2 Volatility correlations among cryptocurrencies

This section presents the results from the ADCC-GARCH model of Cappiello et al. (2006) which is based on the three GARCH specifications – the GARCH (1.1), the GJR-GARCH (1.1) and the E-GARCH (1.1). As in the case of volatility, the best specification for each cryptocurrency was chosen based on the minimisation of the information. From Table 5.9 below, the θ_1 and θ_2 coefficients were statistically significant for all the three cryptocurrency pairs. These coefficients capture the effect of past shocks and past dynamic conditional correlations on current dynamic conditional correlations among the three cryptocurrencies. Their simultaneous significance indicates the presence of time-varying correlations across the three cryptocurrencies. Similarly, from Table 5.10 based on the sentiment-augmented models, both coefficients were significant. Overall, the evidence of time-varying volatility correlations suggests that a DCC-GARCH framework was appropriate in modelling such correlations among the three cryptocurrencies – both with and without sentiment. The stationarity condition, $\theta_1 + \theta_2 < 1$, was met for all the pairs, confirming the admissibility of the model.

However, the θ_1 coefficients went up while the θ_2 decreased in all the instances when investor sentiment was introduced to the mean and variance equations. In other words, the inclusion of sentiment increased the measured effect of past shocks and lowered the measured effect of past dynamic conditional correlations on current dynamic conditional correlations. This is indicative of the significant impact of sentiment on the volatility correlations among the cryptocurrencies. The failure to include sentiment in the examination of volatility correlations may result in the understating of the effect of past shocks and overstating of the effect of past dynamic conditional correlations. This would result in poor measurement of volatility correlations. The inclusion of sentiment also lowered the average dynamic conditional correlations as shown by a decline in the mean statistic. Likewise, there were lower maximums and minimums in all three instances following inclusion of sentiment. This indicates that there is a component of dynamic conditional correlations that investor sentiment explains and should, therefore, be included in these estimations.

In the unaugmented models, the asymmetry parameter, g, was statistically insignificant. However, the same parameter became significant in the sentiment-augmented models. This suggests that in the latter models, negative market momentum tends to strengthen the co-movement between markets more than positive momentum of equal magnitude. This is in line with the contagion effect across the cryptocurrencies. The daily average volatility correlations were generally positive over the sample period. However, they were less than 1, implying the presence of diversification benefits across these cryptocurrencies. However, the correlations were highest between Bitcoin and Ethereum and lowest between Bitcoin and Ripple. This was expected, considering the market capitalisations of these three currencies. Even when investor sentiment was included, the same pattern emerged. This suggests that market capitalisation may be a factor that influences the correlation between assets. The standard deviation was also lowest in the Bitcoin-Ethereum correlations in both instances, which highlights this significance of market capitalisation of these currencies.

Table 5. 9 ADCC GARCH for the cryptocurrencies (unaugmented)

	BTC-ETH	BTC-XRP	ETH-XRP
θ1	0.049036***	0.071532***	0.028623***
θ2	0.945627***	0.922139***	0.969712***
g	0.000621	-0.003800	-0.000796
ρ1.2 (μ)	0.809457	0.682767	0.763011
ρ1.2 (max)	0.977931	0.962315	0.934077
ρ1.2 (min)	0.496671	0.120209	0.287298
ρ1.2 (σ)	0.096395	0.152852	0.134094

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Source: Own estimations (2021)

Table 5. 10 ADCC GARCH for the cryptocurrencies (augmented)

	BTC-ETH	BTC-XRP	ETH-XRP
θ1	0.079810***	0.082425***	0.064328***
θ2	0.896667***	0.916679***	0.910094***
g	-0.023001***	-0.020638**	-0.015693**
ρ1.2 (μ)	0.781556	0.641426	0.719722
ρ1.2 (max)	0.967818	0.961046	0.875328
ρ1.2 (min)	0.419340	-0.044615	0.216793
ρ1.2 (σ)	0.080675	0.171603	0.101483

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Source: Own estimations (2021)

5.5.2.3 Volatility spillovers among the cryptocurrencies

In investigating the volatility interactions among the cryptocurrencies, dynamic analyses were conducted. This followed Diebold and Yilmaz (2009, 2012, 2014) by using a 200-day width rolling window to allow for time-varying and nonlinear spillover characteristics to be investigated. This is in contrast to the static framework which may miss the effects of a myriad changes that have been occurring in the cryptocurrency market that may have affected the interactions of the cryptocurrencies. Table 5.11 and 5.12 reports the results from the estimations based on the Diebold-Yilmaz index. The "From" column sums the share of volatility shocks in the total variance of the forecast error from one cryptocurrency to the other two cryptocurrencies. By definition, they are equal to 100 percent minus the own share of the total forecast error variance (Xiao and Huang, 2018). The "To others" row represents the contribution to the forecast error variances from one cryptocurrency to the other cryptocurrencies in the model. The net spillovers indicate the dominance of a particular cryptocurrency in transmitting or receiving information to and from other cryptocurrencies. A positive value suggests dominance, while a negative value suggests the subordination of a given cryptocurrency (Villeneuve, 2020).

The total directional connectedness results in Table 5.11 show that Ethereum (58.90 percent) was the largest transmitter of shocks to all cryptocurrencies, followed Bitcoin (51.55 percent) and lastly, Ripple (45.70 percent). With regards to the total directional connectedness from other cryptocurrencies, Ethereum (55.04 percent) received the most spillovers, followed by Bitcoin (52.46 percent) and Ripple (48.66 percent). These results highlight how Ethereum is the most connected to other cryptocurrencies, despite having a lower market capitalisation than Bitcoin. Similar patterns emerged when residuals from the sentiment-augmented models were employed. Ethereum (58.69 percent) was the largest transmitter of shocks to all cryptocurrencies, followed Bitcoin (51.35 percent) and lastly, Ripple (45.71 percent). With regards to the total directional connectedness from other cryptocurrencies, Ethereum (54.83 percent) received the most spillovers, followed by Bitcoin (52.31 percent) and Ripple (48.61 percent). The slight decline in most of the figures indicate that investor sentiment accounts for some of the spillovers.

The net dynamic volatility spillovers indicate both Bitcoin (-0.91 percent) and Ripple (-2.95 percent) were net receivers of volatility. On the other hand, Ethereum (3.86 percent) was a net transmitter of volatility. This finding is inconsistent with the prominent position of Bitcoin.

From the sentiment-augmented models, the value on Ethereum (3.86 percent) did not change whereas the values on Bitcoin (-0.96 percent) and Ripple (-2.90 percent) only changed slightly. The latter two changes confirm the impact of sentiment on volatility spillovers, albeit marginal. The total connectedness index fell from 52.05 percent to 51.92 percent, indicative of investor sentiment's impact on volatility spillovers of cryptocurrencies. To avoid the overestimation of these spillovers, investor sentiment needs to be considered. The changes also occurred in the pairwise estimations of volatility spillovers between pairs of cryptocurrencies. The diagonal elements of the connectedness table represent the own connectedness were the highest under the unaugmented models (47.54 percent, 44.96 percent and 51.34 percent) and the augmented models (47.69 percent, 45.17 percent and 51.39 percent). This suggests that own volatility spillovers were higher than cross-volatility spillovers.

Table 5. 11 Dynamic connectedness table for the cryptocurrencies (unaugmented)

	BTC	ETH	XRP	From others
BTC	47.54	31.73	20.73	52.46
ETH	30.07	44.96	24.97	55.04
XRP	21.48	27.17	51.34	48.66
To others	51.55	58.90	45.70	156.16
Including own	99.09	103.86	97.05	TCI
NET	-0.91	3.86	-2.95	52.05

Source: Own estimations (2021)

Table 5. 12 Dynamic connectedness table for the cryptocurrencies (augmented)

	BTC	ETH	XRP	From others
BTC	47.69	31.56	20.75	52.31
ETH	29.87	45.17	24.96	54.83
XRP	21.48	27.13	51.39	48.61
To others	51.35	58.69	45.71	155.75
Including own	99.04	103.86	97.10	TCI
NET	-0.96	3.86	-2.90	51.92

Source: Own estimations (2021)

Figure 5.9 below highlights the dynamism in the pairwise measure of volatility spillovers. Therefore, using a static model would have been misleading. Some slight changes can be noted between the unaugmented-based estimations and the augmented estimations. This also applies to Figures 5.10 to 5.13 which depict the volatility spillover from other cryptocurrencies, to other cryptocurrencies and the net spillovers. These figures also highlight the dynamism noted in the Figure 5.9. Of particular interest in the change from net receiver to net transmitter of Bitcoin in 2021. This is in line with the finding that the market or asset that experiences the most volatility is likely to be the one that transmits the most volatility. Bitcoin has experienced quite a number of shocks so it is conceivable that it would turn from being a net receiver to being a net transmitter.

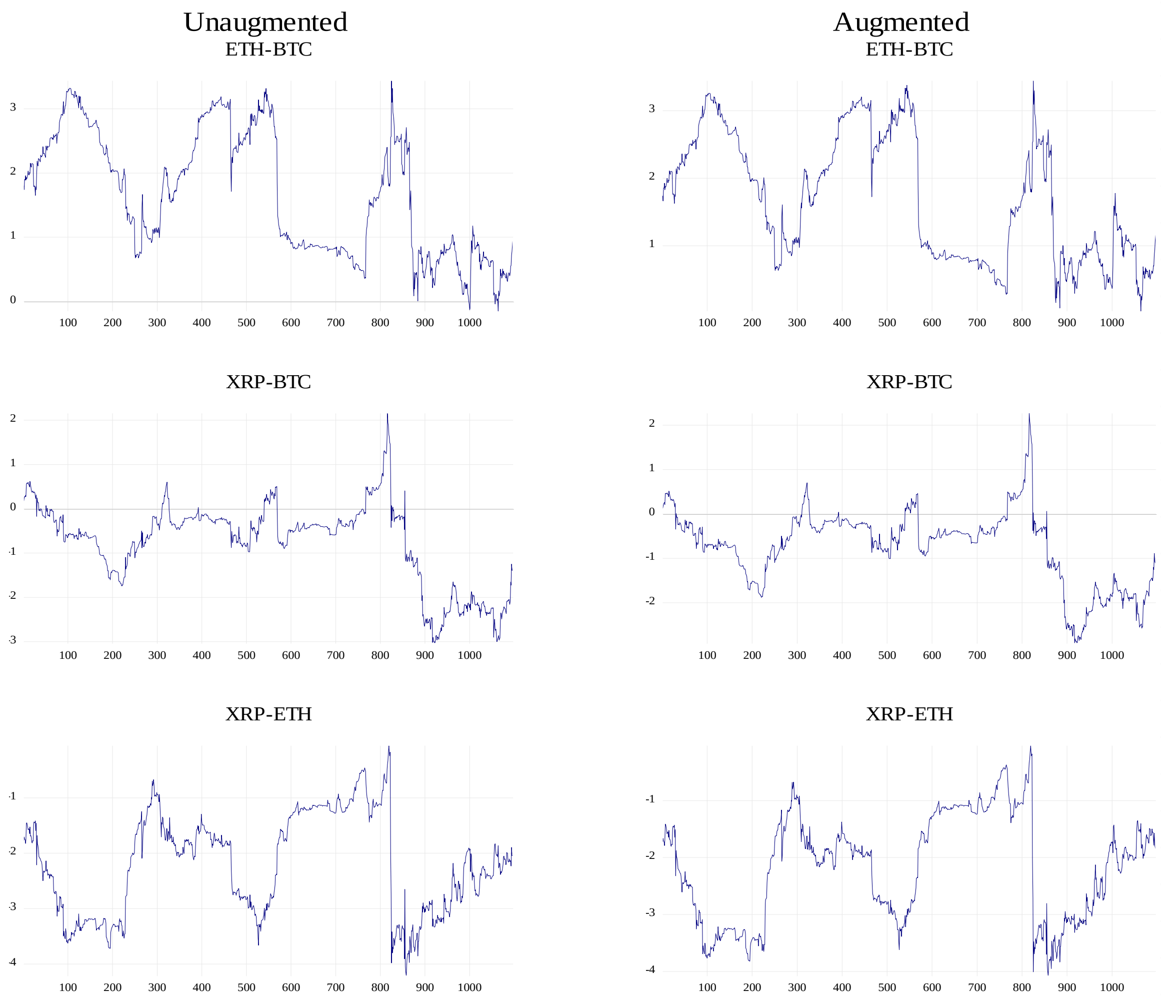

Figure 5.9 The pairwise dynamic spillovers between cryptocurrencies

Source: Own depiction (2021)

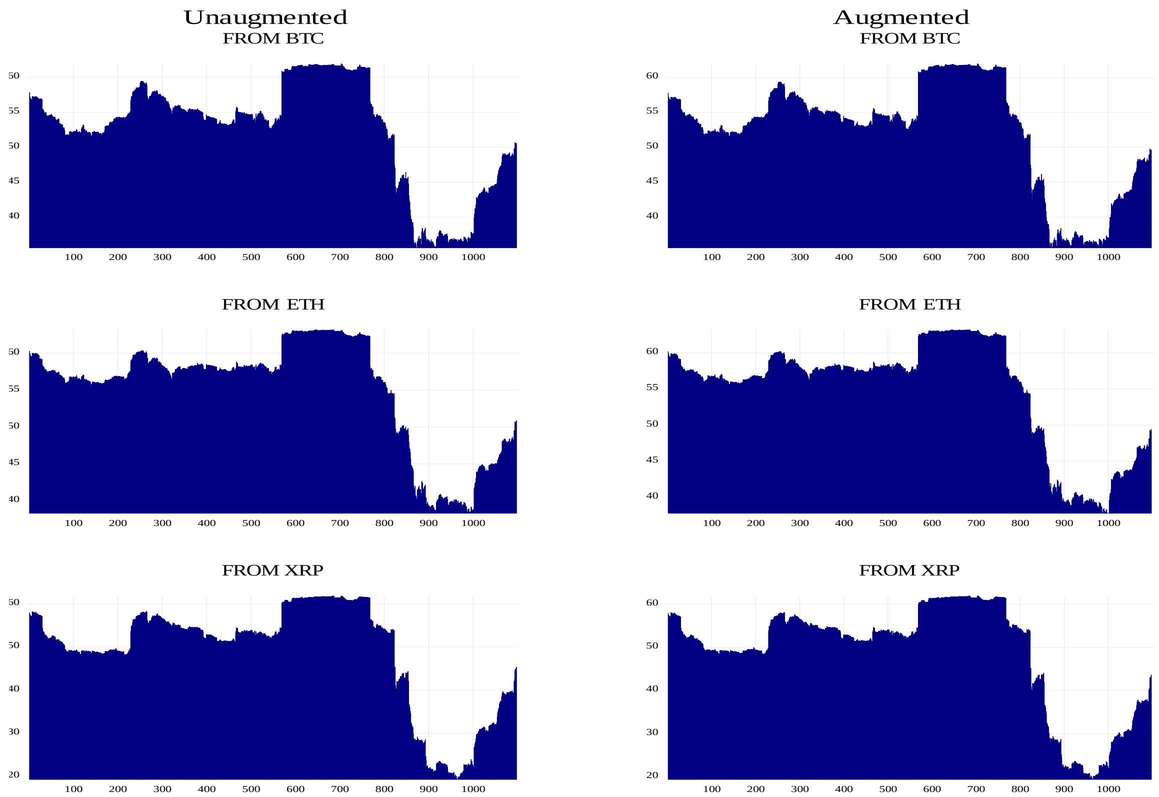

Figure 5.10 The total dynamic spillovers from cryptocurrencies

Source: Own depiction (2021)

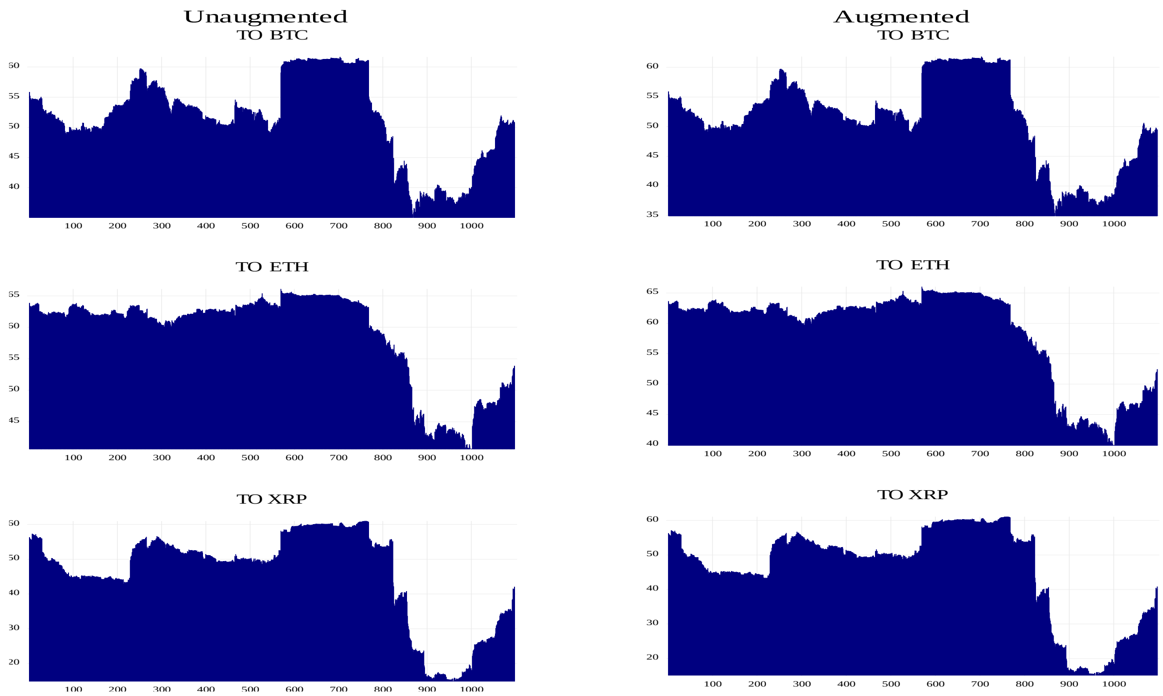

Figure 5.11 The total dynamic spillovers to cryptocurrencies

Source: Own depiction (2021)

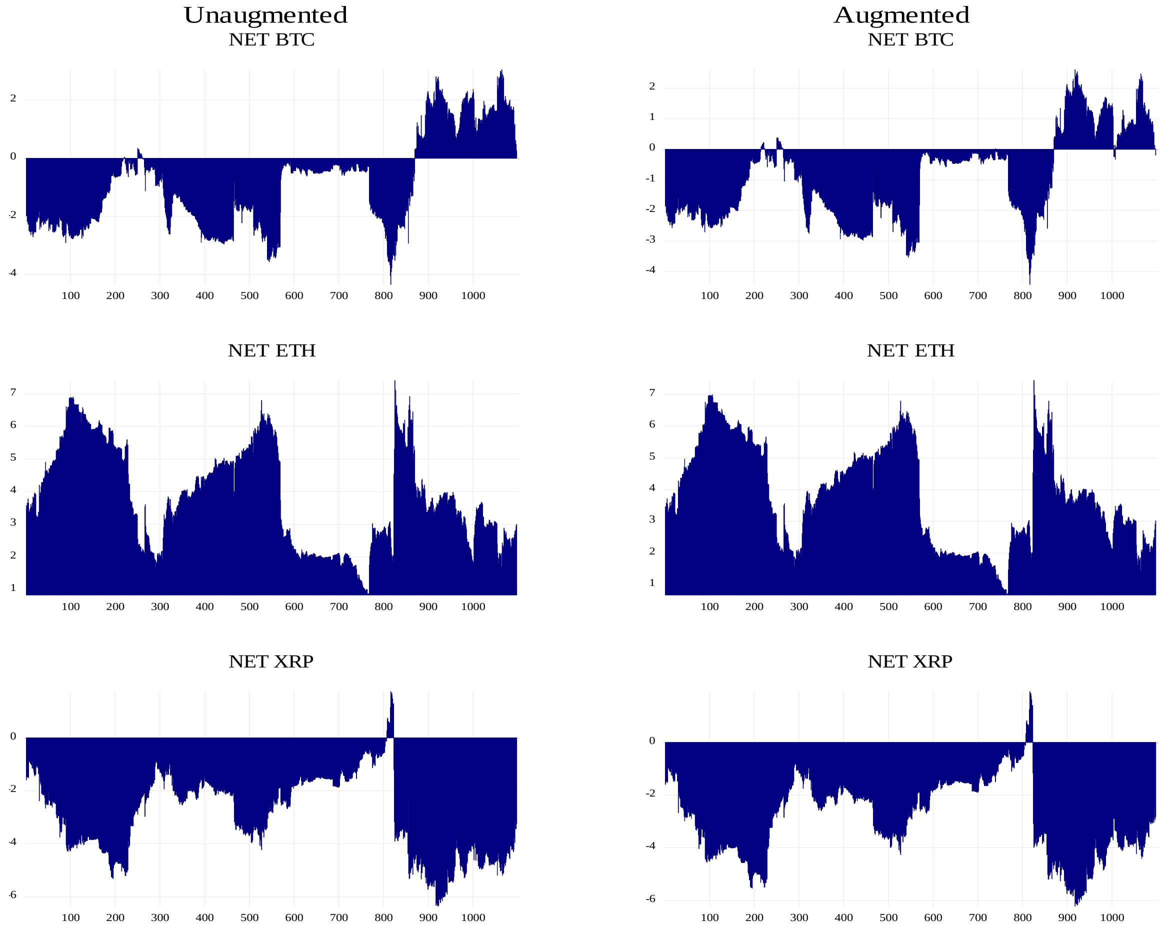

Figure 5.12 The net dynamic cryptocurrency spillovers

Source: Own depiction (2021)

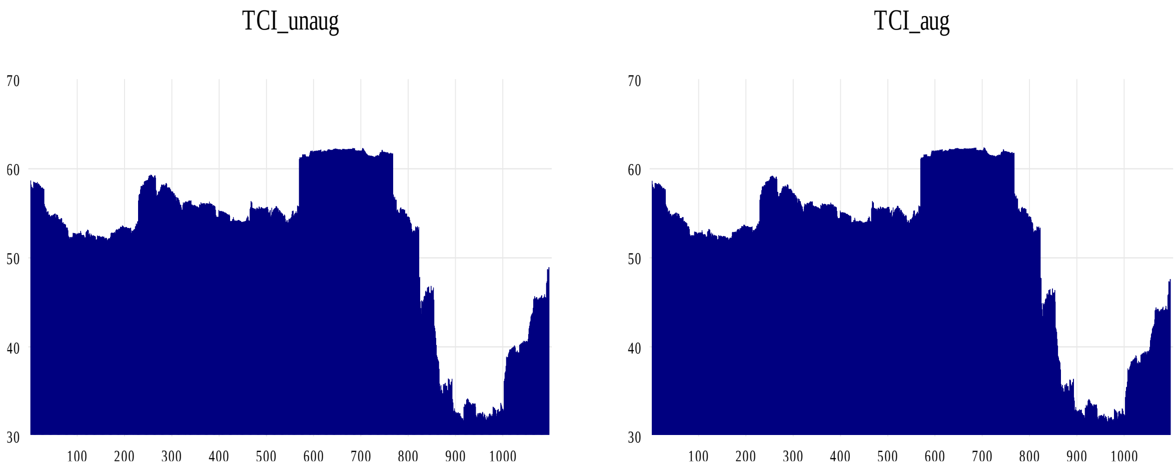

Figure 5.13 The total dynamic spillover index

Source: Own depiction (2021)

5.5.2.3 The Toda and Yamamoto results

Table 5.13 presents the results of the Toda-Yamamoto tests over the entire study period. In all equations for the overall period, using the information criteria, two lags were considered suitable. Based on a test between Bitcoin and investor sentiment, a uni-directional causality from investor sentiment to Bitcoin was found at the 10% significance level (0.0766*). A uni-directional causality from investor sentiment to Ethereum was also found at the 10% significance level (0.0543*). However, based on Ripples returns, the results were insignificant, proving that investor sentiment did not have a causal relationship with investor sentiment. This implies weak evidence of causality from investor sentiment to Bitcoin and Ethereum. The absence of significant causality from any of the cryptocurrencies to investor sentiment suggests that cryptocurrencies return changes cannot be used to measure sentiment. This is in line with what Muguto et al. (2021) reported.

Table 5.14 presents the results of the Toda-Yamamoto tests in the high sentiment periods. Surprisingly, there were no significant coefficients to indicate any form of causality between investor sentiment and the respective cryptocurrencies. Table 5.15 presents the results of the Toda-Yamamoto tests in the low sentiment periods. There is evidence of uni-directional causality between all three cryptocurrencies and investor sentiment. The strongest causality was found to be from investor sentiment to Bitcoin, significant at the 1% level (0.0064***). This was followed by the causality from investor sentiment to Ethereum (0.0321**) and Ripple (0.0425**), both at the 5% significance level. The finding was in line with Perry-Carrera (2018), who analysed the VIX, which is a portion of this study's sentiment index and Bitcoin. The analysis found that investors find alternative sources of risk during lower volatility to maintain their portfolio risk. Therefore, investors turn to Bitcoin for an additional source of risk to balance their portfolios. This is contrary to the a priori expectation where investor sentiment was expected to have a more significant causality on the cryptocurrencies in high sentiment periods rather than low sentiment periods.

The a priori expectation is based on the finding that sentiment-driven traders usually participate significantly in financial markets when sentiment is high (Chi et al., 2012; Ryu et al., 2017; Chakraborty and Subramaniam, 2020). Therefore, one would expect to see greater interaction between financial asset returns and investor sentiment measures in the high sentiment periods than in the low sentiment periods. However, it is possible that cryptocurrencies may have detached themselves from traditional assets, where investors trade cryptocurrencies in periods when traditional asset returns are lower. Therefore, investors may be inclined to include cryptocurrencies in portfolios of investments to earn higher returns. Andrianto and Diputra (2017) found that including cryptocurrencies in a portfolio will earn higher returns; however, the returns are dependent on the amount of cryptocurrency allocation. This is consistent with the findings by Burggraf et al. (2020). In line with the full period results, cryptocurrencies cannot be used to gauge sentiment level on the market, a finding consistent with Muguto et al. (2021).

Table 5. 13 Overall study period causality

Test	Dependant	Excluded	Prob.
Bitcoin vs sentiment	Bitcoin	Sentiment	0.0766*
	Sentiment	Bitcoin	0.2336
Ethereum vs sentiment	Ethereum	Sentiment	0.0543*
	Sentiment	Ethereum	0.1865
Ripple vs sentiment	Ripple	Sentiment	0.2843
	Sentiment	Ripple	0.4528

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively

Table 5.14 High sentiment period causality

Test	Dependant	Excluded	Prob.
Bitcoin vs sentiment	Bitcoin	Sentiment	0.4128
	Sentiment	Bitcoin	0.5304
Ethereum vs sentiment	Ethereum	Sentiment	0.3641
	Sentiment	Ethereum	0.3468
Ripple vs sentiment	Ripple	Sentiment	0.5659
	Sentiment	Ripple	0.1755

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively

Table 5.15 Low sentiment period causality

Test	Dependant	Excluded	Prob.
Bitcoin vs sentiment	Bitcoin	Sentiment	0.0064***
	Sentiment	Bitcoin	0.8375
Ethereum vs sentiment	Ethereum	Sentiment	0.0321**
	Sentiment	Ethereum	0.7930
Ripple vs sentiment	Ripple	Sentiment	0.0425**
	Sentiment	Ripple	0.7699

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively

5.6 Chapter summary

This chapter reported the results from the tests – GARCH (1,1), ADCC-EGARCH, Diebold and Yilmaz volatility spillover index and the Toda-Yamamoto – that were carried out to examine the cryptocurrency volatility, volatility spillovers and the effect of global investor sentiment. From the GARCH (1,1), Bitcoin and Ethereum returns were found to be influenced by investor sentiment, while the volatility of the three cryptocurrencies has been affected by investor sentiment. These findings confirm objectives that is examining the volatility of cryptocurrency and the effects of investor sentiment, respectively. Based on the ADCC-EGARCH model, the low sentiment model found that spillovers occurred between Bitcoin and Ethereum and Bitcoin and Ripple in both short and long-run shocks. In the high sentiment period, Bitcoin and Ethereum contained spillovers in the long run only, while Bitcoin and Ripple contained spillovers in both short and long-run shocks. Ethereum and Ripple did not have spillovers in either sentiment period, implying spillovers originate from Bitcoin. These findings confirms the objectives, that is, the presence of spillovers and the effect of investor sentiment. Based on the Toda-Yamamoto model, within the overall period, there were uni-directional causality from investor sentiment to Bitcoin and investor sentiment to Ethereum. The low sentiment period contained uni-directional causality from investor sentiment to all three cryptocurrencies, while the high sentiment period did not contain causality between investor sentiment and the cryptocurrencies. These findings confirm the studies objectives. As a result, it was found that investor sentiment has an effect on cryptocurrency volatility and spillovers, where behavioural biases are the cause of the irrationality of investors in the market.

Chapter 6: Conclusion and recommendations

6.1 A review of the research objectives

In recent years, the development of cryptocurrencies has been drastically supported by the widespread adoption of the new financial asset by companies, institutional investors and countries. The driving force has mainly been the technological advancements and advantages of cryptocurrencies over fiat currency, such as anonymity (Al Shehhi et al., 2014), quicker transactions and lower fees (Inshyn, Mohilevskyi, and Drozd, 2018) and simplified international transfers (Dumitrescu, 2017). As a result, Bitcoin and other developed altcoins such as Ethereum and Ripple have been sought after by retail and institutional investors alike. Further, more recent developments of cryptocurrencies, such as smart contracts, which provide speed, safety, accuracy and autonomy (CorporateFinanceInstitute, 2021), are now monitored by certain countries aiming to regulate and implement cryptocurrency as an official form of payment.

However, despite the widespread adoption, the market faces ongoing issues of volatility and manipulation. As the market is unregulated internationally, many investors use cryptocurrency for their own manipulative benefits. For instance, Gandal et al. (2018) examined the price manipulation of Bitcoin during the earlier stages of Bitcoin and found that the USD/BTC exchange rate rose from $150 to $1000 within two months. This was due to suspicious trading activity that led to this sudden spike. Further, Li et al. (2020) explained that investors belong in various social media groups such as Telegram that promotes pump and dump schemes. Upon analysing 500 cryptocurrencies, the authors found that within the first 70 seconds of a pump and dump, the prices increased by 25% on average, with trading volume increasing by 148 times and a reversal thereafter. After an hour, most of the initial effects disappeared. Apart from investors directly manipulating prices based on trades, high profile individuals such as Elon Musk have been found to manipulate cryptocurrency prices indirectly (Daniel, 2021). In this instance, referring to Elon Musk, due to his reputation and financial status, a post on Twitter regarding his opinion on cryptocurrencies has a large impact on prices. Daniel (2021) stated that many financial individuals believe that Elon Musk should be faced with charges of manipulation; however, as the market is unregulated, the power of regulatory authorities is limited.

While the adoption of cryptocurrencies continues, the market high and persistent volatility has captured much attention recently (Chu et al., 2017; Klein et al., 2018; Walther et al., 2019). Numerous factors were associated with the drivers of volatility, such as the uncertainty of cryptocurrency by many individuals (Colon et al., 2021) and high-profile losses, which creates fear among smaller investors in the market (Bloomberg, 2021). The disagreements regarding the intrinsic value also contributed to the volatility in the market as many individuals have opposing views (Hayes, 2017; Romanchenko et al., 2018). Overall, the effects of volatility were exacerbated by speculators and noise traders in the market as they invest without the use of fundamental information.

Based on the factors of volatility previously mentioned, the study asserted that investor sentiment is a plausible explanation for the enhanced effects of the volatility and volatility spillovers. Therefore, the study aimed to analyse the nature of volatility and volatility spillovers among cryptocurrencies and whether they are subject to global investor sentiment. The study then set out to:

- Examine the nature of volatility of cryptocurrencies
- Examine the nature of volatility spillovers among the cryptocurrencies in terms of magnitude and direction
- Determine whether global investor sentiment influences the nature of volatility and volatility spillovers amongst cryptocurrencies

The results in the study are important to policymakers who can regulate the market to provide stability and those who invest in this market to understand the volatility that this market experiences.

Based on these objectives, the study employed the three highest market capitalised cryptocurrencies – Bitcoin, Ethereum and Ripple. The three cryptocurrencies were chosen as they represented a significant portion of the cryptocurrency market. A set of five investor sentiment proxies – the global price of gold, the global price of oil, the US dollar index, Bloomberg commodities index and the Vix were used to construct the sentiment index. The proxies were chosen as they are important financial assets in the market that can depict the level of sentiment. The analysis was based on the period between 2 February 2018 to 24 August 2021 to examine the cryptocurrency market.

For the method of analysis, three approaches were adopted, namely, the GARCH model, the ADCC-GARCH model and the Toda-Yamamoto model. To analyse volatility, there were numerous alternatives, such as the CEV model (Yuen et al., 2001) and the Heston model (Heston, 1993). However, the GARCH model was chosen to be most suitable as it allows for the testing of volatility (Brooks, 2014) and also expanded to factor in not only the magnitude but the direction of returns (Engle, 2001). The models provided a thorough analysis of the volatility movements of cryptocurrencies and the effects of investor sentiment. The following sections provide a summary of the results for each of the objectives as mentioned above.

6.2 Summary of findings

6.2.1 What is the nature of the volatility of cryptocurrencies?

To examine the nature of volatility, GARCH models were used based on all three cryptocurrencies, together with the cryptocurrency and sentiment index included. Volatility is said to be persistent if today's return has a large effect on the unconditional variance of many periods in the future, as described by Christianti (2018). Volatility persistence was further explained by Christianti (2018) that assets with volatility persistence indicate that returns today has a big influence on predicting the volatility of returns in the future. In terms of volatility persistence in cryptocurrency returns, it was found that Bitcoin had the highest volatility persistence among cryptocurrencies. Ripple followed this, and lastly, Ethereum. This result was consistent with Katsiampa et al. (2019), where it was found that all cryptocurrencies possess high levels of persistence, but Bitcoin persists the most. Similarly, Caporale et al. (2018) found cryptocurrencies such as Bitcoin to have high persistence. The finding implied that cryptocurrencies are predictable, which therefore represents evidence of market inefficiency.

Mean reversion refers to the case where the volatility exhibited by a financial asset will tend to move towards its average level over time (Goudarzi, 2013). With the occurrence of mean reversion, it essentially presents evidence against the EMH of Fama (1970). Based on the results found in the study, all three cryptocurrencies displayed the effect of mean reversion. Bitcoin was found to have the highest mean reversion value, followed by Ripple and Ethereum. This implied that Bitcoin took the longest to revert to the mean, and Ethereum was the fastest. Narayan and Prasad (2007) explained that the mean reversion occurrence contradicts the EMH as market efficiency is achieved when there is a quick and accurate response to the relative information based on the random walk. This indicates that cryptocurrencies are not efficient, and their volatility persists for long periods.

Brooks (2014) described volatility clustering as the tendency of the asset returns to occur 'in bunches,' where there are prolonged periods of high volatility and prolonged periods of low volatility. It was found that the unaugmented and augmented models displayed high significance at the 1% level. A similar result to the volatility persistence was found where Bitcoin contained the highest levels of volatility clustering. Thereafter, Ripple and Ethereum followed. The findings were similar to those of Katsiampa (2017), where the study found that volatility clustering occurred in both short and long-run components. The result of this study was found contrary to Tan et al. (2020), where the authors found Bitcoin to have the lowest volatility clustering and Ethereum to have higher levels of volatility clustering. However, the results differed based on the period used. This study used a period of uncertainty and bearish behaviour in the market, whereas Tan et al. (2020) used a period of bullish behaviour. As a result, during periods of higher volatility and uncertainty, Bitcoin experiences the highest levels of both volatility persistence and clustering.

Risk premium is the additional return that investors expect for bearing risk (Brooks, 2014). Cryptocurrencies are recognised as risky as assets (Tiwari et al., 2019). Therefore, investors in the cryptocurrency market expect additional returns for taking on large risks. Upon analysing the three cryptocurrencies over the chosen period, a common finding was that the cryptocurrencies did not reward investors for taking additional risks. A plausible explanation may be that the period examined was a bearish phase in the cryptocurrency market, where prices were falling. This meant that returns were significantly less in comparison to a bullish market. This is consistent with Leirvik (2021) findings, where it was found that investors get compensated with higher returns; however, it is time-varying. This implied that only certain periods, such as a bullish market, allows the benefit of a risk premium.

As the study considered three volatility models – the GARCH (1,1), E-GARCH and the GJR-GARCH – only one model was chosen among the three. Based on the SBIC values of the models, the GARCH (1,1) model was chosen as the optimal model among the three cryptocurrencies. As such, asymmetries could not be accounted for as the GARCH (1,1) is a symmetric model. The model, however, was suitable for examining the volatility. For instance, Dyhrberg (2016) examined Bitcoins' volatility using an asymmetric model and found that Bitcoin was not prone to leverage effects. Similarly, Cheikh et al. (2019) examined Bitcoin, Ethereum and Ripple and found that there were no asymmetries. Therefore, to analyse the nature of the volatility of cryptocurrencies, a symmetric model was sufficient.

6.2.2 What is the nature of volatility spillovers among cryptocurrencies?

To get a more detailed approach regarding the occurrence of volatility spillovers, the data were separated into high and low sentiment periods using the average return analysis. The results in this paper were consistent with those from Koutmos (2018), Ji et al. (2018), Yi et al. (2018) and Kumar and Anandarao (2019). It was found that the cryptocurrency market is prone to spillovers in both low and high sentiment periods, while lower sentiment periods in the short run contained more volatility spillovers. Overall, both sentiment periods shared the long-run persistence of shocks on the dynamic conditional correlation based on the long run. With the addition of the asymmetries, it was found that cryptocurrencies were prone to asymmetries in the low sentiment period compared to the high sentiment period.

Based on the direction of the volatility spillovers in the market, the market capitalisation influenced the spillover that occurs. For instance, regardless of the sentiment period analysed, Bitcoin was found to be the cryptocurrency in which the volatility spillovers primarily originated. The results showed volatility spillovers from Bitcoin to Ethereum and Bitcoin to Ripple; however, both low and high periods did not reveal spillovers between Ethereum and Ripple. The finding was consistent with Kumar and Anandarao (2019), where the authors found evidence of spillovers between Bitcoin and Ethereum but nil between Ethereum and Ripple. The findings indicated the presence of herding behaviour when faced with shocks in the Bitcoin market. As the cryptocurrency is the largest and most renowned, the volatility in Bitcoin influences the market, which causes uncertainty among the smaller altcoins.

6.2.3 Does global investor sentiment influence volatility and volatility spillovers?

To better understand the cryptocurrency volatility and volatility spillovers, a variety of approaches thereby analysed the effects of investor sentiment on cryptocurrency volatility. However, as cryptocurrencies were renowned for their co-movement and contagion in the market, as found by Katsiampa (2018) and Koutmos (2018), the study investigated whether the volatility spillovers were found within high or low sentiment periods. To further confirm the results found from the first two models, a causality test was implemented to examine the causality between each cryptocurrency and the Sentiment index within the high and low sentiment periods.

Based on the results from the volatility tests, it was found that investor sentiment affected Bitcoin, where higher levels of volatility persistence were found. Similarly, the Bitcoin-sentiment model found an increase in volatility clustering in comparison to the Ethereum and Ripple sentiment models. Therefore, it was found that investor sentiment increases the volatility in only Bitcoin. When examining the mean reversion, investor sentiment caused Bitcoin to revert to the mean the slowest among all augmented and unaugmented models. This implied that Bitcoin investors tend to increase volatility for longer periods. Despite the cryptocurrencies possessing high volatility, it was found that all three cryptocurrencies did not reward investors for the additional taken, based on the risk premium results. By combining the results of the tests to analyse the nature of volatility of the cryptocurrencies, it was found that investor sentiment particularly influences Bitcoin the most in the market. The findings suggest that investors prefer Bitcoin as it is the most renowned cryptocurrency, which then causes volatility in that cryptocurrency. The results are consistent with Nasekin and Chen (2020), who found that the sentiment contribution to cryptocurrency volatility is significant.

Upon examining the volatility spillover tests, investor sentiment effects were found in the lower sentiment period. In contrast, the higher sentiment periods depicted fewer volatility spillovers in comparison to the low sentiment period. This case was found by the Bitcoin and Ethereum tests and the Bitcoin and Ripple tests. The sentiment index consisted of traditional financial assets. This implied that a lower sentiment period relates to lower returns in those financial assets and vice versa for a higher period. Cryptocurrencies experienced volatility spillovers in lower sentiment periods, suggesting that the cryptocurrency market was more active for investors looking for alternative investment opportunities. As such, cryptocurrencies experienced higher levels of spillovers in the low sentiment period as the markets contained additional investors. Yi et al. (2018) found a similar result, where the connectedness among cryptocurrencies fluctuated cyclically. The connectedness increased during periods of unstable economic conditions, resulting in higher activity in the cryptocurrency market.

The causality test was used thereafter and confirmed the results. Overall, the results showed causality from the Sentiment index to each of the cryptocurrencies examined based on the low sentiment period. No causality was found on the higher sentiment period, coinciding with the results of the volatility spillover tests where low spillovers occurred. Finally, the overall period was analysed for causality and found that Bitcoin and Ethereum faced causality from the Sentiment index. The results from the Toda Yamamoto test suggested that during periods of lower activity in other financial assets, that is, a low sentiment period, investors turn to cryptocurrency as an alternative form of investments.

6.3 Implications of findings

The EMH asserted that all investors are rational. However, the study provides evidence of the effects of investor sentiment on the cryptocurrency market by means of behavioural biases. These findings imply that cryptocurrencies do not follow the traditional financial theories, and thus, price movements may be better understood by accounting for behavioural biases. In terms of investors, the implications of the study's findings reveal that investors should be wary of the cryptocurrency market, as cryptocurrency investors' rationality differ from those of other financial investors. As the market is dominated by irrational traders and the fact that cryptocurrencies do not have an official intrinsic value, the sentiment in the market should be considered prior to investing to profit from and avoid large losses.

From a regulatory perspective, the study has implications for policymakers alike. The cryptocurrency faces excessive volatility. As the cryptocurrency market is unregulated in many countries, the market is posed with illegal activities such as pump and dump schemes. While this scenario occurs, other investors in the market contribute to the large sell-offs based on the fear, which is fueled by the significant decreases in the prices. This relates to the studies findings of investor sentiment and its correlation with the volatility in the market. By finding that the cryptocurrency has an issue of investor sentiment causing price fluctuations, policymakers can use the information to instil regulations on scenarios such as price manipulation to prevent excessive volatility. Furthermore, analysing the sentiment and introducing regulations may prevent bubbles and a financial crisis from occurring.

The study also has implications from a scholar's perspective. As cryptocurrencies have not been vastly examined, the study contributes to the pool of information. The study provided an insight into the workings of cryptocurrencies and examined the volatility movements and the effects of investor sentiment. This helps understand the cryptocurrency market and its movements for further examination. This also helps by illustrating the importance of understanding the investors perspective and their reaction to the market as all investors are not bound to rationality, as the EMH stated. Overall, understanding the effects of sentiment on cryptocurrencies can provide vital insights into the future of cryptocurrency academia.

6.4 Limitations of the study

Based on the theme of this study, numerous limitations were presented due to the market being relatively new. For example, creating a composite index has been cumbersome, where determining the perfect proxies is always challenging. According to Da et al. (2010), a sentiment measure should be direct, as it should be verifiable by an objective external measure of behaviour. However, in this study, indirect measures in the form of proxies were used to create a composite index. While the index has been shown to capture the sentiment at a macroeconomic level, it is conceivable that the index does not perform well at the microeconomic level. As the study is based on an international perspective of sentiment, a direct measure such as surveys could not be possible. In addition, as explained in section 4.2.2, surveys may provide inaccurate answers due to dishonesty and misunderstanding. As a result, the unavailability of a direct measurement of sentiment becomes a weakness of the study. While proxies may be an indirect measurement, a combination of proxies in an index helped understand the sentiment in the global financial market.

A further limitation was the number of cryptocurrencies used in the study. While the study examined the three cryptocurrencies, which consisted of a significant portion of the cryptocurrency market, a wider variety of cryptocurrencies would help examine more of the market. For instance, the twenty highest market capitalised cryptocurrencies could be examined as the utilities offered by these coins provide a competitive advantage over Bitcoin, which can cause a shift in the market. As such, analysing a broader spectrum will help understand the cryptocurrency market regarding investor sentiment, volatility and volatility spillovers.

In terms of methods, the study was limited based on valuing the pricing of cryptocurrencies. This could have been done using an appropriate asset pricing model such as the Capital Asset Pricing Model (CAPM). The model would be able to analyse cryptocurrency pricing and the expected returns. An approach similar to Shen et al. (2020) could be used to determine the validity of the cryptocurrency returns to the CAPM. However, the study focused more on the volatility of returns and investor sentiment. In contrast, the CAPM assumes investors are rational, and the markets are efficient, which presently opposes the nature of cryptocurrencies.

6.5 Recommendations for future study

Considering the limitations mentioned above, the study makes various recommendations for further research into the effects of investor sentiment on cryptocurrencies. Future studies on cryptocurrencies should expand on the number of proxies used for investor sentiment in a composite index. This approach can be relative to prior studies proxies. A direct approach can also be taken, whereby the trading volume, Google search volumes, and the cryptocurrency market's liquidity can be compared against the Sentiment index. This will help determine a correlation and an indication of the volatility in the market based on the level of sentiment.

A broader time frame should be used where the study can examine cryptocurrencies at different states in the market, such as a bullish market, consolidation phase and a bearish market. This approach will then be able to verify the sentiment levels in each phase and understand the behavioural biases present. Further, when observing a more extended study period, a larger number of cryptocurrencies could be examined to illustrate the growth and movements of the market. As years have passed, the cryptocurrency market has surpassed many milestones, such as the trillion-dollar and two trillion-dollar market value. Therefore, a more extensive study period could examine the growth of the cryptocurrencies and the newer cryptocurrencies that provide a competitive advantage over Bitcoin.

Based on the model limitations, future studies could incorporate the CAPM model into their studies to examine the returns of cryptocurrencies. For instance, an approach similar to Shen et al. (2020) could be used where a significant number of cryptocurrencies would be used to examine its returns. However, the analysis would differ as investor sentiment could be taken into account in the CAPM model for cryptocurrencies. This approach would then be able to examine cryptocurrency returns and thereafter examine the sentiment influence on the returns together with the volatility.

6.6 Conclusion

By combining the three approaches mentioned above, the study aimed to examine the nature of volatility and volatility spillovers among cryptocurrencies and whether are they subject to global investor sentiment. The findings in the preceding chapter suggest that investor sentiment strongly affects the volatility in the market. This implies that investors are prone to behavioural biases, which drastically influences the cryptocurrency market movements. This indicated that the cryptocurrency market might not follow traditional financial theories such as the EMH to explain the movements in the market.

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Appendix

Appendix A1: Estimations

Bitcoin

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.001988	0.080036	-0.024845	0.9802
AR(1)	0.775179	0.134325	5.770923	0.0000
MA(1)	-0.794448	0.129001	-6.158448	0.0000
	Variance Equation			
C	0.626191	0.420996	1.487406	0.1369
RESID(-1)^2	0.120814	0.052194	2.314710	0.0206
GARCH(-1)	0.866593	0.050472	17.16973	0.0000
GED PARAMETER	0.776921	0.077518	10.02244	0.0000
R-squared	0.005449	Mean dependent var		-0.020202
Adjusted R-squared	0.000834	S.D. dependent var		4.498284
S.E. of regression	4.496408	Akaike info criterion		5.519071
Sum squared resid	8713.824	Schwarz criterion		5.584765
Log likelihood	-1190.638	Hannan-Quinn criter.		5.545002
Durbin-Watson stat	2.007588			
Inverted AR Roots	.78			
Inverted MA Roots	.79			

Bitcoin - Sentiment

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.050722	0.068460	-0.740894	0.4588
DSENTIMENT	1.828225	0.523150	3.494647	0.0005
AR(1)	0.682037	0.171760	3.970867	0.0001
MA(1)	-0.698905	0.169429	-4.125047	0.0000
	Variance Equation			
C	0.596337	0.441868	1.349582	0.1771
RESID(-1)^2	0.125526	0.052996	2.368600	0.0179
GARCH(-1)	0.870627	0.049293	17.66245	0.0000
DSENTIMENT	-6.846152	4.455651	-1.536510	0.1244
GED PARAMETER	0.751511	0.073919	10.16663	0.0000
R-squared	0.009091	Mean dependent var		-0.030786
Adjusted R-squared	0.002161	S.D. dependent var		4.498074
S.E. of regression	4.493211	Akaike info criterion		5.507249
Sum squared resid	8661.058	Schwarz criterion		5.591860
Log likelihood	-1183.319	Hannan-Quinn criter.		5.540650
Durbin-Watson stat	2.013186			
Inverted AR Roots	.68			
Inverted MA Roots	.70			

Ethereum

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.392233	0.145678	-2.692472	0.0071
AR(1)	-0.563884	0.249705	-2.258196	0.0239
MA(1)	0.614679	0.234808	2.617793	0.0089
	Variance Equation			
C	6.614773	4.945686	1.337483	0.1811
RESID(-1)^2	0.127522	0.085117	1.498184	0.1341
GARCH(-1)	0.697883	0.180428	3.867927	0.0001
GED PARAMETER	0.840840	0.085074	9.883580	0.0000
R-squared	0.004612	Mean dependent var		-0.380981
Adjusted R-squared	-0.000007	S.D. dependent var		5.812786
S.E. of regression	5.812808	Akaike info criterion		6.152129
Sum squared resid	14562.94	Schwarz criterion		6.217824
Log likelihood	-1328.012	Hannan-Quinn criter.		6.178060
Durbin-Watson stat	2.079617			
Inverted AR Roots	-.56			
Inverted MA Roots	-.61			

Ethereum – Sentiment

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.362763	0.153929	-2.356691	0.0184
DSENTIMENT	2.689039	0.851942	3.156363	0.0016
AR(1)	0.124969	0.095521	1.308279	0.1908
MA(1)	-0.109072	0.101176	-1.078045	0.2810
	Variance Equation			
C	10.11513	4.474273	2.260733	0.0238
RESID(-1)^2	0.141828	0.090924	1.559857	0.1188
GARCH(-1)	0.596732	0.159679	3.737074	0.0002
DSENTIMENT	-40.88434	15.27610	-2.676360	0.0074
GED PARAMETER	0.859707	0.090247	9.526102	0.0000
R-squared	0.009294	Mean dependent var		-0.398377
Adjusted R-squared	0.002366	S.D. dependent var		5.808188
S.E. of regression	5.801313	Akaike info criterion		6.128796
Sum squared resid	14438.10	Schwarz criterion		6.213407
Log likelihood	-1317.884	Hannan-Quinn criter.		6.162197
Durbin-Watson stat	2.032108			
Inverted AR Roots	.12			
Inverted MA Roots	.11			

Ripple

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.268707	0.139275	-1.929322	0.0537
AR(1)	0.391508	0.220725	1.773735	0.0761
MA(1)	-0.498450	0.205079	-2.430523	0.0151

	Variance Equation			
C	4.104081	2.438965	1.682714	0.0924
RESID(-1)^2	0.153007	0.070871	2.158932	0.0309
GARCH(-1)	0.726387	0.110735	6.559690	0.0000
GED PARAMETER	0.955002	0.099167	9.630255	0.0000
R-squared	-0.004621	Mean dependent var		-0.273955
Adjusted R-squared	-0.009283	S.D. dependent var		5.732176
S.E. of regression	5.758720	Akaike info criterion		6.111322
Sum squared resid	14293.19	Schwarz criterion		6.177016
Log likelihood	-1319.157	Hannan-Quinn criter.		6.137253
Durbin-Watson stat	1.746409			
Inverted AR Roots	.39			
Inverted MA Roots	.50			

Ripple – Sentiment

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.388817	0.136555	-2.847324	0.0044
DSENTIMENT	1.718353	1.173224	1.464642	0.1430
AR(1)	0.395140	0.136073	2.903885	0.0037
MA(1)	-0.524465	0.126048	-4.160845	0.0000
	Variance Equation			
C	5.380589	3.161856	1.701718	0.0888
RESID(-1)^2	0.162033	0.078651	2.060169	0.0394
GARCH(-1)	0.678174	0.139088	4.875843	0.0000
DSENTIMENT	-10.11231	10.91285	-0.926642	0.3541
GED PARAMETER	0.967827	0.101767	9.510238	0.0000
R-squared	-0.004841	Mean dependent var		-0.314919
Adjusted R-squared	-0.011867	S.D. dependent var		5.674853
S.E. of regression	5.708427	Akaike info criterion		6.102353
Sum squared resid	13979.45	Schwarz criterion		6.186965
Log likelihood	-1312.159	Hannan-Quinn criter.		6.135754
Durbin-Watson stat	1.732735			
Inverted AR Roots	.40			
Inverted MA Roots	.52			

Appendix A2 – ADCC-EGARCH high sentiment period spillovers

Bitcoin - Ethereum

	Coefficient	Std. Error	z-Statistic	Prob.
theta(1)	0.033595	0.020863	1.610238	0.1073
theta(2)	0.962004	0.026661	36.08337	0.0000
theta(3)	-0.005366	0.007017	-0.764714	0.4444
Log likelihood	-1169.896	Schwarz criterion		11.02849

Avg. log likelihood	-2.670996	Hannan-Quinn criter.	10.89934
Akaike info criterion	10.81184		

Bitcoin - Ripple

	Coefficient	Std. Error	z-Statistic	Prob.
theta(1)	0.131955	0.065619	2.010927	0.0443
theta(2)	0.710196	0.170549	4.164169	0.0000
theta(3)	-0.079443	0.040755	-1.949304	0.0513

Log likelihood	-1184.316	Schwarz criterion	11.16018
Avg. log likelihood	-2.703917	Hannan-Quinn criter.	11.03102
Akaike info criterion	10.94352		

Ethereum - Ripple

	Coefficient	Std. Error	z-Statistic	Prob.
theta(1)	-0.053959	NA	NA	NA
theta(2)	0.733806	NA	NA	NA
theta(3)	0.015372	NA	NA	NA

Log likelihood	-341.6323	Schwarz criterion	3.464436
Avg. log likelihood	-0.779982	Hannan-Quinn criter.	3.335283
Akaike info criterion	3.247783		

Appendix A3 – ADCC-EGARCH low sentiment period spillovers

Bitcoin - Ethereum

	Coefficient	Std. Error	z-Statistic	Prob.
theta(1)	-0.026329	7.42E-09	-3546190.	0.0000
theta(2)	0.743682	0.000482	1542.308	0.0000
theta(3)	-0.006304	9.50E-07	-6632.327	0.0000

Log likelihood	269.3941	Schwarz criterion	-2.145992
Avg. log likelihood	0.623597	Hannan-Quinn criter.	-2.276377
Akaike info criterion	-2.364760		

Bitcoin - Ripple

	Coefficient	Std. Error	z-Statistic	Prob.
theta(1)	-0.046081	6.03E-08	-764312.6	0.0000
theta(2)	0.803957	4.40E-07	1825755.	0.0000
theta(3)	-0.032985	3.31E-06	-9950.567	0.0000

Log likelihood	-268.2017	Schwarz criterion	2.831747
Avg. log likelihood	-0.620837	Hannan-Quinn criter.	2.701362
Akaike info criterion	2.612979		

Ethereum - Ripple

	Coefficient	Std. Error	z-Statistic	Prob.
theta(1)	-0.032120	NA	NA	NA
theta(2)	0.963182	NA	NA	NA
theta(3)	0.007374	NA	NA	NA
Log likelihood	-642.2932	Schwarz criterion		6.295557
Avg. log likelihood	-1.486790	Hannan-Quinn criter.		6.165172
Akaike info criterion	6.076789			

Appendix A4 – Overall period causality

Bitcoin - Sentiment

Dependent variable: BITCOIN

Excluded	Chi-sq	df	Prob.
SENTIMENT	5.138185	2	0.0766
All	5.138185	2	0.0766

Dependent variable: SENTIMENT

Excluded	Chi-sq	df	Prob.
BITCOIN	2.908291	2	0.2336
All	2.908291	2	0.2336

Ethereum - Sentiment

Dependent variable: ETHEREUM

Excluded	Chi-sq	df	Prob.
SENTIMENT	5.826022	2	0.0543
All	5.826022	2	0.0543

Dependent variable: SENTIMENT

Excluded	Chi-sq	df	Prob.
ETHEREUM	3.358692	2	0.1865
All	3.358692	2	0.1865

Ripple - Sentiment

Dependent variable: RIPPLE

Excluded	Chi-sq	df	Prob.
SENTIMENT	2.515600	2	0.2843
All	2.515600	2	0.2843

Dependent variable: SENTIMENT

Excluded	Chi-sq	df	Prob.
RIPPLE	1.584759	2	0.4528
All	1.584759	2	0.4528

Appendix A5 – High sentiment period causality

Bitcoin - Sentiment

Dependent variable: BITCOIN

Excluded	Chi-sq	df	Prob.
SENTIMENT	0.670696	1	0.4128
All	0.670696	1	0.4128

Dependent variable: SENTIMENT

Excluded	Chi-sq	df	Prob.
BITCOIN	0.393544	1	0.5304
All	0.393544	1	0.5304

Ethereum - Sentiment

Dependent variable: ETHEREUM

Excluded	Chi-sq	df	Prob.
SENTIMENT	0.823844	1	0.3641
All	0.823844	1	0.3641

Dependent variable: SENTIMENT

Excluded	Chi-sq	df	Prob.
ETHEREUM	0.885064	1	0.3468
All	0.885064	1	0.3468

Ripple - Sentiment

Dependent variable: RIPPLE

Excluded	Chi-sq	df	Prob.
SENTIMENT	0.329529	1	0.5659
All	0.329529	1	0.5659

Dependent variable: SENTIMENT

Excluded	Chi-sq	df	Prob.
RIPPLE	1.835185	1	0.1755
All	1.835185	1	0.1755

Appendix A6 – Low sentiment period causality

Bitcoin - Sentiment

Dependent variable: BITCOIN

Excluded	Chi-sq	df	Prob.
SENTIMENT	10.11557	2	0.0064
All	10.11557	2	0.0064

Dependent variable: SENTIMENT

Excluded	Chi-sq	df	Prob.
BITCOIN	0.354711	2	0.8375
All	0.354711	2	0.8375

Ethereum - Sentiment

Dependent variable: ETHEREUM

Excluded	Chi-sq	df	Prob.
SENTIMENT	6.880902	2	0.0321
All	6.880902	2	0.0321

Dependent variable: SENTIMENT

Excluded	Chi-sq	df	Prob.
ETHEREUM	0.463851	2	0.7930
All	0.463851	2	0.7930

Ripple - Sentiment

Dependent variable: RIPPLE

Excluded	Chi-sq	df	Prob.
SENTIMENT	6.317838	2	0.0425
All	6.317838	2	0.0425

Dependent variable: SENTIMENT

Excluded	Chi-sq	df	Prob.
RIPPLE	0.522956	2	0.7699
All	0.522956	2	0.7699

Appendix B1: Ethical clearance letter

UNIVERSITY OF
KWAZULU-NATAL
INYUVESI
YAKWAZULU-NATALI

29 June 2021

Mr Sahil Rathilal (214552787)
School Of Acc Economics&Fin
Westville

Dear Mr Sahil Rathilal,

Protocol reference number: 00006103
Project title: Cryptocurrency volatility, volatility spillovers and the effect of global investor sentiment

Exemption from Ethics Review

In response to your application received on 28 June 2021 , your school has indicated that the protocol has been granted **EXEMPTION FROM ETHICS REVIEW.**

Any alteration/s to the exempted research protocol, e.g., Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through an amendment/modification prior to its implementation. The original exemption number must be cited.

For any changes that could result in potential risk, an ethics application including the proposed amendments must be submitted to the relevant UKZN Research Ethics Committee. The original exemption number must be cited.

In case you have further queries, please quote the above reference number.

PLEASE NOTE:
Research data should be securely stored in the discipline/department for a period of 5 years.

I take this opportunity of wishing you everything of the best with your study.

Yours sincerely,

[redacted] 29 June 2021

Prof Josue Mbonigaba
Academic Leader Research
School Of Acc Economics&Fin

UKZN Research Ethics Office
Westville Campus, Govan Mbeki Building
Postal Address: Private Bag X54001, Durban 4000
Website: http://research.ukzn.ac.za/Research-Ethics/

Founding Campuses: Edgewood Howard College Medical School Pietermaritzburg Westville

INSPIRING GREATNESS

Appendix C1: Turnitin report

Masters paper

ORIGINALITY REPORT

17%	11%	10%	5%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to University of KwaZulu-Natal Student Paper	2%
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3	hdl.handle.net Internet Source	1%
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