UNIVERSITY OF CAPE COAST

CRYPTOCURRENCY AND GLOBAL UNCERTAINTIES

BY

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Thesis submitted to the Department of Finance of the School of Business, College of Humanities and Legal Studies, University of Cape Coast, in partial fulfilment of the requirements for the award of Master of Commerce in Finance

JULY 2024

DECLARATION

Candidate's Declaration

I hereby declare that this thesis is the result of my own original research and that no part of it has been presented for another degree in this university or elsewhere.

Candidate Signature………………….. Date……………….

Name: ……………………………………………

Supervisors' Declaration

We hereby declare that the preparation and presentation of the thesis were supervised in accordance with the guidelines on supervision of thesis laid down by University of Cape Coast

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ABSTRACT

The purpose of this research was to examine the relationship between Cryptocurrency and global uncertainty. To achieve this, monthly data spanning from 2010 to 2022. The measurement of uncertainty was conducted using two indices, namely the World Uncertainty Index (WUI) and the Cryptocurrency Policy Uncertainty Index (CPUI). The independent variables utilised in this study encompassed various Cryptocurrency, namely Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Ripple (XRP), Litecoin (LTC), Monero (XMR), and Dash (DASH) coins. The study's methodology employed an explanatory research design and a quantitative research approach, enabling the use of parametric statistical analysis to examine the relationship between the variables under investigation. The overall conclusion drown from the study is that that investing in Cryptocurrency might be a viable way for investors to hedge against uncertainty on a global scale. Cryptocurrency is more resilient during periods of economic and political volatility and uncertainty in general, since it is not linked to any government or financial institution. Cryptocurrency are still a rather young and unstable asset class, nevertheless. Cryptocurrency challenge traditional financial regulations, as they operate in a decentralized and cross-border manner. Policymakers may need to establish clear and adaptable regulatory frameworks to address issues such as consumer protection, money laundering, tax evasion, and market manipulation Overall, even though Cryptocurrency may offer some benefits during an uncertain moment for the world, it is vital to approach them with prudence and a long-term investment plan.

ACKNOWLEDGEMENTS

My utmost appreciation goes to my supervisors Prof. Daniel Agyapong and Dr. Peterson Owusu Junior of the Department of Finance for the guidance in completing this work. Big thumbs up to Ms. Mary-Pearl Opare-Addo and the MCOM Finance class for their support and contributions towards this work.

DEDICATION

To Mr. Samuel Romulus Okine

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CHAPTER ONE

INTRODUCTION

The contemporary world is replete with uncertainties. Given the inherently uncertain nature of humans, it is difficult to conceive of a world devoid of uncertainties. Current events, such the covid 19 pandemic, political polarisation, foreign conflicts, and the financial catastrophe, have raised concerns about increasing economic unpredictability (Ahir, Bloom, & Furceri, 2022). The emergence of cryptocurrency in today's rapidly changing and globally linked society has generated significant curiosity and discussion. As traditional financial systems grapple with global uncertainty and economic fluctuations, the concept of digital currencies presents an intriguing alternative that has gained traction among investors, governments, and individuals alike. Cryptocurrency, such as Bitcoin, Ethereum, and Ripple, offer decentralized and secure financial transactions, promising a future that transcends the boundaries of traditional banking systems. With growing concerns about global uncertainty stemming from geopolitical tensions, economic crises, and technological disruptions, understanding the role of Cryptocurrency in this landscape becomes imperative (Al-Thaqeb & Algharabali, 2019).

Global uncertainty is affecting financial markets in particular, and markets in general (Benhabib, Liu & Wang, 2019). As we navigate through a world marked by volatility and unpredictability, the relevance of Cryptocurrency has expanded beyond the realm of financial markets. These digital assets have attracted attention from investors seeking refuge from traditional market fluctuations, governments exploring the potential of blockchain technology for secure data management, and citizens in regions experiencing economic instability and currency devaluation. Consequently, this convergence of cryptocurrency and global uncertainty raises a host of critical questions about the implications, risks, and opportunities that lie ahead. (Das & Kannadhasan, 2018).

Background to the Study

Cryptocurrency (cryptos) are digital currencies that rely on cryptographic evidence for transaction confirmation. The cryptocurrency was initially created in 1983 by David Chaum an American cryptographer. These currencies stand out from authorised currencies due to a special trifecta of restricted obscurity, central authority objectivity, and protection from double-spending assaults (Owusu Junior et al., 2020). Inflation and other global concerns have an impact on the value of money, particularly if it is high, and are generally regulated by a nation's central bank (Shaikh, 2020).

Cryptocurrency, on the other hand according to Shaikh (2020) enables global payments by operating outside of central bank laws and inflation

The person who created the very first cryptocurrency in 2008 to perform financial transactions without only relying on banks or governments is known by the pseudonym Satoshi Nakamoto. When Bitcoin was originally made available in 2009 as a digital coin via a peer-to-peer system, interest in Cryptocurrency increased. (Likpa, 2022; Owusu Junior et al., 2020; Punnet. E et al., 2017; Shaikh, 2020;).

In terms of market capitalization, Bitcoin is the most valued cryptocurrency, making up over 50% of the global Cryptocurrency market value (Hazgui, Sebai, & Mensi, 2021). Despite its numerous benefits, Bitcoin has been shown to fall short of its self-governing aspirations, necessitating regulation and oversight by trustworthy third parties in order to progress (Spithoven, 2019). Bitcoin has recently made news due to its record-breaking performance, in addition to legal and technological concerns. The growth of cryptos has increased the choice of investments and diversification opportunities for investors around the world, as well as the variables influencing their market value and efficiency (Owusu Junior et al., 2020).

The preceding comments call for an investigation into the connection between cryptocurrencies and the worldwide factors that impact them. According to Demir, Gozgor, Lau, and Vigne (2018), Bitcoin had its peak monthly capitalisation turnover between November and December 2017, with a beginning and finale value of $111–278 billion. In 2018, the overall market value exceeded three hundred billion dollars hence this sector can only be regarded as experiencing fast growth in only a short amount of time. (Owusu Junior et al., 2020). As of December 2020, Bitcoin had a market capitalisation of $350 billion and a trading volume of roughly $20 billion (Hazgui et al., 2021).

Since its inception on March 2, 2011, the value of Cryptocurrency has skyrocketed, from $0.01 billion on that day to $1057.82 billion on November 2, 2022 (Ranor de Best, 2023; Demir et. al., 2018). Notwithstanding, the seemingly uncorrelated nature of the cryptocurrency's conduct with economic and financial advancements, there has been a growing curiosity in scholarly works to gain a deeper understanding of the economic and financial factors that could affect the cryptocurrency market (Demir et. al., 2018). Several studies contend that the popularity of Cryptocurrency rises during periods of economic uncertainty and low trust in conventional economic and financial organisations (Fang et al., 2019; Demir et al., 2018; Bouri et al., 2017a; Luther and Salter, 2017).

Some have suggested cryptocurrency's potential as a stock market hedge instrument (Guesmi et al., 2019; Fang et al., 2019; Demir et al., 2018; Selmi et al., 2018; Bouri et al., 2017a; Dyhrberg, 2016) might improve the inefficiencies of these structures. Cryptocurrency has been called a hedging and safe-haven instrument against economic instability (Eom et al., 2019; Baur et al., 2018; Cheah and Fry, 2015), but it has also been criticised for its speculative nature, high price volatility (Eom et al., 2019; Aalborg et al., 2019; Brandvold et al., 2015), and scandals and frauds (Selmi et al., 2018) that have accompanied it, have prompted a discussion about its applicability and role in the financial system.

Volatility in Cryptocurrency is mostly caused by the fact that investors are never sure of what their investments will yield in the future. The consequences and predictive capacity of uncertainty on cryptocurrency markets can vary, however, depending on the nature of uncertainty (Lucey et al., 2021). The inability of economic agents to analyse and predict changes in various macroeconomic factors is what economists call "economic uncertainty" (Baum et al., 2009). This means that the direct and indirect effects of economic activities on the macroeconomy often differ from or even go against the expectations of economic agents. To eliminate systemic financial risks, maintain the stable functioning of the financial market, and optimise the allocation of global resources during times of economic turmoil and weak confidence, a thorough understanding and avoidance of the impact of macroeconomic uncertainty on the financial market is essential.

Through directing attention towards crypto-associated data, investors shall attain enhanced entry to policy details and subsequently adapt pertinent approaches. Consequently, it becomes evident that policies wield a crucial influence on the fluctuations experienced in the realm of Cryptocurrency (Li et. al., 2021). Businesses' responses to economic instability are influenced by the characteristics of Cryptocurrency such as decentralisation, data traceability, zero bias, robust security, and automated contract execution. Colon et al. (2021) conducted an analysis of how political and economic uncertainties impact the bitcoin market. Their study highlights that uncertainty plays a significant role in cryptocurrency investment returns, and the market's response to uncertain situations differs based on the specific nature of the uncertainty.

Statement to the Problem

Previous studies have primarily concentrated on Bitcoin as the main digital asset or used Economic Policy Uncertainty (EPU) as a measure of unpredictability, because of Bitcoin's dominant market capitalization. While the Economic Policy Uncertainty (EPU) Index has been utilized in research on Cryptocurrency and global uncertainties, it has garnered less focus compared to alternative indicators of global uncertainty such as the Cryptocurrency Policy Uncertainty Index (CPUI) and the World Uncertainty Index (WUI). This is because it focusses mostly on established economies, resulting in limited representation of developing economies (Ahir et al., 2022). The WUI, as described by Ahir et al. (2022), is a comprehensive index that encompasses both advanced and emerging economies. It spans across 143 nations worldwide.

The WUI is not only exceptional with regard to of coverage, but it also takes into account significant uncertainties and encompasses a broader range of these uncertainties relative to other indicators. To accurately assess global unpredictability, one should include the CPUI and the WUI, which provide extensive coverage of significant occurrences and economies. According to Lucey et al. (2021), the primary factor in the volatility of Cryptocurrency emanates from major events including the Brexit vote, Covid-19 crisis, cryptocurrency exchange hacks, and the China's ICO ban). The CPUI captures this uncertainty.

Due to their speculative nature, cryptocurrency are appealing to individual investors, some of whom may have a different understanding of the available data than larger institutional investors. The effect that uncertainty has on the markets for cryptocurrency will, therefore, vary depending on the specifics of the uncertainty and the underlying digital assets. Second, the factors that affect the volatility of the cryptocurrency market were evaluated. Since the advent of Cryptocurrency, a new form of information asymmetry has emerged, influencing other markets and posing a serious danger to monetary order (Akyildirim et al., 2020). The majority of studies on crypto and uncertainty examined the relationship using simple linear regression (Demir et al., 2018; Yen & Cheng, 2021).

Due to spurious correlation, and the use of ordinary least squares (OLS) as a technique for measuring correlation are unproductive (Das, 2015; Yen & Chen, 2021) and susceptible to outliers (Demir et al., 2020). The study also utilised the WUI and CPUI as an uncertainty proxy instead of the widely used EPU. Investors must be aware of how crypto relates to elements that could potentially affect their market value and returns, such as uncertainty in the global economy. This is relevant given the significant role of cryptos in the financial markets. Wavelet analysis was used to examine the relationship between uncertainties and Cryptocurrency in this study. The wavelet analysis was used to determine correlations between sequences and developments over time and across scales and can be used to identify potential drivers of the cryptocurrency market over short- and long-term periods. The mean reversion property of time series in aggregate can only be demonstrated by means of walk approach tests. In turn, prolonged cycles with varying frequencies can be shown by wavelet analysis of cryptocurrency returns.

Purpose of the Study

The purpose of this study is to investigate the relationship between Cryptocurrency and global uncertainty.

Research Objectives

The study precisely aims to:

1. Examine the time and frequency domain relationship between cryptocurrency and world uncertainty.
2. Assess the causal relationship between cryptocurrency and world uncertainty.
3. Examine the safe haven asset / hedge properties of Cryptocurrency in times of uncertainty.

Research Hypotheses

Based on the research objectives, the following hypotheses were investigated in the study.

1. H_1: Cryptocurrency has time and frequency relationship with global uncertainty
2. H_2: Cryptocurrency has a causal relationship with global uncertainty.
3. H_3: Cryptocurrency act as a hedge in global uncertainty.

Significance of the Study

This work contributes significant advancements to the current corpus of research. An evident relationship may be shown among the variables cryptocurrency, world uncertainty index, and cryptocurrency policy uncertainty index, as opposed to the economic policy uncertainty index. The uncertainty being studied, specifically global uncertainty and uncertainty related to cryptocurrency policies, is primarily independent of the actions of investors in cryptocurrency markets and other relevant parties. Therefore, it is feasible to make conclusions based on the findings of this empirical study.

The scarcity of literature on the relationship between cryptocurrency returns and uncertainty, as well as the absence of studies specifically examining the world uncertainty index and the cryptocurrency policy uncertainty index, make the findings of this study highly valuable for investors. Investors should be cognizant of the linkages between crypto returns and uncertainty. This is due to the nature of cryptos and their impact on financial markets. The discoveries made from this study will guide investors in the crypto market when selecting these assets for their portfolios. For instance, knowledge of an asset's behaviour in uncertain trading circumstances can help determine whether it is suitable as a hedge, safe haven, or diversification tool.

Delimitation

The study delves into the connection between cryptocurrency and global uncertainty using monthly data from 2010 to 2022. Based on the literature, this research uses two indices to quantify global uncertainties thus the world uncertainty index and the cryptocurrency uncertainty as a means of measuring global uncertainties

Limitations

The study was conducted on 7 Cryptocurrency introduced in the last six years. In other words, the study was restricted or limited to only Cryptocurrency with historical data spanning six years. Some cryptos that are performing well and with high capitalization were not added due to inadequate historical data. Hence, the results from this study may not be applicable to all known Cryptocurrency.

Organisation of the Study

This study is divided into five components. Chapter one, which serves as the introduction, addresses the justifications for the study, the description of the problem, the objectives, hypotheses, significance, the scope, and structuring of the work. The follow-up section examines empirical and theoretical evidence that backs the claim that cryptocurrency usage correlates with increased global unpredictability. The study's methodologies are addressed in the third chapter. Chapter 4 presents and discusses the findings, with a specific emphasis on the existing literature. The fifth and last chapter of the study presents results, conclusions, and suggestions.

CHAPTER TWO

LITERATURE REVIEW

Introduction

This chapter gives a summary of the theoretical and empirical research that has been conducted on the topic Cryptocurrency and global uncertainty. In the theoretical review, the pertinent theories that were used for the study were brought to light, while the empirical data gives insights drawn from past research.

Theoretical Review

The adaptive market hypothesis, which is backed by the heterogeneous market hypothesis was used in addition to the and modern portfolio theory, in the study to explain how Cryptocurrency and global uncertainty are related.

Adaptive market hypothesis

People are mostly reasonable, but they sometimes overreact during times of high market volatility (Lo, 2004). According to Neely, Weller, and Ulrich (2009), the adaptive market hypothesis (AMH) is a reliable predictor of markets in the face of uncertainty. The market's evolutionary environment might shift in response to significant changes or economic shocks, making previously useful heuristics potentially harmful. This shows that, in the presence of uncertainty, the efficient market hypothesis might not hold true. Cryptocurrency, notably Bitcoin, are regarded as effective in the face of uncertainty (Kurihara & Fukushima, 2017; Noda, 2021; Tiwari et. al., 2018), and hedging and diversifying assets (Demir et al., 2018; Wang, Xie, Wen & Zhao, 2019; Yen, & Cheng, 2021).

According to the Adaptive Market Hypothesis (AMH), individuals are driven by their own self-interests, make mistakes, adapt, and learn from them. To accurately predict variations in cryptocurrency prices as time goes by, it is necessary to utilize the AMH while considering the fluctuating conditions in the market (Khursheed, Naeem, Ahmed & Mustafa, 2020). The AMH is an efficient predictor of markets in the midst of uncertainty (Neely et al., 2009). In accordance in the AMH, investors tend to engage in satisfactory behaviour rather than maximising their gains. When significant changes or economic turbulence occur, the natural cycles of the market change, and previously successful strategies may become detrimental. This shows that under uncertain conditions, the EMH might not be reliable.

Prior studies on the connection between market efficiency and AMH have a narrow focus, which makes it challenging to pinpoint specific AMH effects. The heterogeneous market hypothesis (HMH) of Müller et. al., (1997) is congruent with the adaptive market hypothesis (AMH), which postulates that various events and structural changes cause markets to evolve. During difficult times, investors are likely to respond to the cryptocurrency market and various market characteristics, particularly when trying to build the best possible portfolio. An important implication of the AMH is that risk premia change in accordance with how individuals' preferences change over time. A testable hypothesis resulting from these phenomena is that autocorrelation in return series has a time-varying structure and is influenced by the state of the financial markets (Baur et al. 2012; Kim et al. 2011).

Similar findings for the AMH are presented within the context of various asset markets, including foreign exchange, real estate mutual funds (REIT), and energy derivatives (Hall et al. 2017, Charles et al. 2012, and Zhou and Lee 2013). When Khursheed et al. (2020) looked at the various market efficiencies of Cryptocurrency, they found that shifts in market conditions significantly influenced price fluctuations in Cryptocurrency. Additionally, Ghazani and Jafari (2021) conducted a comprehensive analysis of market efficiency for AMH, gold, and cryptocurrencies. Examining the observed outcomes across all markets allowed for the AMH to be confirmed; nevertheless, there were differences in how adaptable the data were. This shows that the best choice to explain the connection between Cryptocurrency and economic ambiguity is AMH.

To examine how the cryptocurrency market adjusts to new information and events, the AMH can be applied to the setting of Cryptocurrency and uncertainty. The price of Cryptocurrency can be affected by a number of variables, from political and economic news to shifts in regulation and technological progress. The AMH suggests that market participants adjust their behaviour based on past experience, so analysing how they have reacted to similar events in the past can help predict how they will react to new events in the future. This can be done using statistical models and machine learning techniques to identify patterns in past market data and then use those patterns to make predictions about future market behaviour. An important aspect of the AMH is that it recognizes that markets are not entirely efficient and that market behaviour can be, to some extent, predictable. This is contrary to the basic efficient market hypothesis, which posits that all important information has already been represented in market prices, making future market movements hard to anticipate.

Overall, the AMH can be a useful tool for understanding how the cryptocurrency market works and predicting how it might react to future events and uncertainties. In the context of Cryptocurrency and global uncertainty, the AMH proposes that cryptocurrency markets are adaptive systems that adapt to changing global conditions. This suggests that the frequency and duration of the correlation between Cryptocurrency and global uncertainty can shift. Cryptocurrency have been found to have either a positive or negative association with global uncertainty, depending on the time period and prevailing conditions. During the COVID-19 epidemic, a study by Ciaian et al. (2021) identified a negative correlation between cryptocurrency prices and global indicators of uncertainty like the VIX index, suggesting investors fled to Cryptocurrency as a safe haven.

In other periods of high uncertainty, such as the Brexit referendum of 2016, however, this association has not been shown. As with other relationships, the one between Cryptocurrency and global uncertainty exhibits temporal nuances in the frequency domain. The association between Cryptocurrency and global measures of uncertainty like the Economic Policy Uncertainty Index (EPU) was shown to be strongest at high frequencies (daily and weekly) and weaker at lower frequencies (monthly and quarterly) in a study by Nadarajah et al. (2021). The temporal and frequency domain relationship between Cryptocurrency and global uncertainty can be better understood with the use of the AMH.

By recognising that financial markets are complex, adaptive systems, the AMH helps us understand the nuanced and dynamic nature of this relationship, which can change over time and across different frequencies. When it comes to the causal relationship between cryptocurrency and global uncertainty, the AMH can help provide insights into how market participants are adapting to uncertainty and how this is affecting the cryptocurrency price. Kristoufek (2018), for instance, looked at the correlation between bitcoin prices and several global indicators of unpredictability such geopolitical risk, economic policy uncertainty, and monetary policy uncertainty. According to the study's findings, economic policy uncertainty has had a major impact on bitcoin prices, demonstrating that market players are adjusting to policy shifts and utilising bitcoin as a hedge.

Similarly, Bouri et al. (2017) used several measures of uncertainty, using indicators like the VIX and the Economic Policy Uncertainty Index, an examination was conducted to explore the link between bitcoin prices and volatility in the worldwide financial markets. The results of the investigation revealed a constructive association between bitcoin prices and fluctuations in global financial market conditions, suggesting the potential use of bitcoin as a shelter by market participants amidst periods of market instability. Overall, AMH can help provide a framework for understanding how market participants adapt to changing market conditions and how this affects the price of cryptocurrency amid global uncertainty.

Modern portfolio theory

The modern portfolio theory heavily emphasizes diversification. Investors can optimise their outcomes by strategically integrating the two most viable assets, taking into account their risk tolerance. It is important to evaluate the risk and return of each investment in relation to the overall risk and yield of the portfolio, instead of considering them separately (Adediran, Yinusa & Lakhani, 2021). In their study, Qin, Su, and Tao (2021) analyzed the role of Bitcoin in mitigating risk by way of diversifying during times of high volatility and unpredictability. Amidst global trade tensions and a challenging landscape, businesses and institutions have the opportunity to utilize the Bitcoin market to enhance their investment strategies (Qin et al., 2021).

Another research conducted a selection of a cryptocurrency portfolio based on its risk-taking capability, and Bitcoin, Ethereum, and XRP emerged as the top performers in terms of risk-adjusted returns. These studies, in addition to others, confirm the importance of the Modern Portfolio Theory (MPT) in describing how cryptocurrencies can be used to create an investment portfolio that considers risk. The emergence of current portfolio theory signifies a substantial advancement in the mathematical representation of financial markets. The notion recommends spreading your assets around to protect yourself against volatility in the market and your company's specific dangers. The Modern Portfolio Theory (MPT) is a method for making investment decisions that takes into account the interplay between risk and return and provides guidance on how to identify, estimate, and manage these two factors.

The notion that investors need to be paid for taking risks and the subsequent quantification of the link between risk and return are at the heart of portfolio theory. Diverging from conventional security analysis, which centres on the attributes of singular assets, portfolio theory redirects its focus to the statistical interconnections amongst the securities comprising the entirety of the portfolio (Edwin and Martins, 1997). The purpose of modern portfolio theory is to select a group of assets that, as a whole, are less hazardous than any individual asset, and this concept of diversification is mathematically formulated. This makes sense intuitively because the value of various assets tends to move in opposite directions.

However, diversification reduces risk even if asset returns are not negatively correlated; in fact, it even works when correlations are positive. The Modern Portfolio Theory (MPT) assumes that an asset's return follows a normal distribution, or more typically an elliptically dispersed random variable of risk defined as the standard deviation of return, and that a portfolio's return is equal to the weighted combination of the investment income. The goal of MPT is to lower the overall variation in portfolio returns by merging different assets whose returns are not fully positively correlated. The rationality of investors and the efficiency of markets are further presumptions of modern portfolio theory. The core idea behind the MPT is that assets in a portfolio shouldn't be chosen based solely on their own merits. Instead, you should think about how each asset's price shifts in light of the price shifts of the rest of your portfolio. Greater predicted returns typically indicate greater risk (Taleb, 2007). The MPT elucidates the process of selecting a portfolio with the utmost anticipated yield for a specified level of jeopardy, or the minimum attainable hazard for a given level of foreseen return, however, unless negative asset holdings are possible, the desired expected return cannot be higher than the available security with the highest yield.

Uncertainty is a key factor in cryptocurrency investing, and MPT can help investors navigate that uncertainty. One way to incorporate uncertainty into MPT is to use probabilistic models to estimate the expected returns and risks of different Cryptocurrency. This approach considers the instability of the cryptocurrency market and the interconnections among distinct Cryptocurrency. Another way to include uncertainty in MPT is to use scenario analysis. This approach analyses the impact of various future scenarios on the portfolio's expected returns and risks. For example, an investor might analyse the impact of a major security breach on a cryptocurrency exchange or the impact of a government ban on Cryptocurrency. Portfolios of several Cryptocurrency can be constructed using MPT to achieve maximum expected returns within a specified risk profile. MPT can also help investors manage uncertainty by incorporating probabilistic modelling or scenario analysis into the investment decision-making process.

MPT assumes that assets are normally distributed and that their expected returns and risks can be quantified using mean and variance. However, this assumption has been challenged by empirical evidence suggesting that financial assets are not normally distributed and exhibit fat tails, skewness, and kurtosis. Consequently, this has resulted in the emergence of substitute options of theories and models that attempt to address these issues, such as the model of Lucey & Baur. Lucey and Baur (2010) proposed a new approach to portfolio diversification that includes hedge and safe-haven investing. They defined hedge assets as those that show negative correlation with the market, while safe-haven assets are those that show low correlation with the market and exhibit low volatility during times of financial stress. The authors argued that including these assets in a portfolio could improve the risk-reward profile, particularly during times of market turbulence. One way to integrate hedge and safe-haven assets into the traditional MPT framework is to use a mean-variance optimization model that incorporates these assets.

Mokhtarian and Rapkin (2014), for example, utilised this method to examine the best way to divide up your portfolio between hedge funds and safe havens in the US stock market. One way to integrate hedge and safe-haven assets into the traditional MPT framework is to use a mean-variance optimization model that incorporates these assets. Conditional value-at-risk (CVaR) is one method that takes into consideration the potential for significant losses during market downturns and the unequal distribution of asset returns. Studies examining the efficacy of hedging and safe-haven investing in limiting exposure to risk have taken this tack. Examples include Zaremba et al. (2018) and Che et al. (2020).

Overall, the risk-return profile of investment portfolios can be improved by include hedge and safe-haven investments and by redefining diversification, especially during times of market instability. However, there is no universally applicable formula for determining the optimal allocation of these assets; rather, it relies on investors' risk aversion and investment goals. As a new type of asset, Cryptocurrency have proven useful as a hedge against risk and a haven from volatility. For instance, some scholars contend that, like gold, bitcoin could serve as a safe haven during periods of economic unpredictability, political unrest, or market turbulence. Others contend that bitcoin could serve as a hedge against inflation and currency depreciation. The place of Cryptocurrency in an investor's portfolio can be examined using MPT. An investor may be able to lower overall portfolio risk and boost profits by including cryptocurrency in a diversified portfolio.

Dyhrberg (2016) found that diversifying a stock and bond portfolio with Bitcoin improved risk adjusted returns and decreased volatility. Bitcoin's safe-haven features, according to Bouri et al. (2018), are context-dependent, meaning they change depending on the type of economic uncertainty that investors encounter. Bitcoin, in particular, can be a shelter amid global financial crises but not local ones. In conclusion, MPT can assist investors in creating diversified portfolios that contain Bitcoin and other Cryptocurrency, which may increase risk-adjusted returns and decrease portfolio volatility. Cryptocurrency can be a safe haven or a hedge against economic uncertainty, but this is conditional on the type of uncertainty investors confront and the unique features of each cryptocurrency.

Empirical Review

Economic uncertainties

Financial instabilities

In recent decades, there has been a growing concern over uncertainties, especially policy uncertainty (Ahir et al., 2022; Zhang et. al., 2019; Davis, 2016;). The uncertainty of a country can impact the markets of other nations, subject to the size and robustness of their economy (Ahir et al., 2022). Uncertainty encompasses both global and local factors such as GDP growth and corporate expansion, in addition to events such as elections, wars, and climate change. The concept of uncertainty encapsulates the volatility and anxiety that individuals, business entities, and government experience regarding potential future events (Ahir et al., 2022). Recent media and academic coverage of significant financial developments has brought more attention to the issue of uncertainty (Al-Thaqeb & Algharabali, 2019).

According to Al-Thaqeb and Algharabali (2019), economic uncertainty refers to the presence of, and the potential impact of, unexpected shifts in the economic environment and governmental initiatives affecting businesses. The unpredictability of markets is made worse by the lack of clarity surrounding fiscal, regulatory, and monetary policy. Political uncertainty, as defined by Baker et al. (2016) defines economic risk as the potential negative impact resulting from a lack of understanding on the form and trajectory of prospective policy initiatives and regulatory systems. Due to the unpredictable nature of the economy, both businesses and individuals are delaying their expenditures and investments. The long-term impact of policy ambiguity in the future is limited. This implies that various additional factors, including both immediate and enduring ones, have an impact on uncertainty (Al-Thaqeb & Algharabali, 2019).

World uncertainty index

The World Uncertainty Index is the weighted average of individual country uncertainty indices for both developing and advanced economies. Canada, Australia,China, Germany, France, Japan, Russia, South Korea, Portugal, Spain, and the United Kingdom are only some of the established economies represented in the comprehensive index, along with several representatives from growing and developing Asia and Africa. The WUI is more comprehensive and accurate than other uncertainty indices because it includes recent events like the US-China trade tensions, European sovereign debt crisis, Brexit, the financial credit crunch, the coronavirus pandemic, and the ongoing problems between Russia and Ukraine in its analysis.

The World Uncertainty Index (WUI) reflects the prevalence of the word "uncertainty" in the reports of economic intelligence units from 143 countries, including both developing and industrialised economies. The index is consistent in its methodology and draws on key concerns related to political and economic developments from a single source (Ahir et al., 2022). The index's wide data coverage makes it superior to similar indexes that just cover a subset of the market. Studies comparing economies across countries have revealed large differences in the amount of uncertainty they present, with developed economies often providing less uncertainty than the rest of the world. It is not just that growing economies are more vulnerable to natural calamities like floods, but also to domestic political shocks like coups, revolutions, and wars. Since they are less prepared to deal with external shocks and face a wide range of them, their economies are more vulnerable as a result (Ahir et al., 2022).

Cryptocurrency efficiency and inefficiency

Previous research has confirmed the market's efficiency but described it as moderately efficient (Tiwari, Jana, Das, & Roubaud, 2018; Vidal-Toms, & Ibaez, 2018; Kurihara & Fukushima, 2017). A recent investigation affirms the information efficiency of the Bitcoin market. Subsequent returns within the Bitcoin market are anticipated to be stochastic, yet the market does not exhibit weak efficiency (Kurihara and Fukushima 2017). Tiwari et al. 2018 assert that the Bitcoin market demonstrates efficacy, aligning with the discoveries of (Vidal-Toms & Ibaez, 2018), countering earlier research that suggested the Bitcoin market lacked informational efficiency. Preceding the 2018 bitcoin crisis, multiple investigations were conducted (Bariviera, 2017; Urquhart, 2016) showed how inefficient the bitcoin market was. The bitcoin market and its associated yields are widely seen as inefficient at the moment (Urquhart, 2016). During the first half of the study period, everyday returners exhibited persistent behaviour, but their early activity was more information-efficient.

The logarithmic difference between intraday highs and lows during the time period demonstrates long memory (Bariviera, 2017). Vidal-Tomás et al. (2019) broadened the scope of these observations and concluded that pricing and volatility are caused by a distinctive dynamic mechanism, and the conclusions were confirmed by Al-Yahyaee et al. (2020). Quantile regression was utilised by the researchers to explore the factors that determine efficient markets. Because of signs of long memory and multifractality, the bitcoin market is inefficient (Al-Yahyaee et al., 2020). All altcoins are weak-form inefficient by nature and will become more inefficient with time (Vidal-Tomás et al., 2019). While Dash was found to be the least inefficient market, Litecoin was found to be the most inefficient. Increased liquidity enhances the efficiency of Cryptocurrency based on quantiles, but higher volatility reduces it (Al-Yahyaee et al., 2020). These findings, when paired with the findings of other studies, substantiated the explanation for the market crash of 2018.

Hedge and safe haven of cryptocurrency

New definitions of “diversification”, "hedge", and "safe haven" are presented at length in the works of Baur and Lucey (2010) and Baur and McDermott (2010). These meanings are frequently employed in studies involving hedging and safe havens. When anxiety levels grow, prudent investors seek out safe haven assets. In times of uncertainty, the price of a safe haven asset shouldn't fluctuate as much as the item in question. Over time, a strong safe haven will have a negative correlation with other assets or portfolios. There is zero time-varying correlation between a weak safe haven and any other asset or portfolio. In this scenario, the selected time period is the one with elevated levels of uncertainty.

Simply put, a safe haven is the most reliable kind of protection during times of unpredictability. So, a hedge is an asset that is virtually comparable to another but has a negative correlation or no correlation on average with that asset rather than a specific asset over a given time period. When there is a lot of unpredictability in the market, the normal correlation between a hedge and another asset may shift, perhaps from negative to positive.

When compared to other assets or portfolios, a strong hedge has a negative correlation on average. Weak hedging occurs when an asset has little or negative correlation with other assets or portfolios. Stocks, bonds, currencies, and commodities have all been identified for their hedging and safe-haven potential. This chapter contains the most well-known and applicable examples. Gold, currencies, and the eventual proof of bitcoin and Cryptocurrency all find refuge there. Gold is one of the most sought-after commodities for studying potential safe-haven investments and hedging strategies.

It's the go-to place when the economy is in flux. Bitcoin has been called "the new gold" because of the speculation that it may one day achieve the same value as gold. Over time, numerous applications have been discovered for gold. From 1986 to 2008, gold was determined to be a direct hedge against the US dollar by Joy (2011), and it continues to be a hedge now against the currency risk associated with the US dollar. Gold can be used as a hedge against stocks and as a haven during volatile stock market periods (Baur & Lucey, 2010).

Gold can be a hedge against the volatility of other commodities like oil (Reboredo, 2013a). Next, prospects for safe haven investments and currency hedging are crucial to the overarching goals of this inquiry. Foreign securities denominated in a foreign currency provide an added risk for investors. Investment returns are vulnerable to shifts in the value of both the domestic and foreign currencies.

Hedge funds and other institutional investors utilise currency swaps to reduce their exposure to foreign exchange rate fluctuations (Takezawa, 1995). In order to establish a minimum value for the foreign currency, one might also invest in a currency futures contract. Currency hedging is conceivable, and not just through the use of these tried-and-true but unscientific methods. Foreign currency hedging against a domestic stock market is demonstrated by Tachibana (2018). Shares in the European market are sometimes hedged with the Swiss franc, and shares in the US market are often denominated in Japanese yen as a safe haven and hedge.

Most importantly, there is now some proof that Bitcoin may be used as a hedge or safe haven. According to Kliber et al. (2019), Bitcoin has the potential to serve as a sanctuary. This is what happened between 2014 and 2017 with Venezuela and Bolivar investments. Based on differences in stock markets, currencies, and economic health, they chose Estonia, Venezuela, Japan, China, and Sweden as the countries to study. Bitcoin's potential as a haven currency was only made clear by the country's terrible economic predicament. Intraday analysis is the primary emphasis of the stochastic volatility method utilised by Urquhart and Zhang (2018).

They conclude that Bitcoin provides a shelter for the Canadian dollar, Swiss franc, and British pound during times of extreme market volatility.Finally, diversification is a crucial role that complements the others of hedging and safe haven. An asset that has a positive (but not perfect) correlation with another asset or portfolio is considered a diversifier, according to the work of Baur and Lucey (2010). It has many of the same characteristics as a hedge, except the direction of the correlation is opposite. Because a diversifier is also an average, its connection with another asset may shift in uncertain times, making it function something like a hedge. The importance of diversity is minimised for the sake of this investigation.

This study adopted Campbell and MacKinley (1997) definition for hedge and safe haven which defines a hedge as a financial strategy or investment made to reduce the possible risks and losses linked to other investments or market movements. In layman's terms, it is a safeguard used by people or businesses to cushion potential losses and offer a degree of assurance under unpredictable market circumstances and a safe haven as a certain kind of asset or investment that is thought to be reasonably secure and stable during periods of market turbulence or economic unrest. Plainly put, it is a form of investment that is thought to be less hazardous and more probable to hold its value, if not increase, during periods when other assets may suffer severe losses.

Cryptocurrency and economic uncertainties

Earlier research on Cryptocurrency, particularly Bitcoin, focused on their features, functions, risks, and volatility, among other things. Popularity, anonymity, mining ease, and market capitalization were all factors in this decision (Al Shehhi et al., 2014). Following its strong price gains in 2017 and subsequent crash in 2018, Bitcoin attracted the attention of a larger community (Wu, Tiwari, Gozgor & Leping, 2021). This necessitates thinking about how various unanticipated factors especially those connected to economic policy, might affect cryptos. The link between EPU and Bitcoin has been studied before. An empirical study was undertaken by Demir et al. (2018) to determine the impact of economic policy uncertainty on Bitcoin returns. Daily Bitcoin returns were predicted using the EPU Index and their accuracy was studied.

Using the Bayesian Graphical Structural Vector Autoregressive model, Ordinary Least Squares, and QQ estimates, the paper demonstrates the EPU's predictive usefulness for Bitcoin returns. It has been speculated that EPU has a negative correlation with Bitcoin returns. However, for both the lowest and highest quantiles of bitcoin returns and EPU, the effect is positive and statistically significant. The research indicates that Bitcoin has potential as a risk-mitigating tool. In an expansion of this research, Shaikh (2020) looked at how EPU affected Bitcoin returns in the USA, UK, Japan, China, and Hong Kong. Bitcoin returns in the United States, China, and Japan were found to be more sensitive to EPU than returns anywhere else. It also demonstrated that EPU negatively affects the Bitcoin market in the United States and Japan, but positively affects it in China.

Kyriazis (2021) looked at how EPU relates to high-end digital assets. The study's primary objective was to provide empirical evidence linking EPU and digital assets. Cryptocurrency like Bitcoin, Litecoin, and Ethereum were considered. The value of Bitcoin is highly correlated with EPU, however the values of Ethereum and Litecoin are only highly correlated with Bitcoin (Kyriazis, 2021). The research also found that commodities like oil had weak positive effects on Ethereum, while the Volatility Uncertainty Index had weak negative effects on both Cryptocurrency. The findings suggest that Ethereum and Litecoin, which are immune to the effects of EPU, could be utilised as a hedge against traditional assets or as a diversifier in comparison to Bitcoin during periods of extreme volatility.

The high correlations between bitcoin, oil, gold, and the EPU index were studied by Hazgui et al. (2021). Bitcoin (BTC), gold, Brent crude oil, and the US EPU index were all studied for their propensity to exhibit asymmetric dependencies and co-movements. Over the course of the sample period, the authors found a positive correlation between BTC and returns on commodity prices at both medium and low frequencies. However, for both medium and low frequencies, the EPU index has a negative correlation with BTC. Medium- and long-term BTC price returns may be forecasted using strategic commodities and the EPU index, according to the findings. A bearish or bullish market is associated with lower and lower BTC returns, respectively, as shown by the correlation between higher and lower EPU swings (Hazgui et al., 2021).

Political and economic uncertainty have had an impact on the Bitcoin market (Colon et al., 2021). The results of the study were analysed in terms of how they affected the cryptocurrency market. The study's findings demonstrated that the Bitcoin market constitutes a substantial insurance policy against international tensions. Later, it became clear that during a bull market in EPU, it might also be seen as a weak hedge and shelter. Finally, it has been argued that Bitcoin's resurgence is strongly correlated with the level of uncertainty in the market. Uncertainty in Chinese economic policy has a favourable effect on bitcoin returns, according to an analysis of the EPU index's impact on bitcoin's daily price movement conducted by Chen et al. (2021).

There is a statistically significant positive effect, but only at the upper quantiles of the current Chinese EPU (Chen et al., 2021). Since a rise in political unpredictability in China is correlated with greater Bitcoin returns, the cryptocurrency can be utilised as a hedge against this risk. A global analysis of cryptocurrency returns and EPU (Muhammad, 2021). The study looked at the EPU indexes and their ability to forecast cryptocurrency gains in the top 10 nations for bitcoin: the US, UK, Canada, Australia, Singapore, the Netherlands, France, and Germany. The EPU indicates that Bitcoin will have a positive return in the near future (Muhammad, 2021). Cryptocurrency may not provide the same level of protection as traditional assets during times of market volatility, according to some research (Muhammad, 2021).

Cryptocurrency performance in a portfolio

Rather than having a single asset which necessitates hedging, most investors have a diversified portfolio. How cryptocurrency should or can serve a unique purpose inside a portfolio is a hotly debated topic in the academic literature. Despite the fact that safe-haven opportunities demonstrate a one-to-one link with a currency, as shown in the aforementioned studies by Kliber et al. (2019) and Urquhart and Zhang (2018). Bitcoin's addition to a diversified investment portfolio may have varied results. Even while addressing this particular practical issue is not the focus of this study, it is nonetheless crucial. The tremendous volatility and lack of correlation to other assets both make it hard to evaluate cryptocurrency as a potential portfolio addition.

Klein et al. (2018) confirm this to be the case, since Bitcoin can't be used to hedge against equities investments, it serves no purpose in a portfolio other than to spread out the risk. However, this may be an exaggeration, as there are various reasons why Bitcoin may be used. There is mounting evidence that Bitcoin can improve the risk-reward profile of a portfolio. Bitcoin, according to Eisl, Gasser, and Weinmayr (2015), can improve the optimal portfolio's risk-return profile. This suggests that Bitcoin's enormous potential for both loss and gain might be leveraged to one's advantage. The conditional value-at-risk framework is employed as the method. The fact that Bitcoin and other assets follow a normal distribution is irrelevant when compared to the more standard mean-variance analysis. Bitcoin does increase the ideal portfolio's value at risk, but its much higher returns more than make up for this increase. In this case, the potential payoff is greater than the potential danger. A drawback of this approach is highlighted by Aslanidis et al. (2019).

Cryptocurrency can have a disproportionate impact on a portfolio's stochastic dynamics due to their high returns and volatility relative to other assets. However, in a well-balanced portfolio, this is easily accounted for by careful allocations. This remark probably applies to a number of Cryptocurrency with a significant market capitalization, as their risk and reward characteristics are comparable. The use of a diversified portfolio of Cryptocurrency is a second justification for Bitcoin's (or any other cryptocurrency's) inclusion in a portfolio. A portfolio is a collection of stocks chosen to spread out risk in the stock market. The cryptocurrency market is no different.

Instead of relying entirely on bitcoin, Brauneis & Mestel (2019) consider the use of a portfolio that includes numerous Cryptocurrency. They point out that there is a chance it might significantly reduce risks. Investors who aren't comfortable with the significant risk of investing in a single cryptocurrency like Bitcoin now have alternatives. This conclusion is supported by the research of Liu (2019), who demonstrates that spreading investment risk across multiple Cryptocurrency can yield superior returns. In conclusion, there are a number of reasonable strategies that can be implemented to improve portfolio performance by include Bitcoin or other Cryptocurrency. Substantial implications for portfolio and risk management and financial engineering will result from the dissimilarities in distribution, risk and reward profile, volatility, returns, and correlation (Osterrieder & Lorenz, 2017).

Initial research into the cryptocurrency industry focused on Bitcoin's legitimacy from a moral and legal standpoint. The economic implications of cryptocurrency are only now beginning to be explored in academic literature. Urquhart's (2016) research on Bitcoin was the first to examine the efficiency of the cryptocurrency market. The study looked at the volume-weighted average price of bitcoin across all exchanges from 2010 to 2016 to draw conclusions. Using a battery of statistical analyses, Urquhart (2016) concluded that bitcoin is not inefficient. Wei (2018) analysed 456 different digital currencies to further his investigation into the performance of weak Cryptocurrency. In order to investigate the connection between liquidity and volatility, Wei (2018) ran the same statistical tests as Urquhart (2016), plus one more. Wei (2018) found that highly liquid Cryptocurrency are less volatile and more efficient than illiquid ones.

Even while the current cryptocurrency market is anything but weak and efficient, the efficiency of Cryptocurrency is on the rise (Urquhart, 2016; Wei, 2018). According to Urquhart (2016) and Wei (2018), Bitcoin is the most efficient cryptocurrency, and Brauneis & Mestel (2018) agree. According to Brauneis and Mestel (2018), the larger and more liquid a cryptocurrency market is, the more efficient it is. Kurihara and Fukushima (2017) looked at daily price anomalies in Bitcoin using similar aggregated data from prior studies. The efficiency of the cryptocurrency market appears to be increasing, as seen by an uptick in efficiency indicators in the second half of the data sample (Kurihara & Fukushima, 2017). Bitcoin's long-term memory and other statistical qualities were investigated by Bariviera et al. (2017), who focused on daily and intraday price fluctuations. They looked at data from 2011–2017 to draw the conclusion that there is no correlation between long-term memory and financial flexibility. According to the data, Bitcoin's volatility declines with time (Bariviera et al., 2017).

Caporale et al. (2018) used two additional approaches to broaden the long-term memory study and incorporate three additional Cryptocurrency in addition to Bitcoin. The research found a positive relationship between past and future values, indicating the possibility of exceptional gains due to market inefficiencies. Lee, Guo, and Wang (2018) reach the same conclusion: because to their low correlation, Cryptocurrency can be used to diversify portfolio risk. The efficient frontier is greatly widened and improved opportunities are presented to investors when the CRIX Index3 is incorporated into a portfolio. Cryptocurrency, they say, are still in the testing phase, and many complicated aspects that could affect risk exposure yet to be discovered (Lee et al., 2018). While Borri (2019) agrees with the findings of prior studies on the link between Cryptocurrency, he suggests that only a limited percentage of Cryptocurrency should be included in a portfolio due to liquidity concerns. According to Brauneis & Mestel (2019), holding a portfolio of different Cryptocurrency is safer than holding only one. Incorporating the CRIX index into a portfolio bolsters Lee et al.'s (2018) findings.

Chapter Summary

Existing research was surveyed on the topic of Cryptocurrency and uncertainty in chapter two of this study. The foundation of the was laid by the modern portfolio theory and the adaptive market hypothesis. The study also covered areas such as the advantages and disadvantages of Cryptocurrency, as well as its ability to act as a hedge or safe haven. The link between

Cryptocurrency and uncertainty was also investigated, along with the empirical evidence supporting it.

CHAPTER THREE

RESEARCH METHODS

Introduction

This section presents the study's methodology, which includes, among other things, an exhaustive description of the research design of the study, model parameters, estimation approach, sources of data and tools for analysing data as well as the description and measurement of model variables.

Research Design

According to research, the main research designs that assist a researcher in approaching a subject are surveys, experiments, sound theory, ethnography, and case studies (Creswell, 2009). A research design, according to Du Toit and Mouton (2003), is a strategy that depicts how the research project will proceed.

Explanatory research is carried out on a less explored issue, requiring prioritization, generating operational definitions, and presenting a model that undergoes more comprehensive investigation. Explanatory research helps a researcher better comprehend a certain subject and examine cause-and-effect links. It is crucial to notice the variation in the variable that is believed to be causing the change in the other variable and then measure the variations in that other variable in order to establish causation. It does not produce results that are significant due to the absence of statistical significance. It influences the data that is gathered.

According to Morris, Allen, Kuratko, and Brannon (2010), descriptive research accomplishes exactly what its name implies: it describes descriptive facts about the population under study without attempting to determine a cause-and-effect relationship. It is employed to provide a precise and factual description of the population under study or to explain a phenomenon or event. A precise description of the what, who, where, when, how, and why the research will be undertaken is necessary for descriptive research design. In order to guarantee that the description covers every phase, a formal design is necessary. The difference between descriptive and exploratory research is that, unlike exploratory research, the former develops a hypothesis up front. This study employs a descriptive research approach to show how Cryptocurrency and global insecurity are related.

Research Paradigm

According to the positivist research paradigm used in this study (Aaker, Kumar, George, and Day, 2001; Yilmaz, 2013; Hays & Wood, 2011), the researcher can grasp the topic within a descriptive, casual framework. According to proponents of the positivist paradigm, this method entails examining a social observation that can be observed in order to draw conclusions and make generalisations (Cooper & Schindler, 2008). The positivist paradigm entails gathering data, utilising statistical significance testing to analyse the data, and then presenting outcomes that are reported quantitatively. This methodology is used because the study entails gathering information about Cryptocurrency as well as some uncertainty indices. The importance for approving or disapproving the formulated hypothesis is tested by additional analysis of the data.

Research Approach

The aim of quantitative studies is to find patterns in large datasets so that they can be applied to larger populations or phenomena. This method is beneficial because it allows for a clearer formulation of the research topic, removes or reduces the subjectivity of assessment, and stays true to the initial research goals, all of which contribute to more reliable findings (Saunders & Townsend, 2016). Explaining, forecasting, and managing phenomena are all possible with the use of the quantitative method (Saunders, Cooke, McColl, Shine, & Peacock, 2010). In order to quantitatively assess the variables and investigate the connections between them, a quantitative methodology was used in this study.

Definition and Measurement of Variables

The variables used in this study are defined to include only dependent and independent variables. The dependent variable for the study are the Cryptocurrency, while the independent variables include the WUI and CPUI.

Economic uncertainty

The study employs two main measures of global uncertainties in light of recent global mishaps. They are the cryptocurrency policy uncertainty index and the world uncertainty index. The global uncertainty indices employed by this study captures major global crises such as the Brexit, the crude oil crush, the COVID-19 pandemic and Russia's invasion of Ukraine. The ability of the uncertainty index to capture the previously mentioned global events and many others will contribute to establishing the safe haven and hedging nexus between economic uncertainty and cryptocurrency.

Cryptocurrency

The cryptocurrency employed for this study employed includes Bitcoin, Ethereum, Dash coin, Litecoin, Monero, Ripple, USDT. These Cryptocurrency were selected based on market capitalization and trade volume. The five largest cryptos by total market value in the month of February 2020 were the following: Ethereum, Bitcoin, XRP, Bitcoin SV, and Bitcoin Cash (Shaikh, 2020). With Bitcoin's value reaching such heights, one could argue that the worth of the remaining cryptos could also reach such heights, with Ethereum in particular recently posing a significant challenge in terms of value. The value of cryptos is of essence to stakeholders including investors notwithstanding the inefficiency of the market. Considering the rate at which the market value of cryptocurrency has increased over the years, one could argue about the performance of the cryptocurrency market in times of uncertainty and this remains an interesting area of study, especially for investors who would rely on such information to make informed decisions.

Ethereum represents a decentralized and open-source blockchain innovation accompanied by its native digital currency, Ether. ETH functions as a foundation for various alternative digital currencies while also enabling the implementation of decentralized smart contracts. The ultimate ambition of Ethereum is to establish a worldwide framework for decentralized applications, granting individuals across the globe the ability to compose and execute software that remains impervious to censorship, disruption, and fraudulent activities. Ethereum pioneered the concept of a blockchain-based smart contract platform. Smart contracts are software programs designed to fulfil agreements among multiple parties over the internet. Their aim is to remove the requirement for trusted intermediaries, thus reducing transaction expenses and enhancing transaction dependability. Since its introduction, Ethereum has remained second-largest cryptocurrency by value in market capitalization. Ethereum market capitalisation is at a current level of 205.74 billion, and down from 330.77 billion one year ago.

Dash is a public blockchain and cryptocurrency with the goal of creating a low-cost, quick, and decentralised system for international financial transactions. Dash aims to be an enhanced alternative to Bitcoin (BTC) by delivering higher levels of anonymity and faster transaction times, as detailed in the project's white paper. Named after the phrase "digital cash," Dash was released in January 2014 after being forked from Litecoin (LTC). Since its launch, Dash has added a number of useful features, such as a two-tier network with stimulated nodes, including "masternodes," and decentralised project governance; InstantSend, which enables immediately settled payments; ChainLocks, which renders the Dash blockchain technology instantly inviolable as well as PrivateSend, which provides additional, opt-in privacy for transactions.

Dash's stated mission on its website reads, "to be the most intuitive and robust payments-focused cryptocurrency in the globe." The initiative operates on a network of masternodes to achieve this goal. These masternodes are servers that are collateralized by Dash and are built to safely provide sophisticated services and administer Dash's proposal system. Masternodes offer an additional service to the network in exchange for a share of the block rewards. InstantSend, PrivateSend, and ChainLocks are just a few of the features they enable. According to coinmarketcap, Dash has a market cap of $789.45 million with a -1.73% change in the last month. DASH's current price is $71.07.

By capitalising on the special qualities of blockchain technology, Litecoin (LTC) facilitates instant, safe, and cheap transactions. The cryptocurrency was developed using the bitcoin (BTC) network, although it differs in a number of ways from Bitcoin (BTC), including its hashing algorithm, its hard cap, and the speed at which its blocks process transactions. Litecoin's cheap transaction fees and fast block times make it ideal for use in micropayments and at the point of sale. On the 7th of October 2011, a free and open-source client for Litecoin was published on Github, and on October 13th, 2011, the Litecoin network officially launched.

Since then, its popularity among users and investors has skyrocketed, and for the most of its history, it has been one of the ten largest virtual currencies in terms of market capitalization. Litecoin, being a blockchain-based cryptocurrency, has cryptographic protections that are nearly impossible to crack. Litecoin, like Bitcoin and a number of other Cryptocurrency, uses the PoW consensus approach to guarantee the instant and accurate confirmation of transactions. The combined power of the Litecoin mining network eliminates the possibility of double spending and other attacks, and guarantees the network's availability at all times. Litecoin's market cap is $7.07 billion, and it's selling for $97.89 per coin right now.

In 2014, the Monero cryptocurrency was released with a single purpose: to safeguard user privacy during financial dealings. Although Bitcoin (BTC) has a reputation for anonymity, due to the public nature of blockchains, it is typically possible to track transactions back to their original source. In contrast, XMR makes use of sophisticated cryptography to conceal both senders and recipients. For Monero, anonymity and security are paramount, with usability and efficacy coming in a close second. All users, regardless of their level of technical knowledge, should be afforded this level of security. The overarching goal of XMR is to enable instant, cheap, censorship-resistant financial transactions. Most people use Monero because of the privacy and anonymity it provides. Cryptocurrency transactions can be made at any time and for any reason without worrying about being monitored by the government, hackers, or anybody else. Since XMR currencies cannot be tracked, businesses cannot ban them for claimed links to criminal activity. Monero has a current market capitalization of $3.00 billion USD.

Tether, based in Hong Kong, issues USDT, a type of stablecoin (cryptocurrency having a stable value) that tracks the value of the US dollar. To ensure that the token supply remains fixed in relation to the US dollar, an amount of US dollars equivalent to the total USDT supply will be held in reserve in the form of US dollars' worth of treasury bills, escrow funds, commercial paper, cash, and reserve repo notes. To combine the decentralised features of Cryptocurrency, which allow for the transfer of funds between users without the need for a trusted third-party middleman, and the stable value of the US dollar, USDT was first released as a genuine coin in July 2014. Users can earn returns of 3% to as much as 20% by lending their stablecoins, which is preferable to storing fiat currency in an account for savings at an average of 0.06%.

One of USDT's defining characteristics is that Tether has pledged to maintain a fixed 1:1 exchange rate with the US dollar. To guarantee that USDT is fully backed by cash and currency equivalents, Tether claims to put aside the same amount of US dollars each time it issues new USDT tokens.

Cryptocurrency are unreliable as a store of value since their value might grow or decrease by 10-20% in a single day due to the extreme volatility of crypto marketplaces. However, USDT is immune to such fluctuations. Because of this quality, USDT is a haven for crypto investors who want to protect their holdings during times of severe volatility without selling all of their coins for US dollars. In addition, USDT facilitates the use of the blockchain to transfer US dollar equivalents across countries, regions, and even continents without the need for a time-consuming and costly third party, such as a bank or financial service provider. Currently the third best in terms of capitalisation USDT has a market capitalisation of $70.43 billion.

Source of Data

The data used in this study are of two broad categories. Firstly, the study employs two uncertainty indexes (World uncertainty index and the Cryptocurrency policy uncertainty index). Data on the cryptocurrency is sourced from CoinDesk at www.coindesk.com/price, while data on the WUI and CPUI are be sourced from https://worlduncertaintyindex.com/ and https://sites.google.com/view/cryptocurrency-indices/the-indices/crypto-uncertainty?authuser=0 , respectively. All indices employed for this data are monthly observations spanning from January 2010 to December 2022. The suggested period was chosen because it covers major global happenings such as Brexit and the emergence of COVID-19 as a global pandemic and the Russia-Ukraine war. The Cryptocurrency included in the sample are based on trading volume and market capitalization. The analysis is based on monthly returns, which are computed as $r_t = \ln P_t - \ln P_{t-1}$, where P_t and P_{t-1} are the current and prior indexes, respectively, and rt is the continuously compounded return.

Model Specification

The study successfully achieved its objectives by employing quantile regression to assess the safe haven and hedge characteristics of cryptocurrency in times of uncertainty. Wavelet analysis was utilized to establish the time-frequency correlation between cryptocurrency and uncertainty, while the Diks Panchenko test was applied to ascertain the presence of a causal relationship between cryptocurrency and uncertainty.

Wavelet approach

To explore the time-frequency dependence of cryptocurrency and global uncertainty, the wavelet approach, which was pioneered by Grossmann and Morlet (1984) and is a useful tool for dealing with financial data typically characterised by non-stationarity, noise, and nonlinearity. Extensive evidence in contemporary research indicates that time series variables exhibit non-stationary behaviour, even though investigators have utilized time-domain and frequency-domain methods to independently examine the causal connections between them. Additionally, time series dataset has significant structural flaws that affect the findings of conventional temporal causality analyses (Adebayo, 2020; Adebayo & Odugbesan, 2020).

The key problem, however, with independent techniques (more precisely Fourier transform forms) concerning the frequency domain, the exclusive emphasis on frequencies tends to neglect valuable details from the time domain (Pal & Mitra, 2017). To tackle these issues, the wavelet coherence method emerged, introducing a noteworthy advancement in breaking down 1D time data into a 2D time-frequency representation (Kirikkaleli & Gokmenoglu, 2020). This method enables the analysis of both short- and long-term causal correlations between cryptocurrency and global uncertainty. Multiscale decomposition techniques give modelling frequency-dependent phenomena a solid foundation. It may be used to analyse how cryptocurrency and global uncertainty results relate to one another. The roots of wavelets (ψ) go back to the Morlet family of wavelets. The equation for $\psi(t)$ is

$$\psi(t) = \pi^{-\frac{1}{4}} e^{-i\omega t} e^{\frac{1}{2}} t^2, p(t), t = 1,2,3 \ldots, T, \quad (1)$$

where Ψ represents a combination of variables, namely location (h) and frequency (z). While z controls the extended wavelet to localize various frequencies, the primary role of the h parameter is to establish the specific temporal position of the wavelet by exchanging it. The construction of $\Psi\ h, z$ may begin with the conversion of ψ through the following transformation:

$$\psi h, z(t) = \frac{1}{\sqrt{z}} \psi \left(\frac{t-n}{z}\right)_{,} h, z \in Rz \neq 0 \quad (2)$$

The continuous wavelet can be produced from ψ as a function of h and z given the time-series data $f(t)$

$$w_p(h, z) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{z}} \psi \left(\frac{t-h}{z}\right) dt \quad (3)$$

The reconstructed times series $f(t)$ with the ψ coefficient is

$$f(t) = \frac{1}{c_\psi} \int_0^{\infty} \left[\int_{-8}^{\infty} |w_f(a, b)|^2 \, da\right] \frac{db}{b^2} \quad (4)$$

The wavelet coherence method is employed based on the primary objective of the current investigation. The primary benefit of the wavelet coherence method over the conventional correlation methodology is, it allows the research to depict any relationship between the two-time series $j(t)$ and $f(t)$ in a combined time and frequency-based causality. The following is the time series' cross wavelet transform (CWT):

$$\mathrm{w}_{\mathrm{F_J(h,z)}} = \mathrm{w_f(h,z)}\overline{\mathrm{w_J(h,z)}} \tag{5}$$

where $\mathrm{w_f(h,z)}$ and $\mathrm{w_J(h,z)}$ stand for the respective CWT of two time series, $f(t)$ and $j(t)$ (Kirikkaleli, 2019). The formula utilized for the wavelet quadratic coherence can be found in the work of Orhan, Kirikkaleli, and Ayhan (2019),

$$\mathrm{R^2(h,z)} = \frac{\left|\mathrm{c}\left(\mathrm{z^{-1}W_{fj}(h,z)}\right)\right|^2}{\mathrm{C(z^{-1}|W_f(h,z)|^2)C\left(z^{-1}|W_j(h,z)|^2\right)}} \tag{6}$$

where C presents the over time smoothing mechanism, with $0 \leq \mathrm{R^2(h,z)} \leq 1$. Obtaining a value of zero for $\mathrm{R^2(h,z)}$ in the wavelet coherence figures indicates that the time-series variables $f(t)$ and $j(t)$ has no correlation between the as $\mathrm{R^2(h,z)}$ approaches 1, this scenario is depicted in blue in the image and implies that the variables $f(t)$ and $j(t)$ correspond on a specific scale (Kirikkali, 2020). Torrence and Compo (1998) put forth a method for detecting the wavelet coherence discrepancies through indicators of deferrals in the wavering of two time series since getting the value of $\mathrm{R^2(h,z)}$ does not offer any way of discriminating a negative correlation from a positive one (Pal & Mitra, 2017). The wavelet coherence phase difference equation is developed as

$$\phi_{\mathrm{f}}(\mathrm{h,z}) = \tan^{-1}\left(\frac{\mathrm{L\{C(Z^{-1}Wfj(h,z))\}}}{\mathrm{O\{C(Z^{-1}Wfj(h,z))\}}}\right) \tag{7}$$

where the imaginary operator and a real operator in equation 7 are represented by L and O respectively.

The wavelet analysis assists in evaluating how these two variables interact over time in the context of researching the relationship between Cryptocurrency and global uncertainty. To address the first objective which examines the time and frequency relationship between cryptocurrency and uncertainty, the wavelet analysis provides insights into the ever-changing patterns and correlations between these two variables at different time horizons. It also helps determine if certain frequency component of the data converge or diverge which will indicate a relationship. Wavelet analysis is utilised to determine adaptive behaviour and market dynamics in response to shifting levels of global uncertainty.

Whether market participants are adapting their investing plans and behaviours to the current market conditions can be determined by examining how various frequency components of the data change over time. Wavelet analysis can indicate the existence of many market regimes or states at various frequencies in relation to the heterogeneous market hypothesis and this will aid pinpoint instances of high or low heterogeneity in the relationship between Cryptocurrency and world unpredictability, showing varying degrees of market efficiency and information distribution over various timelines.

Variational mode decomposition

The VMD method is followed by the demonstration of the quantile and quantile-on-quantile regression. When using VMD with quantile regression, the power of both methods to analyse data with uncertain or variable outcomes. Quantile regression helps to understand different parts of the data's distribution, especially extreme values or outliers. By applying VMD with quantile regression, we can identify underlying patterns and relationships in the data, even when it contains unpredictable variations. In essence, VMD with quantile regression allows us to find meaningful patterns in data that may have irregular or uncertain characteristics, leading to better insights and understanding of the data's behaviour.

VMD is a data-driven technique, meaning it does not rely on any prior assumptions about the signal or its components. This makes VMD highly versatile and applicable to a wide range of signals, regardless of their complexity or underlying characteristics. Other decomposition techniques often make assumptions about the signal, which may limit their effectiveness in certain scenarios. Another advantage of VMD is its ability to adaptively determine the number of modes in a signal. This means that VMD can automatically adjust the decomposition process based on the complexity of the signal, ensuring an optimal representation of the components. In contrast, other techniques often require manual tuning or pre-defined parameters, which can be time-consuming and less accurate

Consequently, the quantile regression employs the findings of the VMD as its input dataset. The intrinsic mode function (IMF) of the VMD is what is denoted as an amplitude-modulated-frequency-modulated signal. The k_{th} mode $U_k(t)$ is presented as

$$U_k(t) = A_k(t)\cos(\emptyset_k(t)) \quad (8)$$

where $\emptyset_k(t)$ is the immediate phase, $A_k(t)$ is the immediate amplitude and its derivative $\omega_k(t) = \emptyset_k(t)$ is the immediate scale. For each mode $U_k(t)$, To generate the analytical signal and ascertain the self-governing frequency spectrum, VMD utilizes the Hilbert transformation. After that, the

Fourier transformation's shifting characteristic is applied to relocate the spectrum of the modes to the baseband. Then, the H^1 Gaussian smoothness is employed to project the bandwidth. The main objective of optimization is to minimize the cumulative spectral widths of all mode functions to the lowest achievable level

$$\frac{min}{\{u_k\},\{\omega_k\}} \left\{\sum_{k=1}^{k} \partial_t \left\| \left[\left(\delta\,(t) + \frac{j}{\pi t}\right) * u_k(t)\right] e_2^{-j\omega_k^t} \right\|\right\} \qquad (9)$$

$$\text{s.t} \qquad \sum_{k=1}^{k} u_k = f$$

where $\{U_k\}$ is mode ensemble and $\{\omega_k\}$ is the analogous center frequency ensemble K is the mode observation. The constraint stipulates that the combined value of all modes must match the original signal. By adding a quadratic penalty term and a Lagrangian multiplier, the following constrained optimisation problem becomes an unconstrained issue:

$$L\,(\{u_k\},\{\omega_k\},\lambda) = \alpha \sum_{k=1}^{k} ||\partial_t \left[\left(\delta(t) + \frac{j}{\pi t}\right) * u_k(t)\right] e_2^{-jw_k^t} ||_2^2 + ||f(t) - \sum_{k=1}^{k} u_k(t)\,||_2^2 + \lambda(t), f(t)\, - \sum_{k=1}^{k} u_k(t) \qquad (10)$$

where α is the penalty parameter and λ is the Lagrangian multiplier VMD employs the Alternating Direction Method of Multipliers (ADMM) for iterative resolution equation 10 above. Eventually, the initial signal is disintegrated into its K IMF constituent parts.

Quantile regressions approach

The quantile regression approach commences with employing linear regressions and subsequently adopts a quantile regression framework to examine the correlation between global uncertainty and the cryptocurrency returns and frequency. As quantile regression analysis (QRA) involves a series of regression curves that fluctuate across quantiles, representing the conditional distribution of the dependent variable, and with quantiles capturing diverse (time-evolving) stages of the dependent variable, it has gained popularity as a method for modelling the varying magnitude and dependency structure since its inception by Koenker and Bassett in 1978.

Quantile functions offer a superior and precise result regarding the influence of factors on the outcome variable compared to conventional linear correlation or regression, or even non-linear regression techniques (Koenker, 2005). Along with the median, which can be perceived as capturing the typical phase of the dependent variable, QRA has the additional advantage of furnishing data on tail dependency (i.e., upper and lower tails) (Chuliá, et al., 2016).

The QRA approach has limitations since it fails to fully grasp interdependence. While it can assess the diverse connection between cryptocurrency returns and global uncertainty at various points in the conditional distribution of the latter, it overlooks the potential impact of uncertainty's magnitude (whether significant or minor) on the relationship with cryptocurrency. Regrettably, quantile regressions are incapable of addressing this aspect. As a result, we opt for Sim and Zhou's (2015) quantile-on-quantile (QQ) methodology instead of the QRA method. The QQ approach allows us to model cryptocurrency returns' quantiles (across different frequencies) as a function of the world uncertainty index's quantiles, enabling exploration of distinct relationships between these variables at each level of their distributions.

Answering these inquiries allows for a more comprehensive understanding of dependency. Various levels of uncertainty are selected, and the potential local influence of each uncertainty level on different quantiles of bitcoin returns is approximated. At present, two methodologies are available for modelling the QQ technique: (1) a triangular system of equations derived from Ma and Koenker's work in 2006, and (2) a single equation regression approach based on Sim and Zhou's research in 2015, which in turn builds upon Ma and Koenker's previous work. This study opted for the second approach, and the reason behind this choice is as follows:

Let θ superscript denote the quantile of cryptocurrency returns, which are indicated by CR. Firstly a model a model for the θ -quantile of cryptocurrency returns as a function of its past lag CR_{t-1} and the world uncertainty is postulated, which is measured by the WUI. Formally, this can be expressed as:

$$CR_t = \beta^{\theta} WUI + \varepsilon_t^{\theta}, \tag{11}$$

where ε_t^{θ} is an error term that has a zero θ-quantile. We allow the relationship function $\beta^{\theta}(.)$ to be unknown, since we do not have a prior on how the crypto returns and WUI changes are interlinked. To examine the linkage between the θ-quantile of crypto returns and θ-quantile of WUI, denoted by WUI^t, we linearize the function β^{θ} (.) by taking a first-order Taylor expansion of β^{θ} (.) around WUI^t which yields the following:

$$\beta^{\theta}(WUI^t) \approx \beta^{\theta}(WUI^t) + \beta^{\theta\prime}(WUI^t)(WUI_t - (WUI^t) \tag{12}$$

Based on Sim and Zheng (2015)'s study, $\beta^{\theta}(WUI^t)$ and $\beta^{\theta\prime}(WUI^t)$ can redefined respectively, as $\beta_0(\theta,\tau)$ and $\beta_1(\theta,\tau)$. Then, equation (9) can be re-written as follows:

$$\beta^{\theta}(WUI_t) \approx \beta_0(\theta,\tau) + \beta_1(\theta,\tau)(WUI_t - (WUI^t) + \varepsilon_t^{\theta} \tag{13}$$

Ultimately, we substitute equation (12) into equation (13) to obtain

$$CR_t = \beta_0(\theta,\tau) + \beta_1(\theta,\tau)(WUI_t - (WUI^t) + \alpha(\theta)CR_{t-1} + \varepsilon_t^\theta \qquad (14)$$

where $\alpha^\theta = \alpha(\theta)$ The expression $\beta_0(\theta,\tau) + \beta_1(\theta,\tau)(WUI_t - (WUI^t)$ describes the relationship between the θ-quantile of crypto returns and the τ-quantile of WUI, given that β_0 and β_1 are doubly indexed in θ and τ. For estimating Equation 14, WUI_t and WUI^t is replaced with their estimated counterparts, WUI_t and WUI^t respectively. To estimate $\beta_0(\theta,\tau)$ and $\beta_1(\theta,\tau)$ the following minimization problem is solved:

$$\min_{\beta_0 \cdot \beta_1} \sum_{i=0}^{n} \rho\theta[CR_t - b_0 - b_1(WUI_t - WUI^\tau \alpha(\theta)CR_{t-1})]K\left(\frac{F_n(WUI_t) - \tau}{h}\right)$$

(15)

where $\rho\theta$ is the tilted absolute value function that provides as a solution, the θ-conditional quantile of CR_t. A Gaussian kernel K (×) is then applied to weight the observations based on bandwidth h (Koenker & Ziao, 2006). We start with a bandwidth of h = 0.05 following Sim and Zhou (2015). The weights obtained are inversely related to the distance of $WUI_t - WUI^\tau$. Thus, the distance of the empirical distribution function from τ (the value of the distribution function of WUI^τ is defined as;

$$F_n(\widehat{WUI}_t) = \frac{1}{n}\sum_{k=1}^{n} I\,[(\widehat{WUI}_k < \widehat{WUI}_t) \qquad (16)$$

Therefore, the QQ regression model, which adapts a region-specific polynomial structure, permits exploring the connection between chosen variables τ-quantiles of WUI and θ-quantiles of cryptocurrency-return based on their corresponding distributions.

Quantile-on-Quantile regression is applied for evaluating how Cryptocurrency function as havens or hedges amidst times of uncertainty. This investigation contributes to the goal of determining if Cryptocurrency can be used as safe havens or hedges. Furthermore, QQ regression is used to relate the modern portfolio theory, which assists investors in developing optimal portfolios while taking the risk-reward trade-off into account. QQ regression is used in this study to examine how Cryptocurrency fit into a portfolio plan while also examining their potential as safe havens or hedges during times of uncertainty.

Non-linear causality test

Based on the works of Diks and Panchenko in 2005 and 2006, the risk of excessively rejecting the null hypothesis of non-causality observed in the study by Hiemstra and Jones in 1994 is reduced when utilising Diks and Panchenko's test. Their method of non-parametric testing for Granger non-causality, which substitutes the global test statistic with an average of local conditional dependency measures, prevents over-rejection. Therefore, for this investigation, the Granger non-linear causality tests introduced by by Diks and Panchenko in 2006, are employed.

Suppose that $X_t^{lX} = (X_{t-\ell}X + 1, \ldots\ldots, X_t)$ and $Y_t^{lY} = (Y_{t-\ell}\,Y + 1, \ldots\ldots, Y_t)$ are the delay vectors, where ℓX, ℓY ≥ 1. The null hypothesis that X_t^{lX} contains additional information about Y_t + 1 is specified as:

$$H_o = Y_{t=1}|\left(X_t^{lX}; Y_t^{lY}\right) \sim Y_{t+1}|Y_t^{lY} \qquad (17)$$

The null hypothesis becomes a statement about the invariant distribution of the (*ℓX* + *ℓY* + *1*) dimensional vector, W_t = (X_t^{lX} , Y_t^{lY} , Z_t), where Z_t = Y_t + 1. If we ignore the time index and we assume that ℓX = ℓY =

1, then the distribution of Z, given that (X, Y) = (x, y), is the same as that of Z, given Y = y. In other words, X and Z are independent conditionally on Y = y, for each fixed value of y, so the joint probability density function fX, Y, Z (x, y, z) and its marginals must satisfy the following relationship

$$\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} = \frac{f_{X,Y}(x,y)}{f_Y(y)} \frac{f_{X,Z}(y,z)}{f_Y(y)} \qquad (18)$$

Diks and Panchenko (2006) show that the restated null hypothesis implies:

$$q \equiv E\,[fX,Y,Z(X,Y,Z)fY(Y) - fX,Y(X,Y)fY,Z(Y,Z)] = 0 \qquad (19)$$

where $\hat{f}_w(W_i)$ is a local density estimator of a dW-variate random vector W at W_i, defined

$\hat{f}_w(W_i) = (2_{\varepsilon_n})^{-d}W\ (n-1)^1 \sum_{jj} \neq {}_i I_{ij}^W$, where $= I_{ij}^W = I\left(\left|\left|W_i - W_j\right|\right| < \varepsilon_n\right), I(.)$ the indicator function and $\varepsilon_n$the bandwidth, which depends on the sample size n. The test statistic, which is a scaled sample version of q in equation (19), is simplified as:

$$T_n(\varepsilon_n) = \frac{n-1}{n(n-2)} \cdot \sum_i \left(\hat{f}_{X,Z,Y}(X_i, Z_i, Y_i)\hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i, Y_i)\hat{f}_{X,Y}(Y_i, Z_i)\right) \qquad (20)$$

where T_n consists of a weighted average of local contributions $(\hat{f}_{X,Z,Y}(X_i, Z_i, Y_i)\hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i, Y_i)\hat{f}_{X,Y}(Y_i, Z_i))$ which tend to zero in probability under the null hypothesis. Diks and Panchenko (2006) provide a proof which states that if $\varepsilon_n = Cn^{-\beta}(C > 0, \frac{1}{4} < \beta < \frac{1}{3}$ for one lag, then the test statistic in equation (20) satisfies the following condition:

$$\sqrt{n}\, \frac{(T_n(\varepsilon_n) - q)}{S_n} \xrightarrow{D} N(0,1) \qquad (21)$$

where $\xrightarrow{D}$ denotes convergence in distribution and S_n is an estimator of the asymptotic variance of $T_n(\cdot)$.

Quantile causality test

Additionally, in order to comprehend the cause-and-effect connection between variable x and variable y within various quantile ranges, Chuang et al., (2009) introduced the concept of Granger causality in quantiles. This approach aims to reveal a more nuanced causal association that considers different quantile levels, examining the causal link between the World Uncertainty Index and cryptocurrency profit. The quantile distribution of Granger causality under certain conditions looks like this:

$$\mathrm{Qyt}(\tau|(y,x)_{t-1}) = \mathrm{Qyt}(\tau|y_{t-1}), \forall\tau \in [a,b] \quad (22)$$

Qyt(τ|(F) denotes the conditional distribution of τ-th quantile. If Equation 22 holds, then X_t does not Granger cause Y_t over the quantile interval [a, b]. The Granger quantile causality is tested using the quantile regression proposed by Koenker and Bassett (1978).

$$Q_{yt}(\tau|(x_{t-1}) = x_0(\tau) + \sum_{i=1}^{j} x_i(\tau)y_{t-i} + \sum_{p=1}^{q} \beta_p(\tau)x_{t-p} \quad (23)$$

τ is the quantile level. β_p is the parameter vector of x_t. $\beta_p = (\beta_1(\tau), \beta_2(\tau), \ldots..\beta_q(\tau))$. If the parameter vector $\beta_p = 0$, then we say that x does not cause y at the quantile level τ. At a specific quantile level, the null hypothesis concerning Granger non-causality is expressed as:

$$H_0: \beta(\tau) = 0$$

For a specific percentile level, the Wald test statistic is employed to examine the null hypothesis. In numerous instances, the focus lies in verifying the absence of causality within certain percentile ranges say $\tau \in$ [a, b]. Koenker and Machado (1999) demonstrated that the Wald statistic procedure exhibits weak convergence. They proposed the sup-Wald test as an approach to examine the validity of the null hypothesis., $H_0:(\tau) = 0$ for the quantile interval $\tau \in$ [a, b].

$$sup_{\tau\in} W(\tau)^{\sup}\ _{\tau\in} \left| \left| \frac{\Psi_q(\tau)}{\sqrt{\tau(1-\tau)}} \right| \right|^2, \quad (24)$$

where $\Psi_q(\tau)$ is the vector of q-independent Brownian bridges equalling $|\tau(1-\tau)|^{\frac{1}{2}}$, N (0, 1q) in distribution. In practice, we test the null $H_0: \beta(\tau) = 0$ for a quantile interval $\tau \in [a, b]$ by the supremum of Wald statistics as

$$Sup - W_t = sup_{i=1,2,3......n} W_t(\tau_i), \quad (25)$$

where $\tau_i \in$ [a, b] with a $= \tau_1 < \tau_2 \ldots\ldots\ldots < \tau_n = b$

The quantile causality test is based on the following quantile function

$$Q_{WUI}(\tau|(CR_{t-1}) = \gamma_0(\tau) + \sum_{i=1}^{j} \vartheta_i(\tau) WUI_{t-i} + \sum_{p=1}^{q} \omega_p(\tau) CR_{t-p} \quad (26)$$

$$Q_{CRt}(\tau|(WUI_{t-1}) = x_0(\tau) + \sum_{i=1}^{j} x_i(\tau) CR_{t-i} + \sum_{p=1}^{q} \beta_p(\tau) WUI_{t-p}. \quad (27)$$

If the parameter vector $\beta_p = (\beta_1(\tau), \beta_2(\tau), \ldots\ldots \beta_q(\tau))$ is equal to zero at the quantile interval τ; then WUI does not Granger cause the cryptocurrency returns. Similarly, if the parameter vector $\omega_p = (\omega_1(\tau), \omega_2(\tau), \ldots\ldots \omega_q(\tau))$ Having a value of zero within the quantile range τ, the WUI is not affected by cryptocurrency returns. The sup-Wald test statistic is employed to assess the collective importance of parameter sets within a specific quantile interval. To determine the causal relationship's direction (positive or negative), the Quantile Vector Auto Regression estimates in Equations 26 and 27 are utilised.

The Diks and Panchenko test and the Granger causality tests are used to assess whether changes in cryptocurrency prices cause changes in uncertainty or whether changes in cryptocurrency prices are the result of changes in uncertainty. This test establishes if these elements are related to one another causally. This strategy is essential to achieving the objective of determining how bitcoin and vulnerability are related causally. Understanding how the adaptive market hypothesis applies to these links and how market players modify their approach in response to fresh knowledge is also helpful.

Chapter Summary

This chapter presented methods employed in conducting the study. The study is based on the post-positivism research paradigm and the quantitative research approach. The study also employed explanatory research as it seeks to examine the relationship between economic uncertainty and the returns of financial assets. The time frame of the study covered a monthly data series from January 2010 to December 2022. The chapter also brings to bear the source, and measurement of the variables under study. This chapter highlights the descriptive statistics as well as the trend analysis that motivated the empirical technique the study employed. The study employed the variational mode decomposition (VMD) technique to decompose the data series and also utilized the quantile regression technique to assess the asymmetric the relationship between the dependent and independent variables. The quantile-on-quantile regression technique was employed as a robust test for the quantile regression estimates. The wavelet analysis was carried out to reveal the time and frequency domain relationship between the dependent and independent variables. Finally, the Disk and Panchenko non-parametric causality and

Granger causality test was employed to test the causal relationship between the dependent and independent variables.

CHAPTER FOUR

RESULTS AND DISCUSSION

Introduction

This chapter presents the result and discussions relating to the study. Bi-wavelet examination is employed to establish the time-frequency correlation between uncertainty and cryptocurrency. To bolster the analysis, quantile regression is introduced, alongside the Diks and Panchenko non-parametric causality assessment and the Granger Causality test. The robustness of the findings of the QR is verified using the QQR. The Variational Mode Decomposition (VMD) technique, which carefully dissects the input signals into variational mode functions (VMFs). These VMFs replicate the original input signals, exhibiting diverse degrees of sparsity. In the context of this research, the VMFs denote short term (M1), medium term (M2 and M3), and long term (M4) timeframes, alongside the original data thus signal. To comprehend the connection between uncertainty and Cryptocurrency, the outcomes of quantile regression coefficients at different quantiles for each VMF, in addition to the original data is shown.

Descriptive Statistics

The tables thus table 1 and 2 shows the descriptive statistics of the dependent variables thus CPUI and WUI and the independent variables thus BTC, ETH, USDT, XRP, LTC, XRM, and DASH.

Table 1

Statistics	CPUI	WUI	BTC	ETH
		Signal		
Mean	0.001	0.004	0.045	0.075
Std. dev.	0.01	0.112	0.209	0.343
Skewness	2.574	0.162	-0.051	0.624

Kurtosis	19.556	4.265	-0.152	0.752
Jarque Bera	1.714***	0.0765***	0.0765***	9.1919***
ADF	-4.938***	-3.9894***	-3.9895***	-3.8324***
PP	-4.938***	-84.563***	-84.563***	-77.958***
		M1		
Mean	0.001	0.000	0.031	0.047
Std. dev.	0.002	0.033	0.07	0.123
Skewness	1.893	-0.045	-0.054	0.088
Kurtosis	2.107	-1.033	-0.876	-1.231
Jarque Bera	78.764***	3.9657	2.807***	5.827
ADF	-1.124	-4.5423***	-2.4346	-2.2347
PP	-2.8669	-35.93***	-4.555	-5.1132
		M2		
Mean	0.001	0.004	0.045	0.075
Std. dev.	0.010	0.0112	0.055	0.105
Skewness	0.088	0.088	-0.041	0.1
Kurtosis	6.03	6.03	-0.833	-0.051
Jarque Bera	154.92***	1.773***	2.5076***	0.1662***
ADF	-9.1678***	-7.2128***	-6.6921***	-5.5555***
PP	-34.553***	-44.481***	-42.349***	-43.929***
		M3		
Mean	0	0	0	0
Std. dev.	0.007	0.074	0.057	0.107
Skewness	-0.354	0.234	0.234	0.039
Kurtosis	10.125	2.842	-0.213	0.342
Jarque Bera	119.31***	3.8124***	1.003***	0.7052***
ADF	-10.421***	-10.478***	-8.747***	-8.111***
PP	-89.661***	-179.17***	-123.54***	-144.79***
		M4 (Residual)		
Mean	0	-0.003	-0.014	-0.027
Std. dev.	0.007	0.007	0.142	0.224
Skewness	-0.413	-0.413	0.134	-0.433
Kurtosis	10.125	10.125	0.026	-0.579
Jarque Bera	435.68***	36.084***	0.3303***	4.2063***
ADF	-4.6621***	-3.3947***	-4.3679***	-4.3841***
PP	-128.97***	-78.406***	-100.7***	-83.889***

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

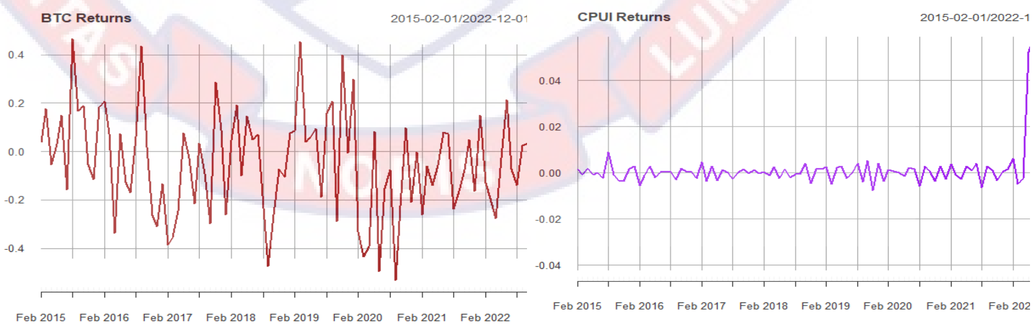
Table 1

Statistics	USDT	XRP	LTC	XRM	DASH
			Signal		
Mean	0	0.037	0.038	0.065	0.034
Std. dev.	0.016	0.44	0.292	0.335	0.331
Skewness	-0.3902	-0.3284	-0.9746	0.1443	1.81
Kurtosis	35.762	6.123	0.866	3.969	0.555
Jarque Bera	5.566***	219.79***	12.054***	94.738***	11.295***
ADF	-8.8778***	-4.4725***	-3.9882***	-3.5627***	-3.4769***
PP	-128.13***	-101.09***	-74.298***	-99.744***	-90.497***
			M1		
Mean	0	0.018	0.009	0.055	0.017
Std. dev.	0.003	0.122	0.109	0.099	0.155
Skewness	0.116	1.203	0.378	0.549	0.589
Kurtosis	2.044	0.472	-0.349	-0.909	-0.079
Jarque Bera	18.722***	25.064	2.7024***	7.9743	5.7196
ADF	-10.973***	-3.9465***	-3.3807***	-3.746***	-3.0905
PP	-35.467***	-4.9096	-11.421	-4.374	-5.5706
			M2		
Mean	0	0.001	0.0001	0	0
Std. dev.	0.003	0.16	0.094	0.0076	0.105
Skewness	0.119	0.106	0.032	0.006	0.007
Kurtosis	2.063	1.065	-0.611	0.345	-1.036
Jarque Bera	19.072***	5.4815***	1.2719***	0.6911***	3.9603***
ADF	-15.008***	-8.7284***	-7.3728***	-8.1356***	-7.4829***
PP	-39.242***	-44.569***	-45.223***	-35.531***	-42.797***
			M3		
Mean	0	0	0	0	0
Std. dev.	0.006	0.123	0.095	0.123	0.113
Skewness	0.791	-0.171	0.007	0.114	0.024
Kurtosis	3.849	0.206	-1.268	0.891	-0.377
Jarque Bera	74.129***	0.78502***	6.0668***	4.0029***	0.4242***
ADF	-16.49***	-11.376***	-11.111***	-9.1777***	-6.968***
PP	-105.54***	-108.8***	-61.625***	-120.68***	-150.64***
			M4(Residual)		
Mean	0	-0.018	-0.028	-0.011	-0.017

Std. dev.	0.012	0.31	0.182	0.224	0.212
Skewness	-1.608	-0.908	-0.481	-0.683	-0.334
Kurtosis	21.836	2.866	0.468	2.237	0.012
Jarque Bera	2042.98***	49.358***	4.9884***	29.745***	1.8597***
ADF	-5.9227***	-4.2889***	-4.7347***	-4.6618***	-7.4239***
PP	-162.18***	-120.77***	-111.78***	-105.7***	-83.984***

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

Tables 1 and 2 depict the data's descriptive statistics for M1 (short-term), M2, and M3 (medium-term), along with M4 (long-term) frequency levels, as well as the signal. The standard deviations illustrate the variations in time series, which can be utilized to explain the volatility in returns among the variables. Upon examining the normality of the data at different decomposed levels, the Jacque Bera test indicates that the data is not distributed normally, which aligns with previous research on the distributions of cryptocurrency returns (Barson et. al., 2022; Shanaev & Ghimire, 2021; Szczygielski et. al., 2020). The ADF and PP tests, designed to assess stationarity robustness, were compared, revealing that all variables exhibit stationarity in their return series, with the exception of M1.



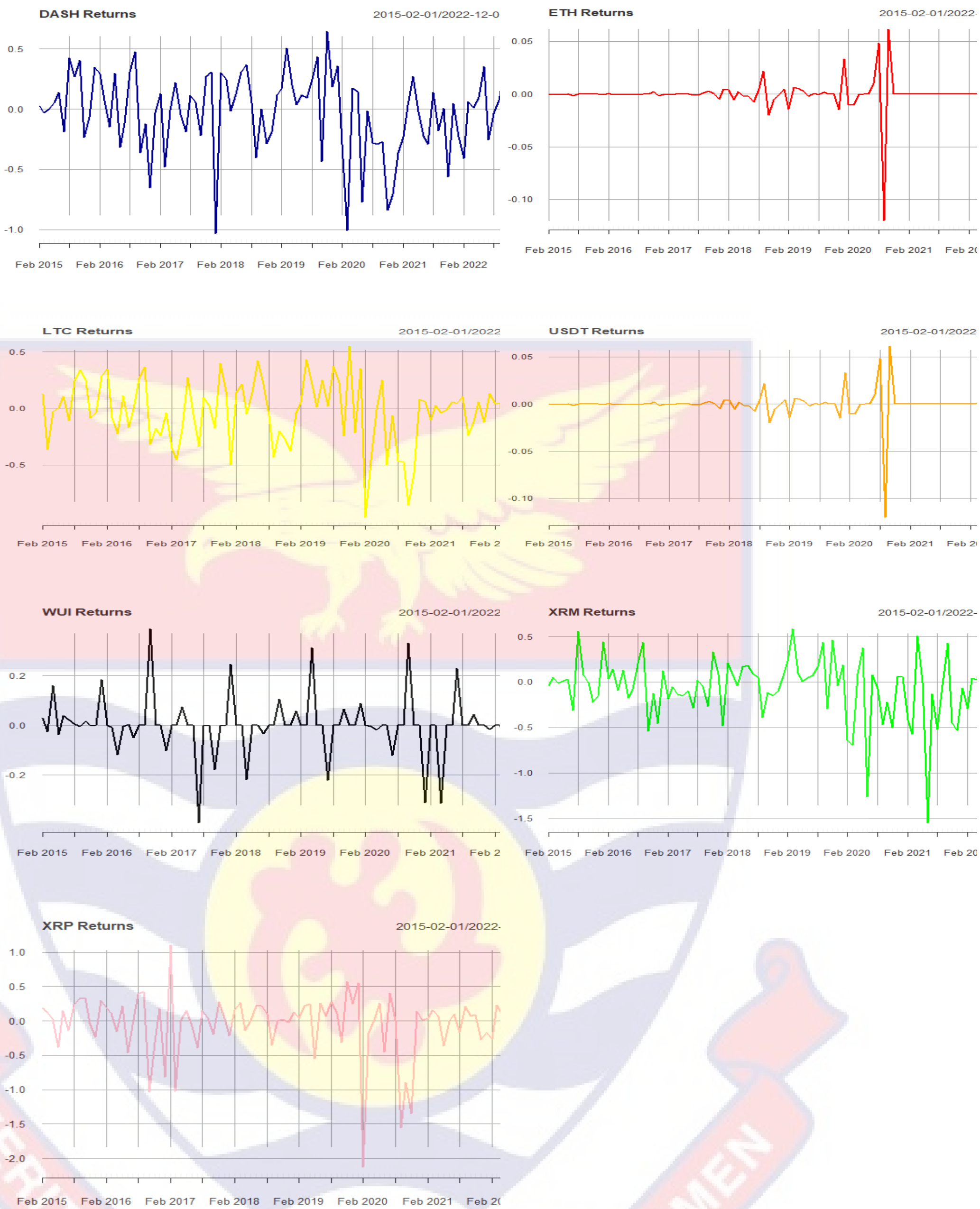
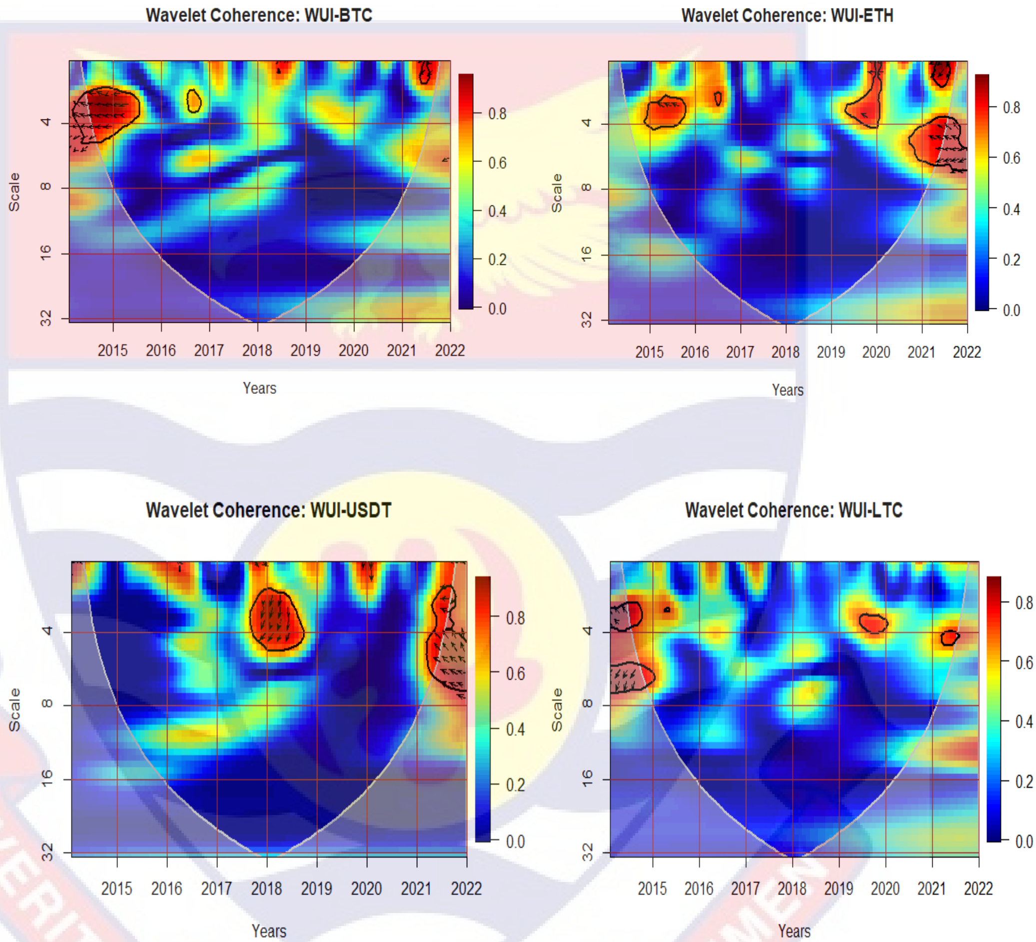


Figure 1: Returns of cryptocurrency

The figures figure 2 and 3 shows the bi-wavelet analysis of the dependent variables thus WUI and CPUI and the independent variables thus BTC, ETH, USDT, XRP, LTC, XRM, and DASH.

Wavelet analysis



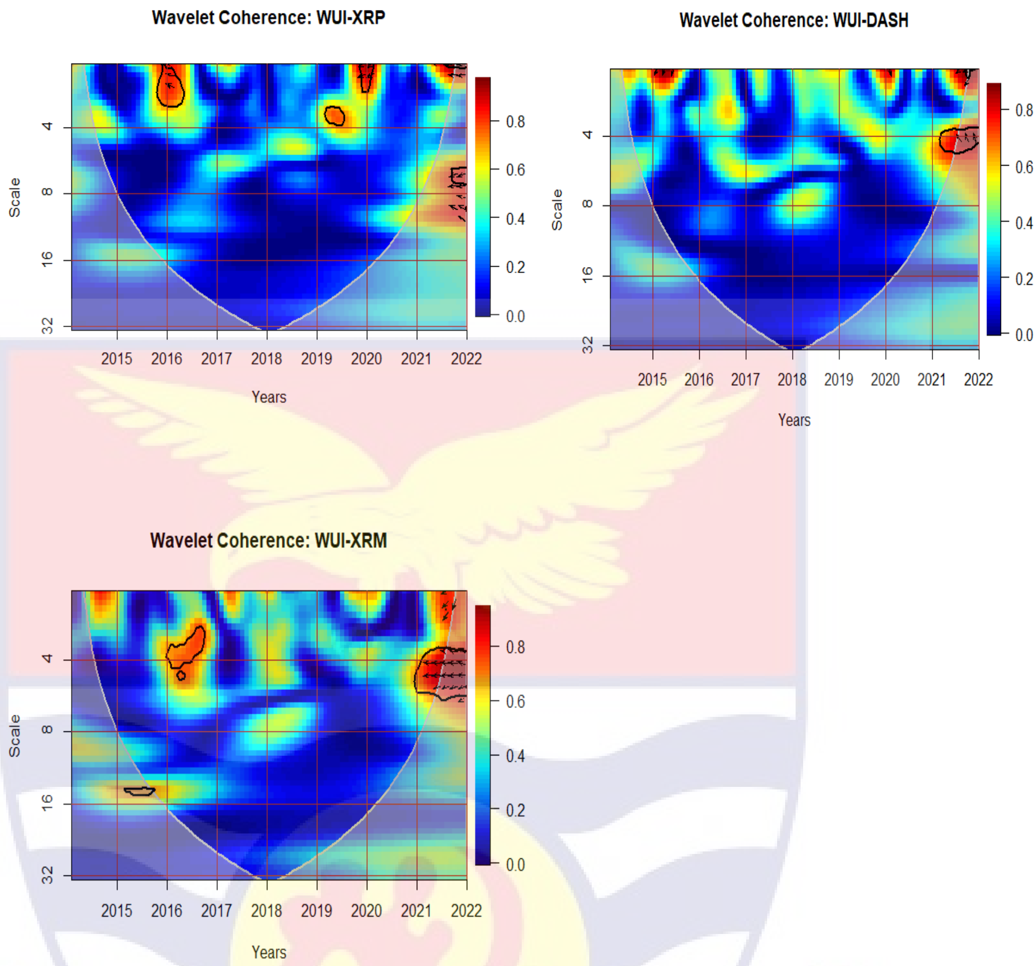
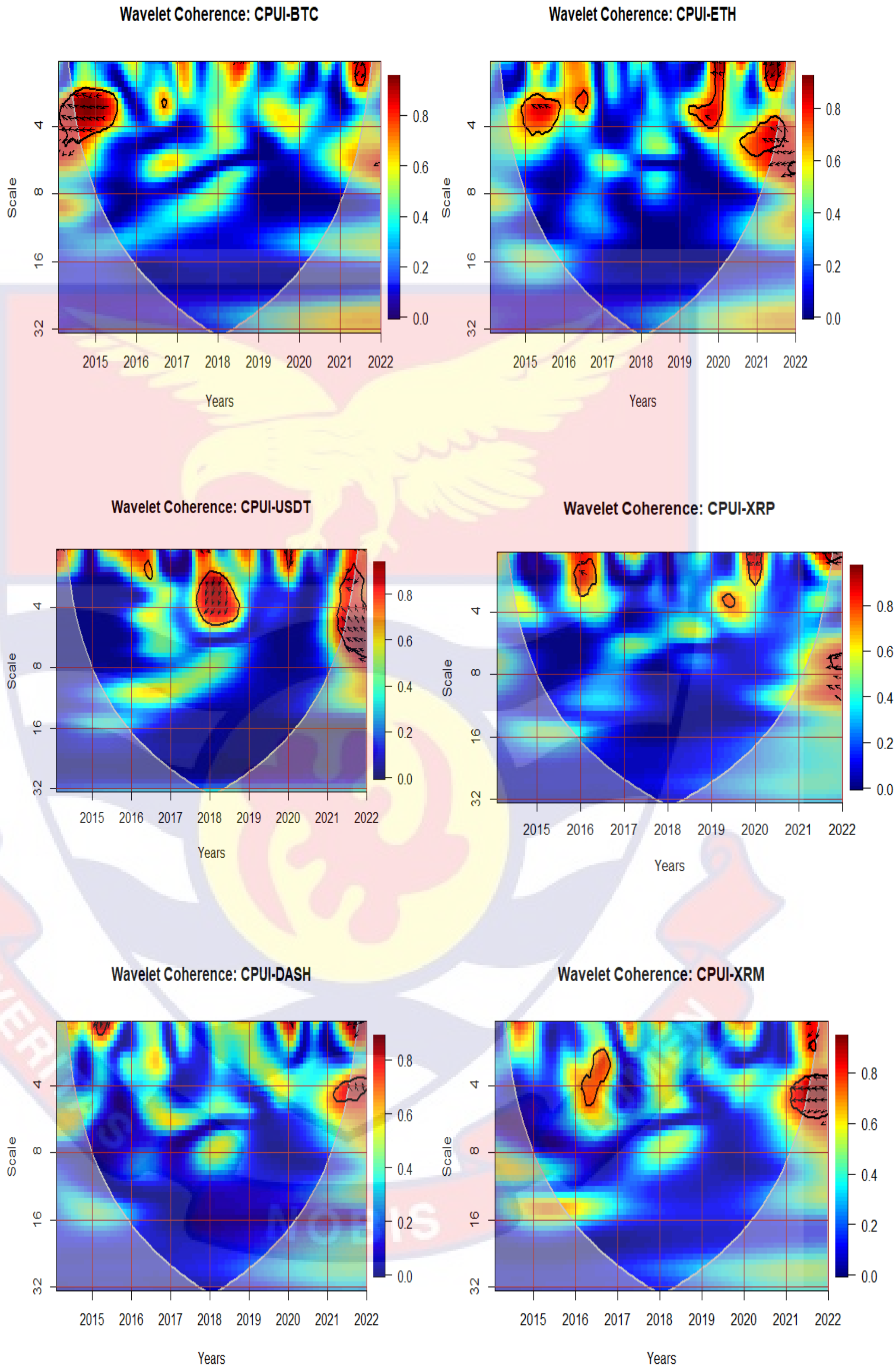


Figure 2: Wavelet coherence of WUI and cryptocurrency


Wavelet Coherence: CPUI-BTC
Wavelet Coherence: CPUI-ETH
Wavelet Coherence: CPUI-USDT
Wavelet Coherence: CPUI-XRP
Wavelet Coherence: CPUI-DASH
Wavelet Coherence: CPUI-XRM
Scale
4
8
16
32
2015 2016 2017 2018 2019 2020 2021 2022
Years
0.0 0.2 0.4 0.6 0.8

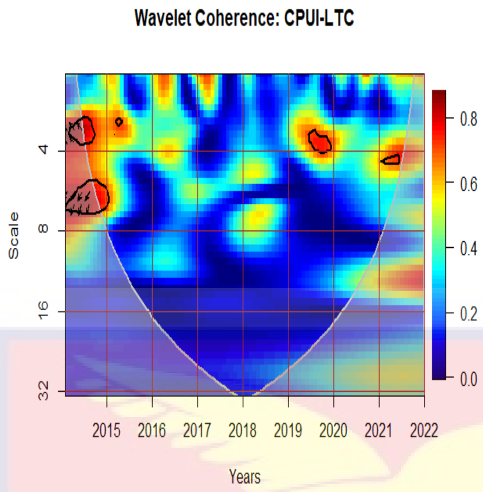


Figure 3: Wavelet coherence of CPUI and cryptocurrency

A consistent correlation was found between WUI and cryptocurrency returns using the wavelet coherence technique. A consistent correlation between uncertainty and cryptocurrency refers to a relationship where the value or behaviour of Cryptocurrency is closely linked to levels of uncertainty in the market or broader economy. In simpler terms, it means that when there is a lot of uncertainty or instability in the world, it tends to affect the value and behaviour of Cryptocurrency. Just like any other investment, Cryptocurrency are influenced by various factors, including market conditions, regulatory changes, global events, and investor sentiment. When faced with considerable doubt, like financial insecurity, political unrest, or financial crises, investors may turn to Cryptocurrency as an alternative investment or store of value. This increased demand may result in higher prices and greater market volatility.

The results are shown in Figures 2 and 3. To view it from another perspective, wavelet coherence offers insights into the intensity of the connection between the global uncertainty index and Cryptocurrency. The more vivid and warmer the red hue, the greater the correlation value for the

$R^2(h, z)$ as stated in equation 6, In wavelet analysis, the brightness and intensity of the colour red indicate the strength of the correlation value. Specifically, when the red colour appears brighter and hotter, it signifies a higher correlation value. Simply put, in wavelet analysis, different colours represent the correlation between different data points or variables. The colour red is typically used to indicate a positive correlation, meaning that the variables tend to move in the same direction. The brightness and heat of the red colour further indicate the strength of this positive correlation. The brighter and hotter the red colour, the stronger the correlation between the variables being analysed. In essence, when analysing data using wavelet analysis, if you observe a red colour that appears brighter and hotter, it suggests a strong positive correlation between the variables being studied. This visual representation helps identify and interpret the strength of the relationship between different data.

As suggested by Sharif et al. (2017) and Orhan et al. (2019), when making a decision, one should consider the arrows within the cone, also known as the cone of influence in the literature. The direction of the arrows in Figures 1 and 2 indicates the direction of the causal relationship or correlation between the uncertainty index and cryptocurrency returns. Figure 1 presents the wavelet coherence in time-frequency space between seven cryptocurrency returns (CRs) and the world uncertainty index (WUI). The lead-lag relationship between the respected CRs and the WUI is depicted in these graphs by phase arrows. For instance, the in-phase arrow suggests that CR and WUI are going in the same direction, whereas the anti-phase arrow suggests that the variables are travelling in the opposite way. In addition, the arrows going right upward and left downward indicate that CRs are in the lead whereas the arrows pointing in the other directions indicate that the WUI is in the lead.

The WUI is in phase for all of our Cryptocurrency in Figure 1 with the exception of DASH, USDT, and XRM, based on our WTC results for the short-term (1-3 months). In this regard, the in-phase movement in BTC, for instance, shows that WUI and BTC returns are moving in the same direction. When examined further, the WUI leads all other relevant Cryptocurrency for the medium-term (6 to 8 months). For instance, the WUI has led and dominated the BTC returns for medium and high frequencies since 2018 correspondingly. A similar pattern can be seen in all of the other Cryptocurrency, with WUI leading the CRs in the medium-term. As for low-frequency (1-3 months), based on our WTC results, we observe that CRS leads WUI for all Cryptocurrency except for DASH. For instance, the WUI detects in-phase arrows between BTC and WUI at a low frequency (this indicates BTC returns are moving in the same direction as the WUI).

In Figure 2, there are in-phase movements between the cryptocurrency returns and the CPUI in the 1–3 months and 6 to 8 months frequency bands but not LTC. As a consequence of COVID-19, coherence follows heterogeneous movement, being negative in the early days of the sample and positive in 2021. The positive relationship also exists during the pandemic period, indicating the hedging capacity of all Cryptocurrency except LTC. Cryptocurrency leads the CPUI at short-term investment horizons during normal and uncertain periods. Conversely, an out-of-phase movement exists between LTC and the CPUI. Additionally, LTC returns lag those of the CPUI and lead CPUI during the COVID-19 and Russian-Ukraine war episodes. Overall, there is an identical or similar association with both cryptocurrency and uncertainty indices, i.e., WUI and CPUI. These findings corroborate with (Balli et. al., 2020; Bouri et. al., 2019; Demir et. al., 2018) who show that Cryptocurrency demonstrate a similar impact on prevailing uncertainties. The study conducted by Balli et al. (2020) focused on Cryptocurrency and aimed to investigate their characteristics and potential factors affecting their value.

One important finding of the study was that Cryptocurrency are highly volatile, meaning their prices can change rapidly and unpredictably. This volatility can be influenced by factors like market sentiment, news events, and regulatory developments. Additionally, the study examined the influence of various macroeconomic factors, such as inflation and interest rates, on cryptocurrency prices. The results indicated that these factors can have an impact on the value of Cryptocurrency, but the relationship is complex and can vary across different Cryptocurrency. Overall, Balli et al. (2020) provided valuable insights into the characteristics and dynamics of Cryptocurrency. They highlighted the volatile nature of Cryptocurrency, their potential for diversification in investment portfolios, and the influence of macroeconomic factors on their prices.

The study by Bouri et. al., (2019) investigates how uncertainty affects the prices and returns of three popular Cryptocurrency. The researchers used statistical methods to analyse data and identify different sources of uncertainty, such as economic policy uncertainty, stock market volatility, and investor sentiment. The findings of the study suggest that uncertainty has a significant influence on cryptocurrency returns. Specifically, higher levels of uncertainty are associated with lower returns in the cryptocurrency market. This implies that when uncertainty increases, investors may become more cautious and hesitant, leading to decreased demand and, subsequently, lower prices for Cryptocurrency. The researchers analysed a wide range of factors that could potentially influence cryptocurrency markets, such as market liquidity, trading volume, investor sentiment, and macroeconomic indicators. They collected and analysed data from various sources to assess the impact of these factors on cryptocurrency price movements.

The findings of Demir et. al., (2018) revealed that several factors play a significant role in the uncertainty of cryptocurrency markets. For example, they observed that low liquidity and high trading volumes can lead to increased volatility and uncertainty. Additionally, they found that investor sentiment, which reflects the overall mood and emotions of investors, can greatly influence cryptocurrency prices. Furthermore, the study highlighted the influence of external factors such as regulatory announcements and macroeconomic indicators on cryptocurrency markets. Changes in regulations or economic conditions can introduce uncertainty and impact the value of Cryptocurrency

The connection between Cryptocurrency and uncertainty indices is more noticeable when looking at short-term investment periods (1–3 months). There is a significant lack of correlation at medium and long-term investment horizons. This means that potential financial gains for cryptocurrency traders and investors are short-lived, and there are fewer financial benefits over the medium and long-term as uncertainties increase. In the short-term, cryptocurrency returns precede both uncertainty indexes (WUI and CPUI), while in other frequency bands, such as the medium and long-term, their movement is generally negative, suggesting that Cryptocurrency lag behind the uncertainty indexes in these periods

In summary, the capacity of Cryptocurrency to act as a hedge diminishes quickly in the face of rising uncertainty. Hence, investors must formulate a well-timed hedging plan to attain financial profits. Furthermore, the prevailing blue regions indicate inadequate coherence or correlation, signifying that Cryptocurrency may not be effective as a hedging tool for long-term investments during periods of uncertainty. It is crucial for investors and crypto traders to safeguard their portfolios from elevated WUI and CPUI.

Summary of lead Lag relationship between WUI and Cryptocurrency

Pair	Lead	Lag
WUI and BTC	BTC	WUI
WUI and ETH	WUI	ETH
WUI and USDT	WUI	USDT
WUI and XRP	WUI	XRP
WUI and LTC	WUI	LTC
WUI and XRM	WUI	XRM
WUI and DASH	WUI	DASH

Summary of lead Lag relationship between CPUI and Cryptocurrency

Pair	Lead	Lag
CPUI and BTC	CPUI	BTC
CPUI and ETH	CPUI	ETH
CPUI and USDT	CPUI	USDT
CPUI and XRP	CPUI	XRP
CPUI and LTC	LTC	LTC
CPUI and XRM	CPUI	XRM
CPUI and DASH	CPUI	DASH

Diks and Panchenko test of causality

Understanding causal relationships is essential for decision-making and risk management in cryptocurrency markets. The Diks-Panchenko test in table 3 aims to determine if there is a causal link between two variables, indicating that changes in one variable directly influence the behaviour of the other. By identifying causal relationships, analysts and investors can gain insights into how specific Cryptocurrency or market uncertainties impact the overall system. Diks and Panchenko non-parametric test is valuable in cryptocurrency and uncertainty analysis due to its ability to capture nonlinear relationships, its data-driven approach, its detection of causality, and its usefulness in understanding the impact of uncertainty factors on cryptocurrency dynamics. By employing this statistical tool, researchers and analysts can gain deeper insights into the complexities of cryptocurrency markets and make more informed decisions.

Table 2

	BTC	ETH	USDT	XRP	LTC	XRM	DASH
Signal							
WUI	-0.438	-0.828	0.106	-0.262	0.313	0.773	0.871
CPUI	0.543	0.515	0.169	-0.343	0.768	-0.748	0.409
M1							
WUI	0.500	1.356	-0.254	0.551	0.967	0.918	0.707
CPUI	1.372	1.204	-0.946	-0.861	0.111	0.132	0.796
M2							
WUI	-0.417	0.987	-0.530	1.315*	1.315	-1.414	-0.398
CPUI	0.019	0.140	-0.998	-1.372	-1.372	1.236	-0.195
M3							
WUI	-0.245	-0.214	-0.684	-0.200	1.397	0.023	0.799
CPUI	0.842	0.925	-0.875	1.079	-1.184	1.782*	-0.473
M4 (Residual)							
WUI	0.405	-0.460	0.032	1.017	-0.706	0.317	1.165
CPUI	1.198	-0.041	-1.519	0.720	0.309	-0.896	0.658

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

The results of the Diks and Panchenko (2006) test, which is a non-parametric causality analysis, regarding the relationship between uncertainty and Cryptocurrency, are shown in Table 3. The study aims to determine whether there is a one-way causal link between these variables, examining whether fluctuations in Cryptocurrency could be influenced by uncertainty. The outcomes of this examination unveil the causal connection between unpredictability and the cryptocurrency market. Table 3 showcases the findings of the Diks and Panchenko non-parametric analysis of causality between uncertainty and the corresponding Cryptocurrency at disassembled frequencies and signal.

From the table there is no causality between uncertainty and the Cryptocurrency except for XRP and XRM where in the medium term thus M2 and M3 it can be seen that the is a causal relationship between WUI and XRP in M2 and XRM and CPUI in X3. The output from the Diks Panchenko test affirms the study by (Corbet et al., 2018; Chai et. al., 2019; Gao et. al., 2020). Corbet et al., 2018 examines the relationship between macroeconomic uncertainty and cryptocurrency returns. The authors found that while macroeconomic uncertainty affects traditional financial markets, it does not significantly influence cryptocurrency returns. They suggest that the decentralised nature and limited regulatory exposure of Cryptocurrency may contribute to their independence from macroeconomic factors. Gao et. al., (2020) uses the Diks-Panchenko test to examine the relationship between macroeconomic uncertainty and cryptocurrency returns.

The authors find that macroeconomic uncertainty is negatively correlated with cryptocurrency returns, suggesting that investors are more likely to sell Cryptocurrency when macroeconomic uncertainty is high. Chai, Li, and Wang (2019). This study examines the relationship between macroeconomic uncertainty and cryptocurrency trading volume. The authors find that macroeconomic uncertainty is positively correlated with cryptocurrency trading volume, suggesting that investors are more likely to trade Cryptocurrency when macroeconomic uncertainty is high.

Granger Causality Test

In contrast to the Diks and Panchenko examination, the Granger causality test in table 4 primarily centers on the forecasting capability of one variable on another. It aids in establishing whether previous values of one variable hold information that enhances the prediction of forthcoming values of another variable. Granger causality mainly assesses how well one variable can forecast future values of another, while the Diks-Panchenko approach aims to pinpoint direct causal connections between variables.

Table 4

	BTC	ETH	USDT	XRP	LTC	XRM	DASH
				Signal			
WUI	0.1974	0.1496	0.3970	2.1606	0.2599	0.0367	0.2991
CPUI	0.0452	0.7151	0.0603	0.1697	0.4372	0.1274	0.1300
				M1			
WUI	3.7566*	6.8751**	0.0243	1.2527	8.7024**	0.4298	5.8065**
CPUI	4.4436*	1.6574	0.0002	1.0308	0.9467	0.3664	0.5157
				M2			
WUI	3.1109	3.0077	0.0899	1.1389	6.6594*	1.6268	0.4006
CPUI	4.7810	3.2540*	0.0143	2.1169	1.3265	0.9821	0.8214

M3							
WUI	0.2602	0.5545	0.4741	1.6108	0.1346	0.1452	0.3300
CPUI	1.0221	1.2078	0.7336	4.1995	0.0818	0.3348	0.4442
M4(Residual)							
WUI	0.1242	0.8060	0.1327	0.1792	0.0249	0.4364	0.3398
CPUI	0.2396	1.0684	0.0274	0.3035	0.2323	0.1675	0.7581

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

Table 4 displays the findings of the Granger causality examination concerning the relationship between uncertainty and cryptocurrency across different frequency components and signals. In the short term (M1), there is evidence to suggest that Bitcoin (BTC), Ethereum (ETH), Litecoin, and Dash are influenced by WUI, demonstrating Granger causality. Similarly, in the medium term, it becomes evident that ETH is influenced by CPUI, while LTC is influenced by WUI. This implies that in the short term a significant Granger causality between uncertainty and Cryptocurrency implies that uncertainty provides meaningful predictive information for cryptocurrency movements beyond their own past values. This suggests that incorporating measures of uncertainty can enhance the accuracy of cryptocurrency price forecasting models. It also implies that changes in uncertainty levels can be used as indicators for potential shifts in cryptocurrency prices or market conditions.

This information can be utilized by investors and market participants to make informed decisions and manage risk exposure. This is in line with the study by (Bariviera & Mensi, 2017; Bouri et. al., 2020; Zhang & Wang, 2022). Bouri et. al., (2020) concluded that the presence of a significant Granger causality between uncertainty and Cryptocurrency may influence investor behaviour and market dynamics. Increased uncertainty may lead to higher volatility, liquidity shifts, or changes in trading volumes as market participants react to uncertain conditions and understanding the relationship between uncertainty and Cryptocurrency can shed light on investor sentiment and decision-making processes within the cryptocurrency market. Bariviera and Mensi, (2017) applied the Granger causality test to examine whether economic uncertainty, as measured by the Economic Policy Uncertainty (EPU) index, Granger causes cryptocurrency returns. They use daily data for four major Cryptocurrency (Bitcoin, Litecoin, Ripple, and Ethereum) and the EPU index.

The authors find that economic uncertainty, as represented by the EPU index, Granger causes cryptocurrency returns. This implies that changes in economic uncertainty can be used to predict future cryptocurrency returns. The study suggests that during the Global Financial Crisis, periods of high economic uncertainty were associated with significant movements in cryptocurrency prices. The study by Zhang & Wang, (2022) used the Granger test to examine the relationship between economic uncertainty and cryptocurrency returns. In this case, the researchers investigated whether economic uncertainty can predict cryptocurrency returns. The researchers used a dataset of daily returns for Bitcoin and the VIX index, as a measure of economic uncertainty. They found that there is a positive relationship between economic uncertainty and cryptocurrency returns. This means that when economic uncertainty increases, cryptocurrency returns tend to increase as well. The researchers also found that the relationship between economic uncertainty and cryptocurrency returns is stronger in the short term than in the long term. This suggests that economic uncertainty may be a more important factor for cryptocurrency investors in the short term than in the long term.

The distinction between the outcomes of Granger causality and the Diks-Panchenko (2006) tests lies in their respective methodologies and objectives. Granger causality primarily examines the ability of one variable to predict future values of another, whereas the Diks-Panchenko framework aims to identify immediate causal relationships between variables. These approaches differ in terms of assumptions, testing procedures, temporal order, and model complexity, leading to potential disparities in their results (Granger, 1969; Diks & Panchenko, 2006). The outcomes of the Granger causality test and the Diks and Panchenko test concerning cryptocurrency and global uncertainty provide valuable insights. These tests help us understand the relationship between cryptocurrency movements and global uncertainty.

The Granger causality test assesses whether changes in global uncertainty cause changes in cryptocurrency prices or vice versa. If the test indicates a significant relationship, it suggests that fluctuations in global uncertainty might influence cryptocurrency prices, or the other way around. On the other hand, the Diks and Panchenko test helps us examine whether there is a feedback loop between cryptocurrency and global uncertainty. If the test shows significant results, it indicates that changes in one of them can lead to reciprocal changes in the other, forming a feedback mechanism. Overall, these tests aid in understanding how Cryptocurrency and global uncertainty are interconnected. The results can be crucial for investors and policymakers to make informed decisions and manage risks associated with Cryptocurrency in a global context of uncertainty.

Quantile regression

Quantile analysis is a method used to study the performance of an investment or asset across various percentiles of its return distribution. It helps us gain valuable insights into how the asset behaves during extreme market conditions, which is essential for determining its hedging or safe haven properties. Quantile regression analysis expands upon traditional regression analysis by estimating the conditional quantiles of a dependent variable. This approach enables us to examine how changes in independent variables impact different percentiles of the dependent variable. By doing so, we can obtain a more comprehensive understanding of the relationship between variables, going beyond the average effect to capture variations across different parts of the distribution. Below are the results from the quantile regression analysis.

Table 3: Quantile Regression of WUI and Cryptocurrency (Signal).

	BTC-WUI	ETH-WUI	USDT-WUI	XRP-WUI	LTC-WUI	XRM-WUI	DASH-WUI
0.05	-0.0506	0.5946	0.0091	-0.0462	0.1900	-0.1684	0.2558
0.1	-0.4344	0.1688	-0.0121	0.3058	-0.2317	-0.5465	0.0901
0.15	-0.4475	0.2206	-0.0064	0.3611	-0.2091	-0.2517	0.0116
0.2	-0.2675	0.3162	-0.0029	0.4189	0.0105	-0.1748	-0.3413
0.25	-0.2139	0.3804	-0.0013	0.3683	0.0140	-0.0110	-0.2245
0.3	-0.0585	0.5373	-0.0006	0.2582	-0.2077	0.1089	-0.3530
0.35	-0.0990	0.4811	-0.0002	0.2967	-0.3387	0.2040	-0.3309
0.4	-0.0481	0.5083	0.0000	0.3670	-0.2825	0.3268	-0.2442
0.45	0.0571	0.3268	0.0000	0.2416	-0.1547	0.3889	-0.1703
0.5	0.2228	0.2165	0.0000	0.1083	-0.0135	0.3137	-0.0760
0.55	0.2003	0.2618	0.0000	0.0742	-0.0007	0.2893	-0.0198

0.6	0.1294	0.1302	0.0000	0.0140	-0.0153	0.2507	-0.0630	
0.65	0.0969	-0.0069	0.0000	-0.1356	0.0682	0.0692	-0.2525	
0.7	0.0328	-0.2964	-0.0003	-0.5565	0.1439	-0.1028	-0.3782	
0.75	0.1123	-0.3646	-0.0003	-0.5749	-0.1073	-0.2636	-0.3996	
0.8	0.0697	-0.0327	0.0003	-0.8604**	-0.1219	-0.3730	-0.3241	
0.85	-0.0602	-0.0853	0.0005	-1.0839**	0.1158	-0.3621	-0.4368	
0.9	-0.1613	-0.1836	0.0134	-1.1626**	0.4383	-0.2361	-0.1142	
0.95	-0.3992	0.2516	0.0312	-0.3607	0.5913	-0.9201	1.0950	
OLS	0.07411*	0.07411*	1.717e-05	0.03822	0.03778	0.06563	0.03452	OLS

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

Table 4: Quantile Regression of CPUI and Cryptocurrency (Signal) Quantiles

	BTC-CPUI	ETH-CPUI	USDT-CPUI	XRP-CPUI	LTC-CPUI	XRM-CPUI	DASH-CPUI
0.05	-3.0950	-4.7500	-0.2640	1.7280	-11.5461***	-2.1020	-0.3040
0.1	-4.8180	-5.9810	0.0710	-0.9920	-8.1540	-5.5710	-1.9770
0.15	-5.5670**	-6.2150	0.0240	-1.4940	-5.1990	-6.3940	-4.8620
0.2	-6.1658**	-6.7234**	-0.0020	-1.9190	-3.5280	-7.0028**	-3.0820
0.25	-5.5384**	-7.3010**	-0.0110	-2.3130	-4.2290*	-7.7201**	-5.6210*
0.3	-5.1823**	-8.6607*	-0.0150*	-3.2050	-4.6272	-8.1983**	-4.8640
0.35	-4.7478*	-9.5196*	-0.0160***	-3.9290	-4.2340	-8.4601**	-5.3930*
0.4	-4.3280*	-9.9916***	-0.0163***	-4.1530	-3.6974	-3.9590	-5.773*
0.45	-3.8650	-10.118***	-0.0117***	-4.8050	-3.6460	-4.4860	-6.015
0.5	-3.6950	-10.333**	-0.0090	-4.0840	-4.1210	-2.2700	-5.205*

0.55	-4.4000	-9.1505***	-0.0094***	-3.6760	-4.912	-2.4720	-5.456**
0.6	-2.5530	-8.3658***	-0.0100	-4.0720	-5.1541	-3.5540	-5.700
0.65	-3.9120	-10.338***	-0.0160	-4.9320	-5.6558	-4.6481**	-8.083
0.7	-4.6690	-11.570**	-0.0155*	-6.7809**	-6.4217	-4.1200	-9.085**
0.75	-6.5596*	-13.139**	-0.0220*	-7.0320*	-7.6139*	-5.2250	-9.606**
0.8	-7.7680	-12.423*	-0.0160	-7.9240	-8.0730	-7.1050	-10.14
0.85	-8.1250	-17.0460	-0.0250	-9.6616**	-10.0620	-9.5370	-10.9830
0.9	-9.3460	-18.054	-0.0860	-10.9700	-11.5690*	-10.2799*	-13.6400
0.95	-11.1440	-18.054	-0.1780	-20.1764	-12.2970	-12.5600	-19.1770
OLS	0.04925*	0.08265*	7.051e-05	0.04323	0.04248	0.07096*	0.03962

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

Tables 5 and 6, provides the estimates of the relationship between uncertainty and cryptocurrency returns, from table 5 with the exception of XRP, where a significant quantile regression coefficient is observed in the lower and mid quantiles between uncertainty and Cryptocurrency. These results affirm studies by (Hasan et. al., 2022; Ciner et. al.,2022; Trabelsi & Nguyen 2020), where these studies suggests that changes in uncertainty do not have a statistically significant impact on cryptocurrency returns at that particular quantile or conditional level. In other words, the relationship between uncertainty and Cryptocurrency may not be meaningful or well-established within that specific range of returns.

This lack of significance could indicate that other factors or variables may play a more dominant role in determining cryptocurrency returns at that particular quantile. It is possible that the impact of uncertainty may be less pronounced or less consistent within that specific range of returns, or it may be influenced by other complex dynamics in the cryptocurrency market, in that case cryptocurrency can be used as diversifiers. Where it is significant, the negative coefficient indicates an inverse relationship between uncertainty and XRP in the upper quantiles. In other words, as uncertainty increases, cryptocurrency returns tend to decrease. This suggests that XRP being significant in the upper quantiles may be perceived as riskier assets during times of higher uncertainty, with other assets in a portfolio the cryptocurrency can be used as a safe haven.

From table 6, it can be seen from lower quantiles, mid quantiles and upper quantiles that all the cryptocurrency are significant against CPUI except USDT and XRP for the lower quantile and XRP and LTC for the mid quantiles. Even though the relationship the in the lower, mid and upper quantiles are significant the coefficients are negative and this shows that when uncertainty in the market or economy is high, it tends to have a dampening effect on cryptocurrency prices or returns, leading to a negative correlation between uncertainty and cryptocurrency performance. This negative coefficient suggests that investors or market participants may perceive the Cryptocurrency as riskier assets during times of uncertainty and, as a result, reduce their exposure to such assets.

Table 5: Quantile Regression of WUI and Cryptocurrency (M1)

	BTC-WUI	ETH-WUI	USDT-WUI	XRP-WUI	LTC-WUI	XRM-WUI	DASH-WUI
0.05	-0.1569	0.2650	0.0091	-0.0044	1.6397**	-1.4675	0.4409
0.10	-0.2187	-0.1372	-0.0121	-0.0398	1.6042**	-0.2336	0.8317
0.15	0.0860	-0.0572	-0.0064	-0.0557	0.8284	-0.0820	0.2166
0.20	0.4834	-0.2576	-0.0029	-0.0203	0.7105*	-0.0114	0.2817
0.25	0.4798	0.1286	-0.0013	0.0266	0.7804*	0.1863	0.0715
0.30	0.0836	0.1922	-0.0006	0.1357	0.6732*	0.2218	0.0403
0.35	-0.0776	0.4493	-0.0002	0.0882	0.4520	0.2812	0.2263
0.40	-0.1156	0.6716	0.0000	-0.0552	0.2600	-0.0050	-0.0667
0.45	-0.1156	0.6966	0.0000	-0.0248	-0.1122	-0.3342	-0.1023
0.50	-0.1107	-0.1669	0.0000	0.3676	-0.5193	-0.1903	-0.4409
0.55	-0.3671	-0.5700	0.0000	0.1816	-0.7303	-0.0424	-0.5104

0.60	-0.3670	-0.6605	0.0000	0.2231	-0.7111	0.1132	-0.6251
0.65	-0.3873	-0.6106	0.0000	0.5192	-0.8550*	0.1054	-0.5206
0.70	-0.2555	-0.5110	-0.0003	0.5682	-0.7093	0.0389	-0.4533
0.75	0.0696	-0.1911	-0.0003	-0.4134	-0.4974	-1.0264	-0.2071
0.80	0.0427	-0.1462	0.0003	-0.2029	-0.4350	-1.0114	-0.1256
0.85	-0.0953	-0.1973	0.0005	-0.0705	-0.6898	-0.7819	-0.5842
0.90	-0.3888	-0.3398	0.0134	-1.7011*	-1.5898*	0.1904	-0.9204
0.95	-0.2889*	-0.5887	0.0312	-1.4675*	-1.3361**	0.1674	-0.4093
OLS	0.030705***	0.04702***	1.066e-07	0.01783	0.008693	0.05458***	0.01671

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

Table 6:Quantile Regression of CPUI and Cryptocurrency(M1).

	BTC-CPUI	ETH-CPUI	USDT-CPUI	XRP-CPUI	LTC-CPUI	XRM-CPUI	DASH-CPUI
0.05	-7.7782***	5.7617*	0.8656***	5.674	6.6297	5.6740***	8.4895*
0.1	-12.8007***	-0.9188	0.5457***	2.7413	-3.5801	2.7413	2.9775
0.15	-19.710***	-6.5879	0.4051***	-1.1577	-5.3987	-1.1577	-6.9694
0.2	-20.5555***	-12.0467***	0.3017***	-2.0508	-5.2663	-2.0508	-8.900***
0.25	-21.2707***	-13.4238***	0.1991*	-4.4702	-7.5629	-4.4702	-9.7164**
0.3	-21.7220***	-16.4557***	0.1808***	-8.2575	-6.7236	-8.2575*	-15.4373***
0.35	-21.8122***	-21.2369***	0.089*	-11.3458	-8.6681	-11.3458**	-17.084***
0.4	-20.939***	0.0378***	0.089	-14.3653	-11.0928	-14.3653**	-17.0496***
0.45	-22.2853***	0.0703***	0.0316	-19.555*	-10.8272	-19.555***	-18.7718***
0.5	-23.155***	0.0871***	-0.0076	-20.2175***	-13.7125	-20.2175***	-19.924***
0.55	-24.5116***	0.1173***	-0.0466	-20.9452***	-13.3914	-20.9451***	-21.3097***

0.6	-25.9673***	0.1269***	-0.0949*	-20.6255***	-14.4028	-20.6255***	-24.075***
0.65	-27.5031***	0.1328***	-0.0949**	-20.9744***	-12.19	-20.9744***	-26.0313***
0.7	-29.7156***	0.1456***	-0.1147*	-25.5743***	-15.9064	-25.5743***	-27.9846***
0.75	-30.1204***	-44.2443***	-0.2157*	-32.2182***	-14.8634	-32.2182***	-30.8141***
0.8	-31.397***	-43.9136***	-0.3037***	-36.2894***	-14.5628	-36.2894***	-32.0479***
0.85	-32.7318***	-44.4449***	-0.4044***	-38.017***	-14.8651	-38.0170***	-37.3835***
0.9	-33.6503***	-47.2009***	-0.5054***	-41.1831***	-16.7819	-41.1831***	-48.0111***
0.95	-36.3487***	-54.232***	-0.8562***	-41.5957***	-30.3783***	-41.5957***	-55.2258***
OLS	0.049312***	0.06928***	1.160e-06	0.03184*	0.01644	0.07034***	0.03294**

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

Table 7 and 8, provides the estimates of the relationship between uncertainty and cryptocurrency returns in the short run thus M1, from table 7 with the exception of LTC, where an insignificant quantile regression coefficient is observed between uncertainty and Cryptocurrency in the lower and mid quantiles, it suggests that changes in uncertainty do not have a statistically significant impact on cryptocurrency returns at the lower and mid quantiles. In other words, the relationship between uncertainty and Cryptocurrency may not be well-established within that specific range of returns.

Where it is significant, thus LTC at the lower and mid quantiles, The positive coefficient indicates a strong relationship between uncertainty and LTC. In other words, as uncertainty increases, cryptocurrency returns tend to increase. In the upper quantiles all cryptocurrency is insignificant except BTC, XRP, and LTC the coefficients are negative and this shows that when uncertainty in the market or economy is high, it tends to have a dampening effect on cryptocurrency prices or returns. The positive significant coefficient shows that cryptocurrency can be used as a hedge in times of uncertainty because as uncertainty rises the value of cryptocurrency also increase, the significant but negative coefficient shows that in a portfolio, cryptocurrency can be used as a safe haven. Where there is no correlation cryptocurrency can be used as diversifiers.

From table 8, it can be seen from the lower quantiles and mid quantiles that all the cryptocurrency are significant against CPUI except LTC and XRP for the lower quantile and LTC for the mid quantiles. Even though the relationship in the lower and mid quantiles are significant the coefficients are negative except for ETH in the mid quantile that shows positive coefficient. The positive coefficient of ETH in the mid quantile shows and this shows that when the uncertainty thus CPUI rises, there is a corresponding increase in the desire to comprehend Cryptocurrency. This negative coefficient in the lower and mid quantile suggests that investors or market participants may perceive Cryptocurrency as riskier assets during times of uncertainty and, as a result, reduce their exposure to such assets. The positive significant coefficient shows that cryptocurrency can be used as a hedge in times of uncertainty because as uncertainty rises the value of cryptocurrency also increase, the significant but negative coefficient shows that in a portfolio, cryptocurrency can be used as a safe haven.

Table 7: Quantile regression of WUI and Cryptocurrency(M2).

	BTC-WUI	ETH-WUI	USDT-WUI	XRP-WUI	LTC-WUI	XRM-WUI	DASH-WUI
0.05	-0.1215	1.5141***	-0.0030	3.8679***	1.0901**	-0.1162	0.0797
0.10	-0.0990	1.8777***	0.0115	3.6746***	1.4303***	-0.0928	0.2308
0.15	-0.0424	1.8446***	0.0088	2.8755***	1.6319***	-0.2717	0.0953
0.20	0.0484	1.4562***	-0.0096	3.0446***	1.7271***	0.0246	-0.0837
0.25	0.1516	1.4140***	0.0013	3.2180***	1.5379***	0.2198	0.0446
0.30	0.0248	1.2640***	-0.0007	3.1765***	1.9530***	0.2713	0.0981
0.35	0.0953	1.4570***	-0.0024	3.0864***	1.9239***	0.0665	-0.1879
0.40	0.2013	1.5426***	-0.0036	2.9225***	1.9133***	-0.0359	-0.2212
0.45	0.1787	1.7032***	-0.0058	2.8977***	1.9504***	-0.0683	-0.1548
0.50	0.0549	1.7960***	-0.0062	2.6793***	1.9924***	-0.1556	-0.1975
0.55	0.1955	1.8693***	-0.0070	2.8749***	1.7515***	0.1045	0.0279

0.60	0.1594	1.7159***	-0.0046	2.8190***	1.8046***	0.0844	-0.0081
0.65	-0.0488	1.5514***	-0.0049	2.6496***	1.9899***	-0.0884	-0.0844
0.70	0.0946	1.4144***	-0.0105	2.8081***	1.9804***	-0.1293	0.0705
0.75	0.1204	1.4295***	-0.0163	2.7824***	1.8867***	-0.0414	0.1891
0.80	0.0659	1.2769**	-0.0044	2.8246***	2.0109***	-0.0300	0.1717
0.85	0.0827	1.7298***	0.0089	3.3631***	1.8246***	-0.0226	0.0883
0.90	-0.1244	2.0121***	0.0079	3.3854***	1.3951***	0.0462	0.1804
0.95	-0.2349	1.8273***	0.0043	4.3599***	1.2106***	-0.0980	0.0955
OLS	0.07411*	0.07411*	1.717e-05	0.03822	0.03778	0.06563	0.03452

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

Table 8:Quantile regression of CPUI and Cryptocurrency(M2)

	BTC-CPUI	ETH-CPUI	USDT-CPUI	XRP-CPUI	LTC-CPUI	XRM-CPUI	DASH-CPUI
0.05	-3.3156	-7.3483	-0.3431	15.2005	8.7894	-1.3631	1.3007
0.1	-2.6317	6.118	-0.2291	-12.2911	-6.5407	-11.426**	-0.4773
0.15	-2.1024	3.9497	-0.176	3.7737	-2.9276	-11.030***	-1.9578
0.2	-2.4806	2.2874	-0.0885	-2.7636	-0.9439	-10.4604***	-2.9486
0.25	-3.5031	-1.8329	-0.0365	-0.4801	-0.0675	-9.0535***	-1.6102
0.3	-2.8326	-1.7236	-0.0224	-1.3065	-1.3995	-8.9020***	-0.6222
0.35	-2.3089	-1.5017	-0.0037	-2.7031	-0.4713	-8.3525***	1.0312
0.4	-1.8693	-2.4308*	-0.0043	-3.2796	-1.5316	-8.0093***	-1.2279
0.45	-2.436	-2.4596	-0.0104	-4.0406*	-0.831	-8.0209***	-2.8593
0.5	-3.1607	-2.8112*	-0.0055	-3.6039*	-0.8355	-7.7245***	-2.5743
0.55	-3.5326	-2.5882	-0.0038	-2.4481	-2.4558	-8.0495***	-1.9931

0.6	-4.2698	-1.7442	-0.0022	-1.5723	0.0818	-8.0979***	-0.7632
0.65	-3.9896	-1.0082	-0.0028	-1.8203	-0.2398	-8.9093***	-2.1365
0.7	-2.3197	-2.2072	-0.0131	-3.1114	0.2108	-8.9501***	1.2073
0.75	-1.991	-2.8189	-0.0392	-0.7139	-0.3936	-9.5298***	-5.3465
0.8	-2.4926	-1.3496	-0.1117	-4.2178	-1.7747	-10.3172***	-1.3926
0.85	-3.0976	2.2314	-0.1826	-7.0226	-2.7507	-10.7981***	-2.1003
0.9	-2.0148	5.5664	-0.24	8.1335	-6.8609	-13.0633***	-0.3051
0.95	-1.8201	11.4876	-0.3687	16.8776	9.207	-0.5782	0.8943
OLS	0.000345	0.0007587	1.225e-08	0.000543	0.0008114	0.0001634	0.0001616

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

Table 9 and 10, provides the estimates of the relationship between uncertainty and cryptocurrency returns in the medium term thus M1, from table 9 with the exception of LTC, XRP and ETH, the other Cryptocurrency are insignificant against uncertainty thus WUI. In the lower, middle, and upper quantiles, a positive quantile regression coefficient is found between uncertainty (WUI) and cryptocurrency prices, pointing to a link whereby greater cryptocurrency values are related with higher levels of uncertainty which is in line with (Zhang et. al., 2022; Wang et. al., 2021; Chen et. al., 2020), These studies show that the price of Cryptocurrency tends to increase when there is greater uncertainty, such as when there is economic instability or geopolitical tension.

This positive coefficient shows that, especially at lower quantiles, uncertainty significantly affects the cause of cryptocurrency price volatility. As a result, it is possible to utilise Cryptocurrency as a hedge in a portfolio and as a safe haven in bullish and bearish markets respectively. In the lower, middle, and upper quantiles of Table 10, XRM is the only significant cryptocurrency. Despite being significant in the lower, middle, and upper quantiles, the relationship's coefficients are negative. This negative coefficient in the lower, middle, and upper quantiles of XRM suggests that during uncertain times, investors or market participants may view XRM as a risky asset and as a result, reduce their exposure to such assets. During such times, Cryptocurrency can serve as a diversifier.

Table 9: Quantile regression of WUI and Cryptocurrency(M3)

	BTC-WUI	ETH-WUI	USDT-WUI	XRP-WUI	LTC-WUI	XRM-WUI	DASH-WUI
0.05	-0.3549	-0.0638	0.0242	0.4866	-0.5506*	0.4927	0.2149
0.10	-0.2487	-0.4810	-0.0018	-0.6209	-0.6666**	0.0126	0.2264
0.15	-0.0045	-0.1470	0.0062	-0.4457	-0.2891	0.3489	0.3808
0.20	0.0561	0.6176	0.0055	-0.1675	-0.4922*	-0.2876	-0.1417
0.25	-0.0337	0.4212	-0.0022	-0.0569	-0.5089*	-0.0040	-0.0061
0.30	-0.0644	0.1862	-0.0009	0.1977	-0.4798	0.0245	0.0149
0.35	0.0245	0.1180	-0.0002	0.4090	-0.6052	-0.0367	0.0668
0.40	-0.0104	-0.0494	-0.0029	0.1502	-0.8674	-0.0971	0.4309
0.45	0.0133	0.0275	-0.0003	0.0638	-0.8631	-0.0206	0.3530
0.50	0.1569	-0.0876	0.0000	0.1682	0.2398	-0.1829	0.3192
0.55	-0.0711	-0.1654	-0.0001	0.0229	0.6569	-0.1255	0.2420

0.60	-0.1062	-0.0536	0.0001	-0.0984	0.7152	-0.0628	0.1097
0.65	-0.0436	-0.0897	0.0003	-0.1283	0.6277	-0.1598	-0.0423
0.70	0.0831	0.0335	0.0012	-0.4109	0.5317	-0.0041	-0.4313
0.75	0.0043	0.0407	-0.0031	-0.1411	0.5081	0.0710	-0.3746
0.80	-0.0188	-0.1042	-0.0122	0.0381	0.6466*	0.0234	-0.3570
0.85	0.0235	0.1470	0.0167	0.0027	0.5639*	-0.0319	-0.1032
0.90	0.1104	0.2270	-0.0150	0.3296	0.4331	0.1767	0.0821
0.95	0.0234	0.4320	0.0467	-0.6205	0.3311	-0.3622	0.6868
OLS	5.915e-05	0.0000954	2.668e-09	8.725e-05	0.0001954	4.555e-05	5.762e-05

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

Table 10: Quantile regression of CPUI and Cryptocurrency(M3)

	BTC-CPUI	ETH-CPUI	USDT-CPUI	XRP-CPUI	LTC-CPUI	XRM-CPUI	DASH-CPUI
0.05	-11.0480*	23.1026	1.3089	6.1671	1.4694	-27.7341	7.5057
0.1	-6.4892	3.7729	0.8729	9.5217	0.4564	-17.4546	4.2567
0.15	-3.1691	-8.6309	-0.2521	6.9251	-2.8591	-16.3739	-6.9833
0.2	-2.1743	-8.0304	-0.2428	9.9257	-1.2334	-13.193	-3.6400
0.25	-1.7306	-6.2891	-0.1264	11.2843	-0.5539	-6.2653	-0.0379
0.3	0.9330	-4.6321	-0.0671	8.1452	-1.9228	-4.5876	-0.7222
0.35	1.8577	1.2710	-0.0119	2.0340	-3.6590	-2.1434	0.7411
0.4	-0.4969	0.4812	-0.0269	2.0153	-2.0013	-0.9080	0.8438
0.45	0.6908	-0.8502	-0.0223	0.9937	-6.1175	0.5969	0.0069
0.5	-2.6079	1.1121	-0.0177*	1.0595	-6.1175	-1.1515	-0.8038
0.55	-1.6411	-3.2553	-0.0200	2.6721	-3.9895	-0.8700	-0.6530

0.6	-2.7700	-0.7225	-0.0300	2.3925	-2.6713	-1.0234	0.3699
0.65	-2.4789	-1.4569	-0.0393	3.8868	-1.8440	-1.5118	1.2382
0.7	-2.7520	-1.8576	-0.0629	4.4494	0.4336	-1.0571	0.8313
0.75	-2.5185	-1.0560	-0.1347	6.8441	-0.3087	0.3167	-0.3949
0.8	-1.0955	-1.9894	-0.1847	8.2297	-2.6919	-0.8460	-5.2251
0.85	-0.2039	-4.6975	-0.3475	11.0441	-3.6899	-10.2366	-5.6830
0.9	1.1137	-1.0459	-0.6016	13.6578	4.2626	-13.8090	4.8860
0.95	-2.5956	-16.0310	1.0200	20.5913*	0.8998	19.6568	-13.0355
OLS	6.066e-05	9.785e-05	3.375e-08	0.0000822	0.000197	4.808e-05	0.0000579

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

The estimates of the medium-term relationship between uncertainty and cryptocurrency returns, or M3, are presented in Tables 11 and 12, from Table 11 with the exception of LTC in the lower and upper quantiles, where an insignificant quantile regression coefficient between uncertainty and Cryptocurrency is seen. Based to the insignificant quantile regression coefficient, variations in uncertainty do not statistically significantly affect crypto returns. With respect to this particular range of returns, the connection between uncertainty and Cryptocurrency may not be solidly proven. LTC in the lower and upper quantiles are examples of when it is significant.

The higher quantiles of the positive coefficient show a strong correlation between uncertainty and LTC. In other words, returns on Cryptocurrency tend to rise when uncertainty rises. The coefficients are negative in the lower quantiles, indicating that there is a tendency for substantial market or economic uncertainty to have a detrimental effect on cryptocurrency prices or returns. This shows that in the bearish market cryptocurrency can serve as a safe haven and in the bullish market market where there is no significance but with positive coefficients cryptocurrency can serve as a weak hedge.

Table 12 demonstrates that, other from BTC for the lower quantile, USDT for the middle quantiles, and XRP for the upper quantiles, all Cryptocurrency are insignificant against CPUI at the lower, middle, and upper quantiles. Despite being significant in the lower and middle quantiles, the association has negative coefficients. The fact that XRP has a positive coefficient in the higher quantile indicates that when CPUI and uncertainty rise, so does interest in buying Cryptocurrency. Because of this, XRP can act as a strong hedge in a bullish market. but with positive coefficients yet not significant, the other cryptos can be considered as weak hedges.

Table 11: Quantile regression of WUI and Cryptocurrency(M4).

	BTC-WUI	ETH-WUI	USDT-WUI	XRP-WUI	LTC-WUI	XRM-WUI	DASH-WUI
0.05	0.1937	0.1576	-0.0239	-0.7108	-1.0217	0.1957	-0.2566
0.10	-0.0463	0.3102	-0.0116	-0.9936	-0.1342	0.0965	-0.3444
0.15	0.1263	0.2270	-0.0201	-0.8716	-0.0036	0.0364	-0.1351
0.20	0.2323	0.0234	-0.0088	-1.1445	-0.1945	-0.2422	-0.2161
0.25	0.1844	0.5030	-0.0060	-1.1677	0.0251	0.0153	0.1618
0.30	0.2167	0.2446	-0.0008	-0.9259	0.2009	-0.1218	0.0302
0.35	0.2807	0.7727	-0.0013	-0.7738	0.1563	-0.1205	0.1111
0.40	0.4034	0.6361	-0.0022	0.1970	0.2290	0.1541	-0.1073
0.45	0.3527	0.4720	-0.0026	0.4665	0.2881	0.1027	-0.1005
0.50	0.2388	0.5239	-0.0036	0.5299	0.3714	0.2222	-0.2637
0.55	0.3612	0.5471	-0.0028	0.4369	0.2518	0.3671	-0.0459

0.60	0.4398	0.2098	-0.0039	0.0174	0.2185	0.3441	-0.4479
0.65	0.4428	0.0976	-0.0046	0.0610	0.2682	0.2192	-0.5704
0.70	0.3506	0.3280	-0.0011	0.1464	0.0518	0.1279	-0.3003
0.75	0.3189	0.2671	-0.0032	0.0871	0.1047	0.0991	-0.2770
0.80	0.5425	0.2493	-0.0070	-0.0228	-0.0065	-0.0266	-0.5277
0.85	0.7227	0.5390	0.0203	-0.3367	-0.0927	-0.0828	-0.2746
0.90	1.0137*	0.1606	0.0107	-0.2680	-0.1915	-0.0870	-0.4246
0.95	0.5621	-0.3781	-0.0159	0.6536	-0.3278	-0.4315	-0.4699
OLS	-0.01310	-0.02592	-1.982e-05	-0.01966	-0.028107	-0.01048	-0.01795

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

Table 12: Quantile regression of CPUI and Cryptocurrency(M4).

	BTC-CPUI	ETH-CPUI	USDT-CPUI	XRP-CPUI	LTC-CPUI	XRM-CPUI	DASH-CPUI
0.05	0.4521	-20.3114*	-0.3863	-17.1575	7.7239	2.1899	-4.2719
0.1	-1.3540	-14.2420	-0.1647	-12.1249	-4.6725	-1.2081	-10.8355
0.15	-3.0366	-8.5535	-0.1346	-8.8836	-2.0218	-6.6158	-12.1316
0.2	-3.3258	-6.3897	-0.0521	-6.6748	-4.1714	-3.7326	-8.5358
0.25	-3.8372	-7.9740	-0.0397	-6.1173	-6.8170	-3.2623	-5.6728
0.3	-3.1780	-5.6532	-0.0249	-4.9120	-7.5731	-2.7426	-2.3943
0.35	-3.0000	-8.2834	-0.0191	-4.7024	-6.6958	-6.0919	-1.5041
0.4	-3.0348	-10.0353	-0.0145	-5.6752	-6.1071	-6.7755	-2.4558
0.45	-2.3023	10.7475*	-0.020*	-5.3797	-3.9692	-7.8921	-3.7070
0.5	-1.6253	-2.9469	-0.0147	-4.0457	-3.3307	-6.2172	-4.0646
0.55	-1.6505	-6.7966	-0.0101	-1.4756	-4.3555	-4.8887	-5.4519

0.6	-2.4359	-5.7090	-0.0249	-0.1139	-4.5969*	-5.7141	-4.5683
0.65	-3.0071	-5.9969	-0.0122	0.0895	-4.1698	-3.8351	-4.5624
0.7	-3.3141	-5.6872	-0.0880	-1.8992	-3.0663	-4.5050	-4.5359**
0.75	-3.8118	-5.0188	0.1119	-2.9689	-2.5391	-5.6694	-4.1862
0.8	-3.9277	-4.7460	-0.2549	-1.2886	-1.7851	-5.7099*	-3.9101
0.85	-2.8197	-4.1633	-0.3643	-4.9790	-3.7324	-5.0146	-10.0403*
0.9	-2.3165	-2.9894	-2.3165	-13.120*	-5.8088	-3.6732	-12.0844*
0.95	-0.7232	-1.4118	-0.7232	-17.7249	-8.5929	-2.5773	-14.4601**
OLS	-0.01438	-0.02773	-1.687e-05	-0.01924	-0.02864	-0.01123	-0.01775

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

Long-term estimates of the relationship between uncertainty and cryptocurrency returns are shown in Tables 13 and 14. Table 13 shows that, with the exception of BTC, which has a quantile regression coefficient of 0.09 in the upper quantiles (bullish market), the relationship between uncertainty and Cryptocurrency is insignificant. It out that cryptocurrency returns are not statistically affected by changes in uncertainty (WUI), and that Cryptocurrency can be used to diversify investments. Where it is significant, such as when BTC is in the upper quantile, the positive coefficient denotes a high association between uncertainty and BTC. To put it differently, as uncertainty rises, bitcoin returns tend to rise, indicating that it can serve as a hedge asset in times of uncertainty.

Table 14 demonstrates that all Cryptocurrency are insignificant against CPUI in the lower, medium, and upper quantiles, with the exception of ETH, which is in the lower quantile, ETH, USDT, and LTC in the middle, and XRP and DASH in the upper quantile. With the exception of ETH in the middle quantile, the coefficients are negative even if the correlation is significant in the lower, medium, and upper quantiles. The fact that ETH has a positive coefficient in the middle quantile indicates that when uncertainty (measured by CPUI) rises, so does interest in purchasing Cryptocurrency (measured by ETH), demonstrating that ETH can serve as a hedge against volatility while other Cryptocurrency serve as diversifiers over the long term.

Summary of frequency-dependent quantile regression result (WUI and Cryptocurrency)

WUI	Signal	Short-term (M1)	Medium-term (M2)	Medium-term (M3)	Long-term (MAgg)
Hedge		LTC (Q = 0.05-0.30)	ETH (Q = 0.05-0.95) XRP (Q = 0.05-0.95) LTC (Q = 0.05-0.95)		BTC (Q = 0.9)
Safe Haven	XRP (Q = 0.80-0.90)	BTC (Q = 0.95) XRP (Q = 0.30)		LTC (Q = 0.05-0.25)	

Note: Q denotes quantiles

Summary of frequency-dependent quantile regression result (CPUI and Cryptocurrency)

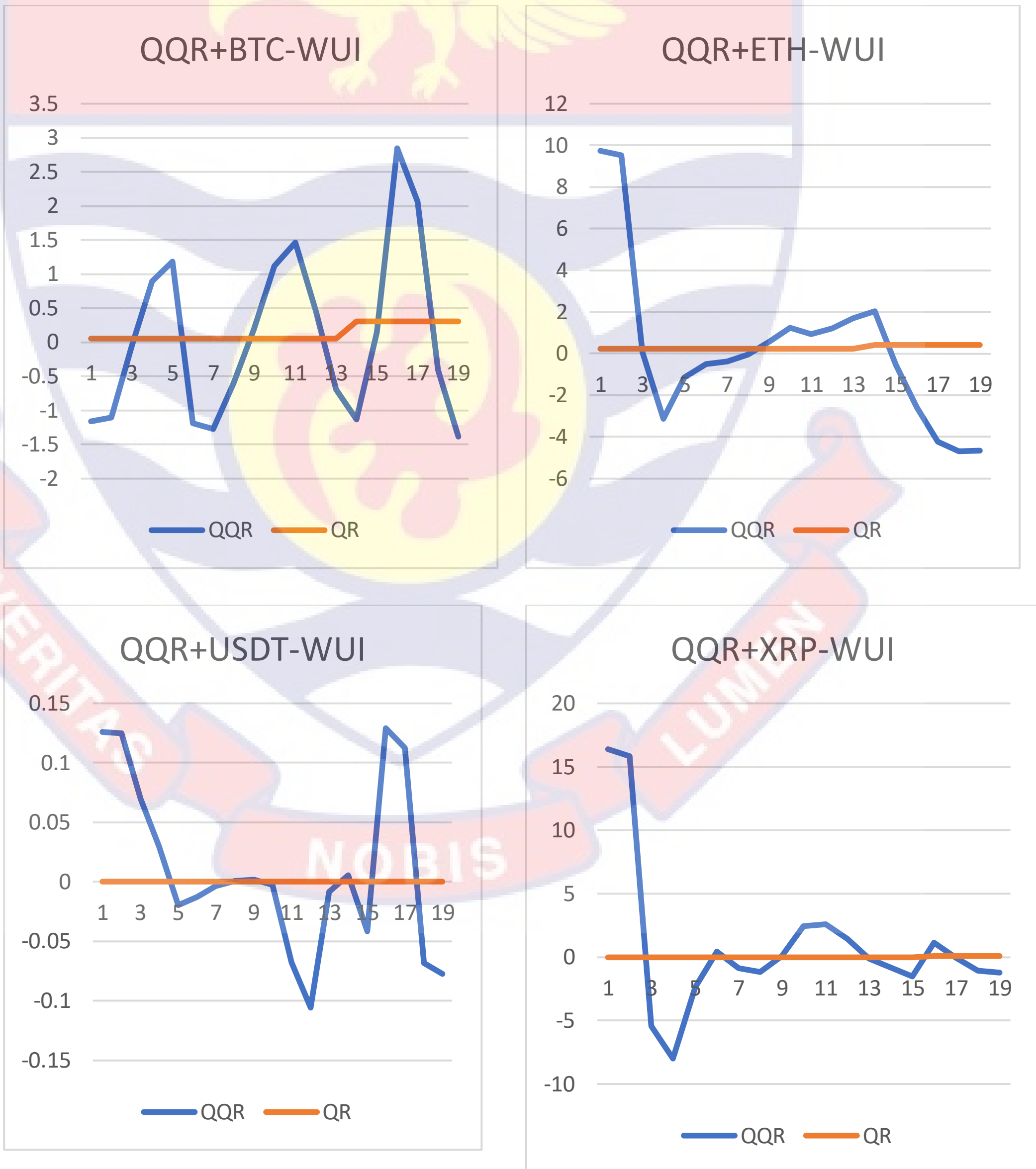
CPUI	Signal	Short-term (M1)	Medium-term (M2)	Medium-term (M3)	Long-term (MAgg)
Hedge		ETH (Q = 0.40-0.70) USDT (Q = 0.05-0.35)			
Safe Haven	BTC (Q = 0.15 – 0.4) ETH (Q = 0.20-0.80) USDT (Q = 0.30-0.55) LTC (Q = 0.75-0.90) XRM (Q = 0.7-0.9) DASH (Q = 0.55-0.75)	BTC (Q = 0.05-0.95) XRP (Q = 0.60-0.95) XRM (Q = 0.60-0.95) DASH (Q = 0.05-0.95)	XRM (Q = 0.05-0.90)	XRM (Q = 0.05) USDT (Q = 0.05)	ETH (Q = 0.05) DASH (Q = 0.75-0.95)

Note: Q denotes quantiles

Quantile-on-Quantile analysis

The figures below show the quantile-on-quantile plots, which is an important tool in quantile regression analysis. It allows to compare the observed response variable's quantiles with the quantiles predicted by the quantile regression model. This plot helps to evaluate how well the model fits the data and identify any patterns that deviate from assumptions such as linearity, homoscedasticity, or normality.

Quantile on quantile of Signal



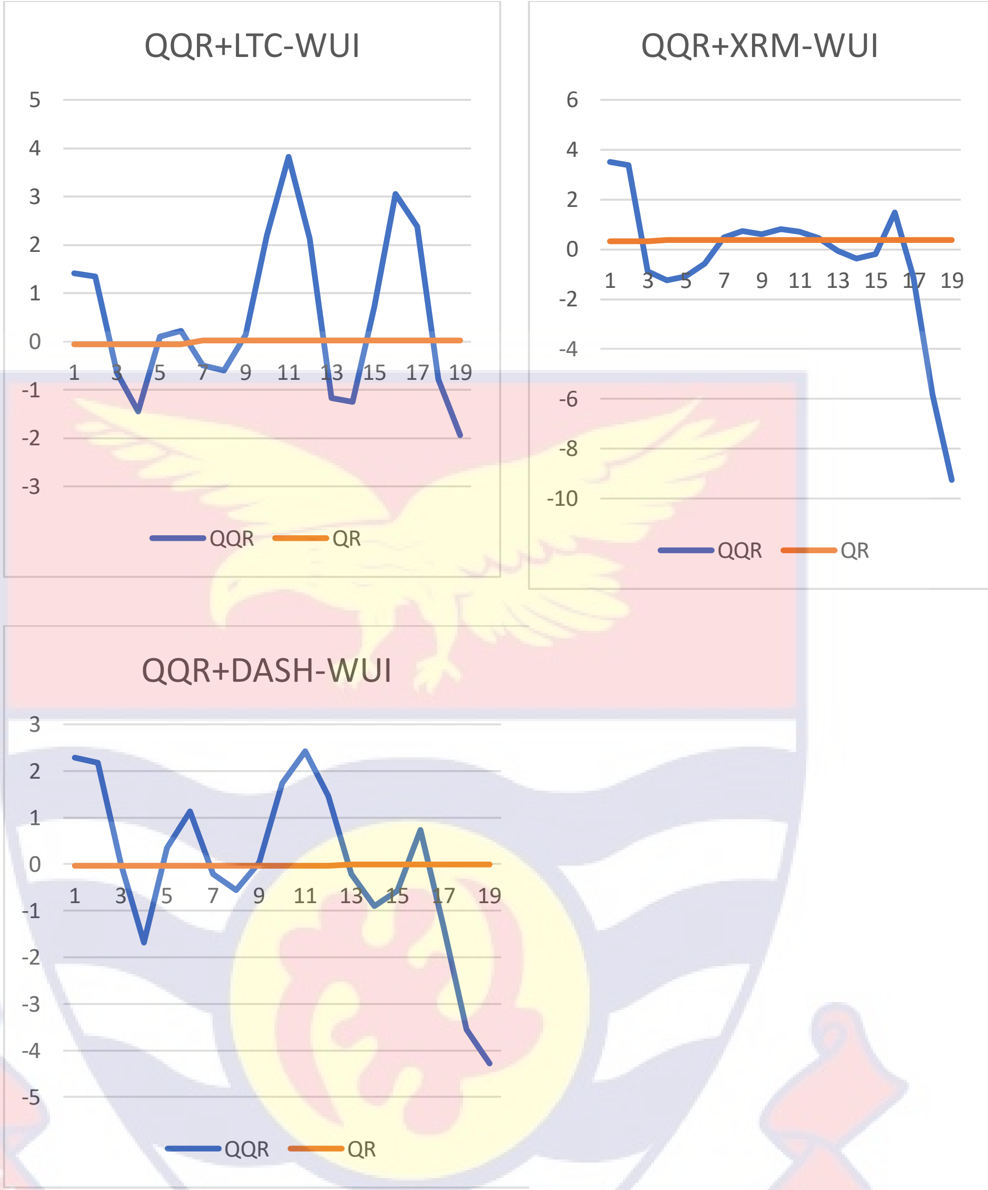
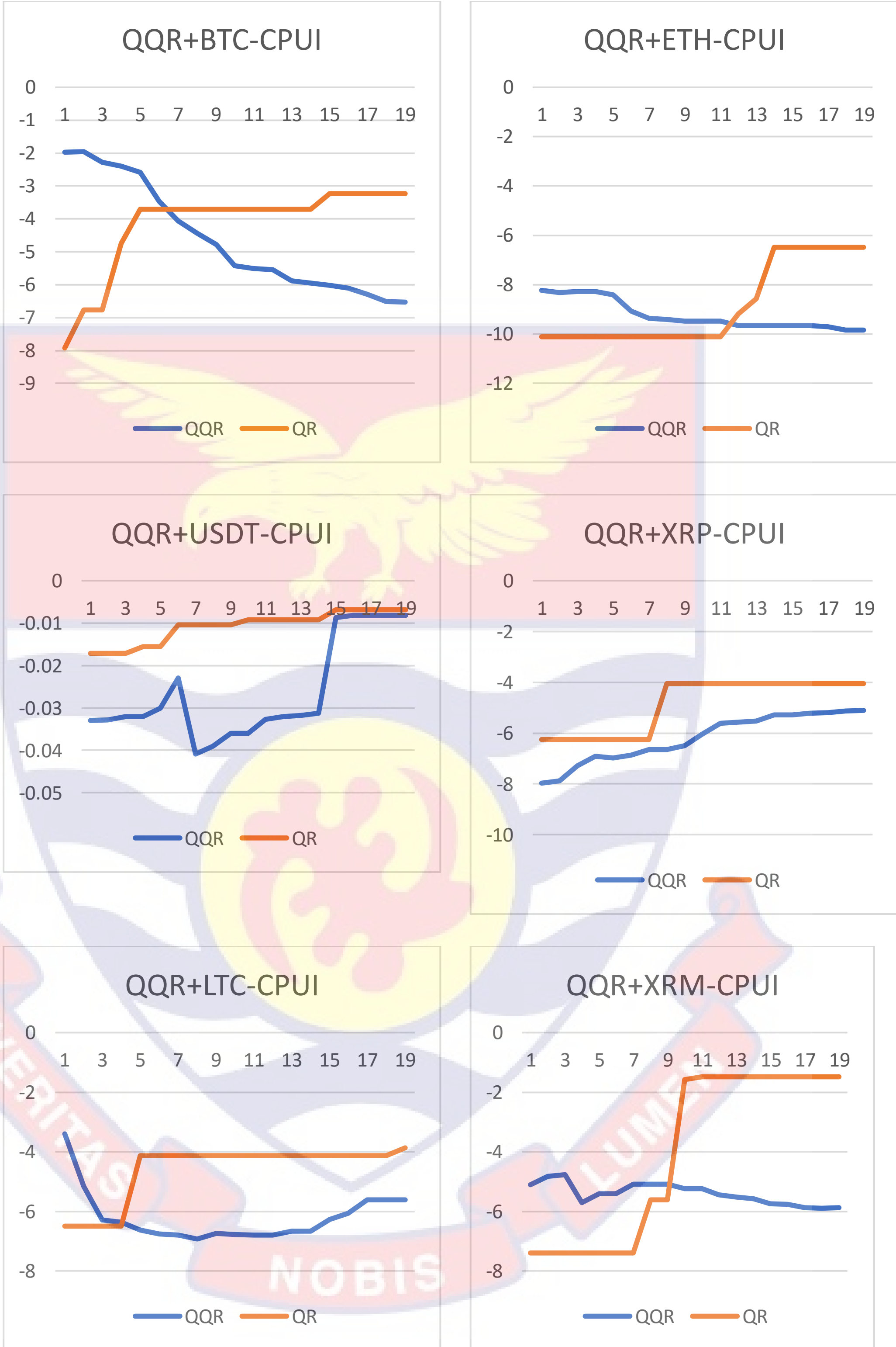


Figure 4: QQR for signal of cryptocurrency and WUI


QQR+BTC-CPUI
QQR
QR
QQR+ETH-CPUI
QQR
QR
QQR+USDT-CPUI
QQR
QR
QQR+XRP-CPUI
QQR
QR
QQR+LTC-CPUI
QQR
QR
QQR+XRM-CPUI
QQR
QR

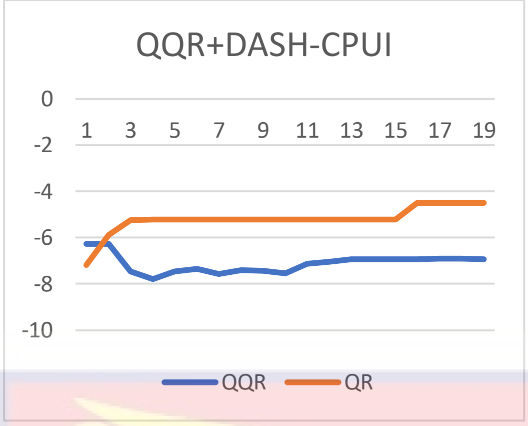
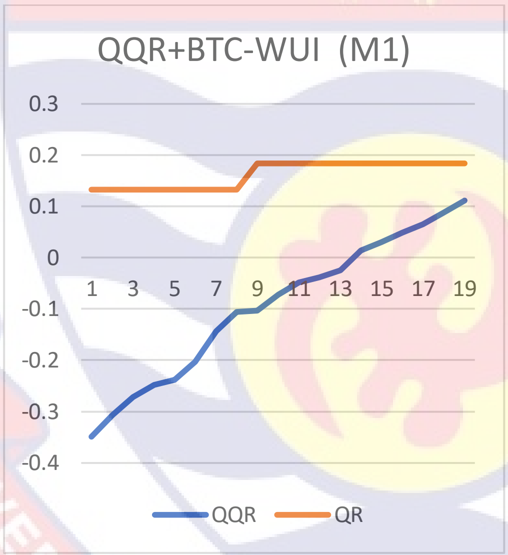
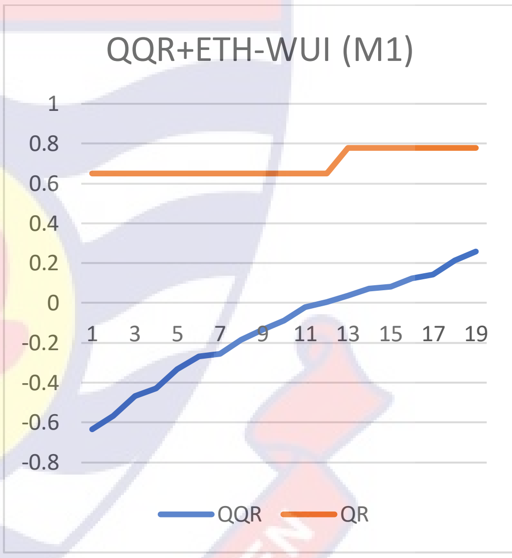
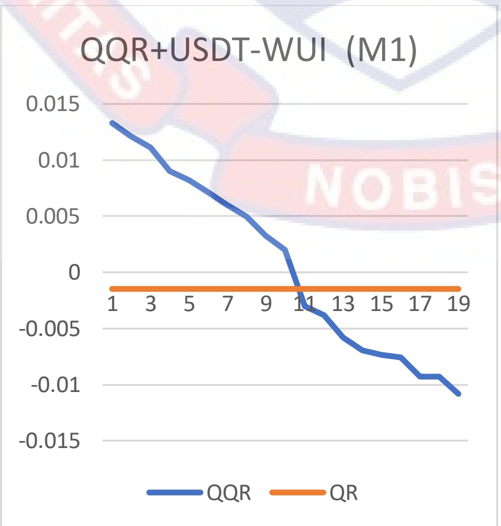


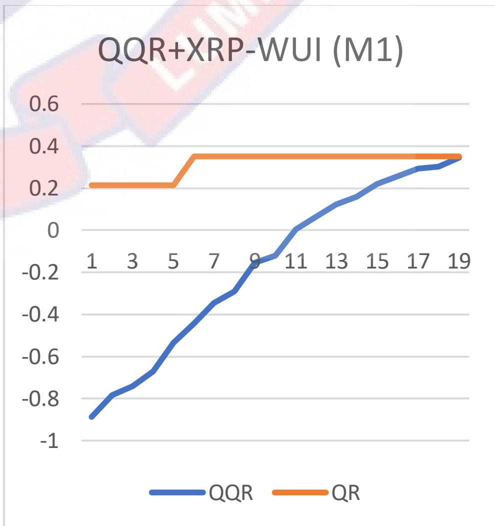
Figure 5:QQR for signal of cryptocurrency and CPUI

Quantile on quantile of M1









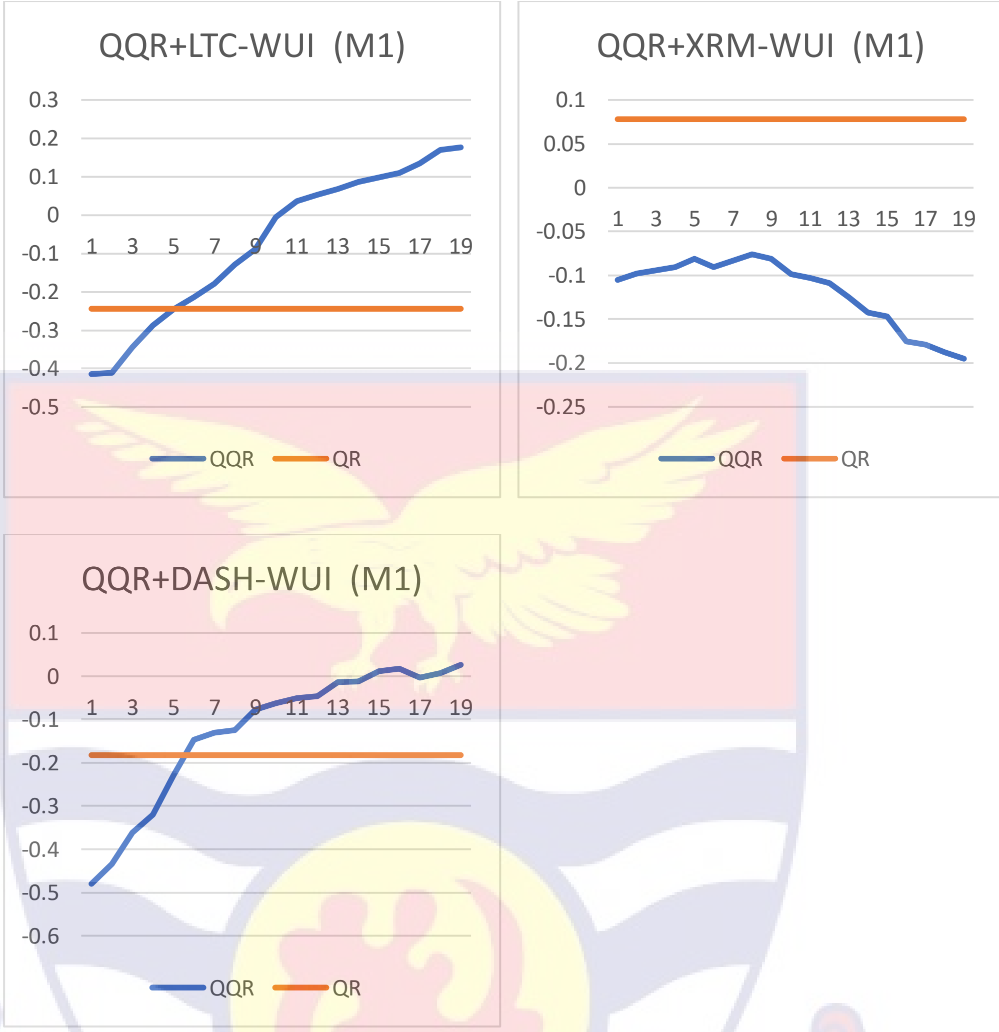
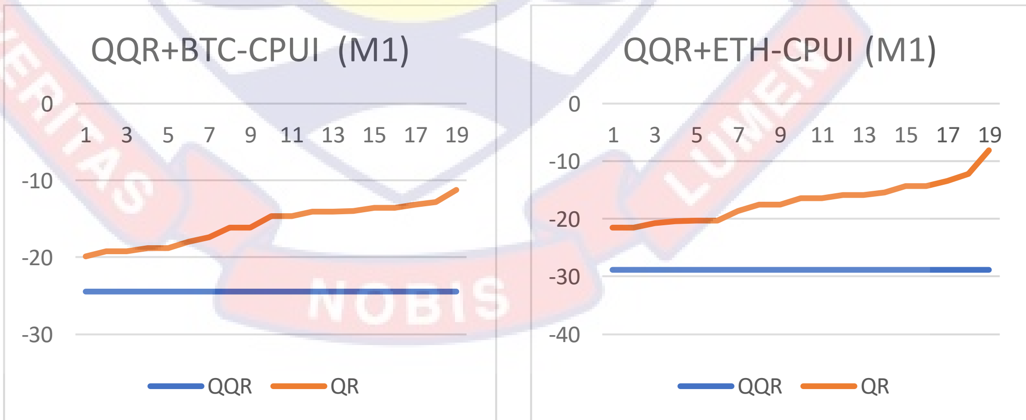


Figure 6:QQR of M1 Cryptocurrency and WUI



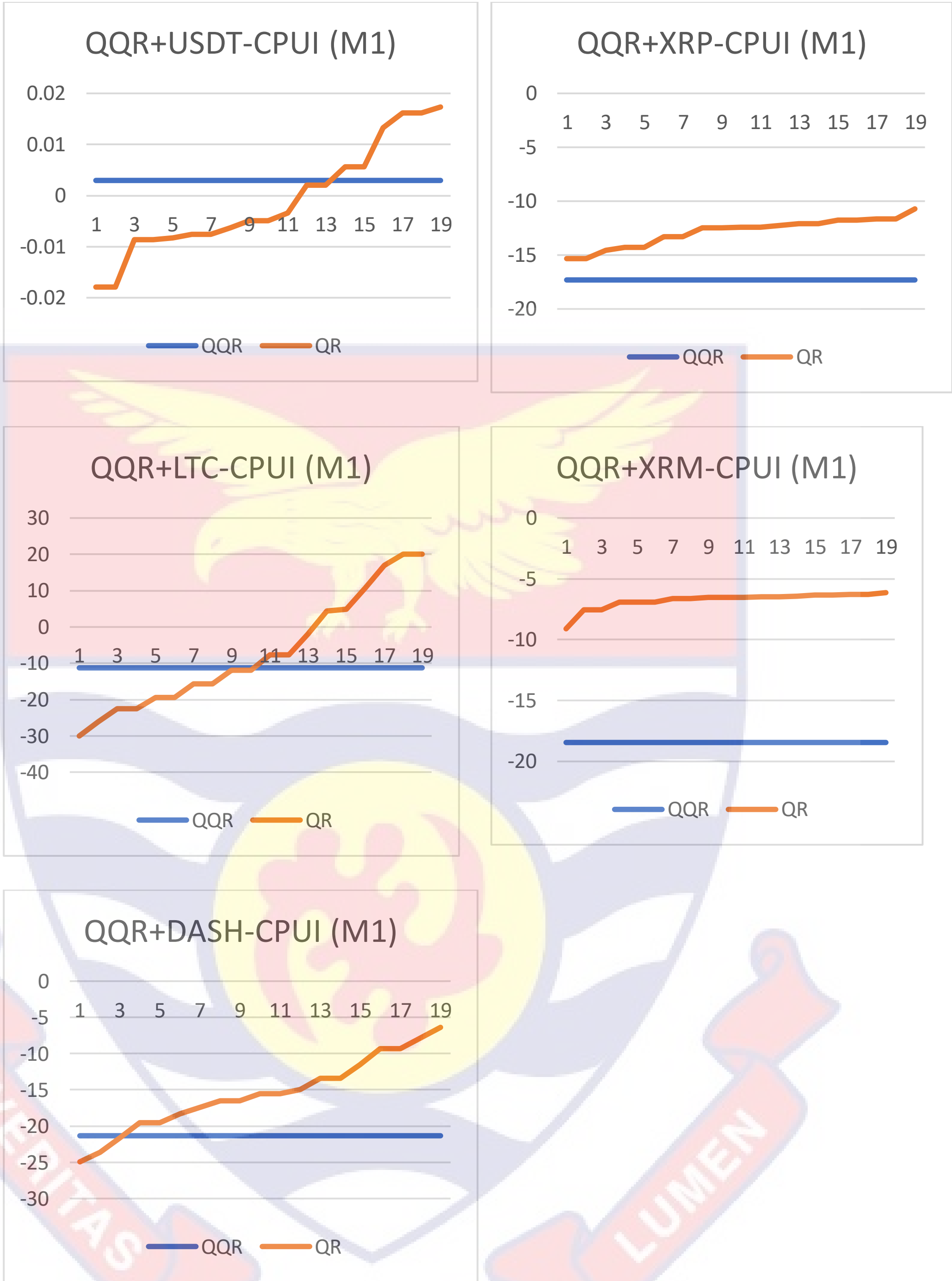
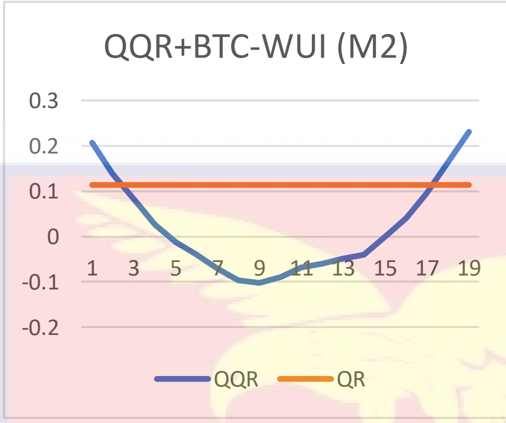
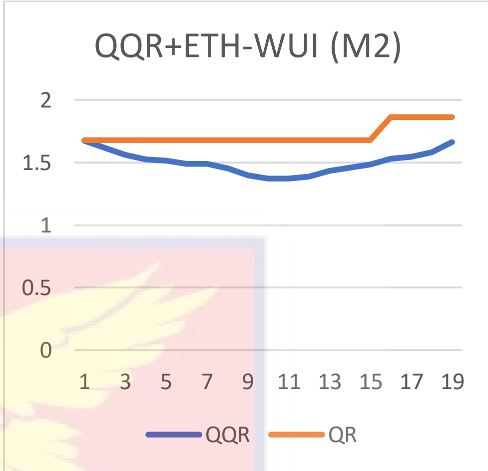
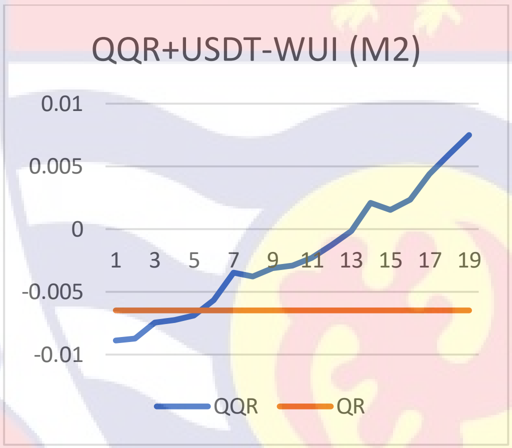


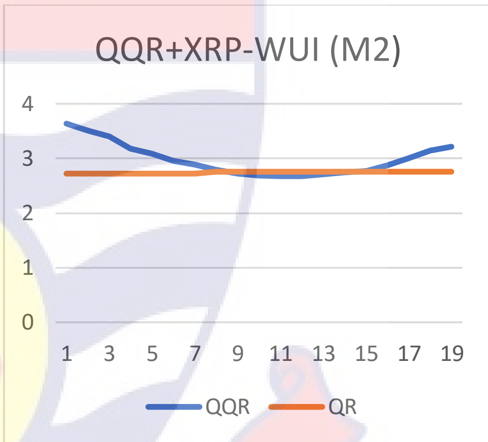
Figure 7:QQR of M1 Cryptocurrency and CPUI

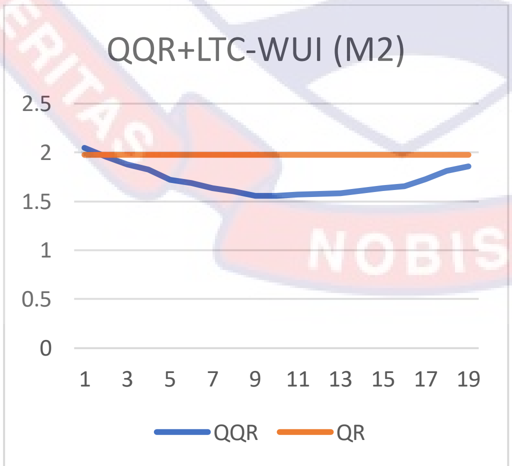
Quantile on quantile of M2

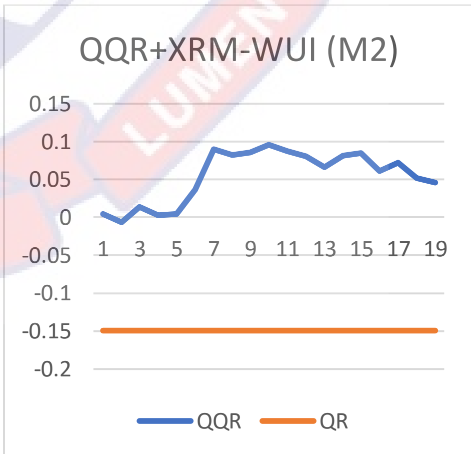












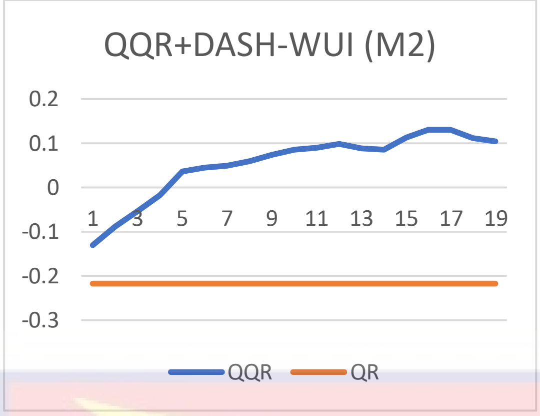
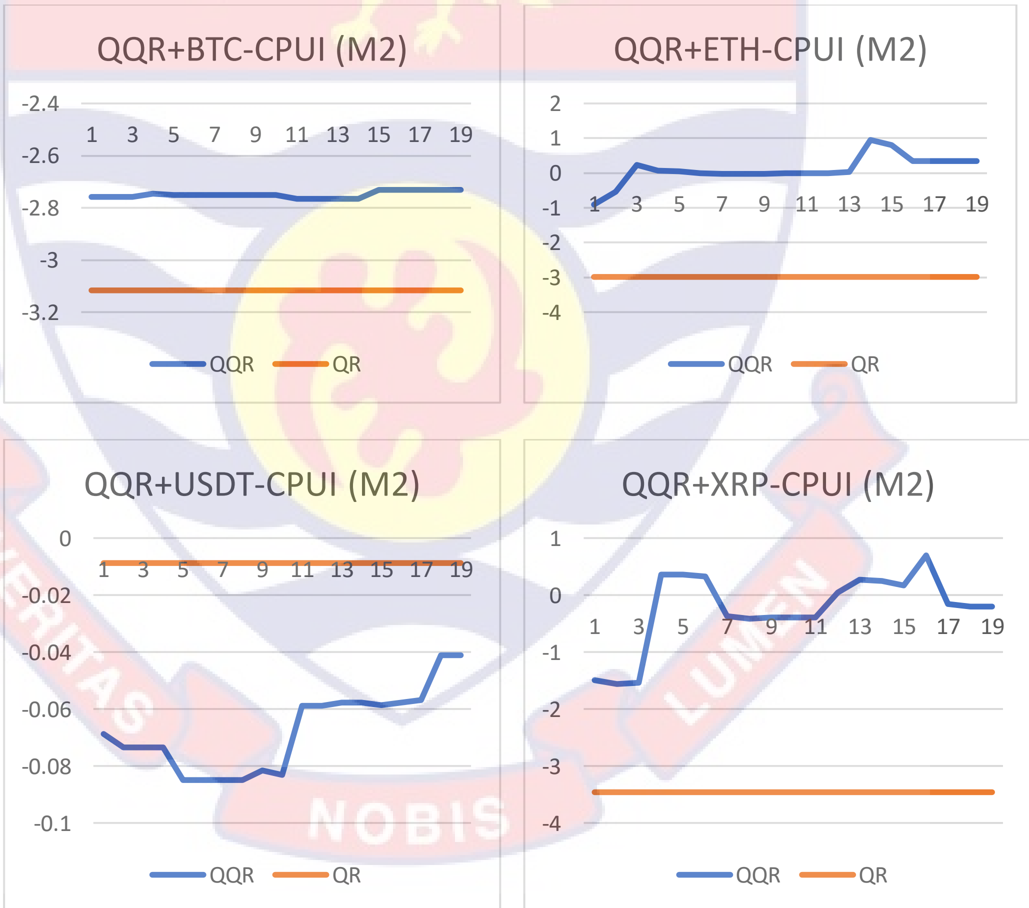


Figure 8:QQR for M2 of Cryptocurrency and WUI



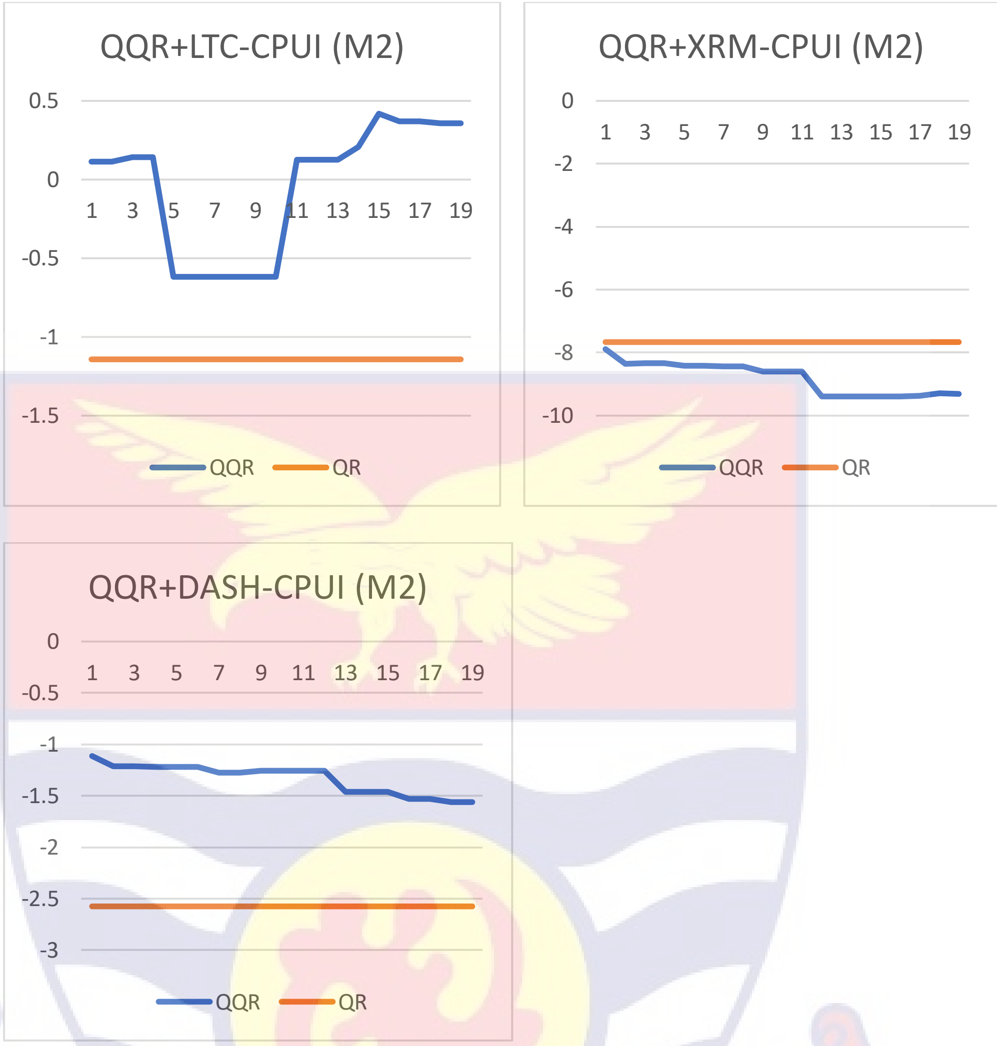


Figure 9:QQR for M2 of Cryptocurrency and CPUI

Quantile on quantile of M3

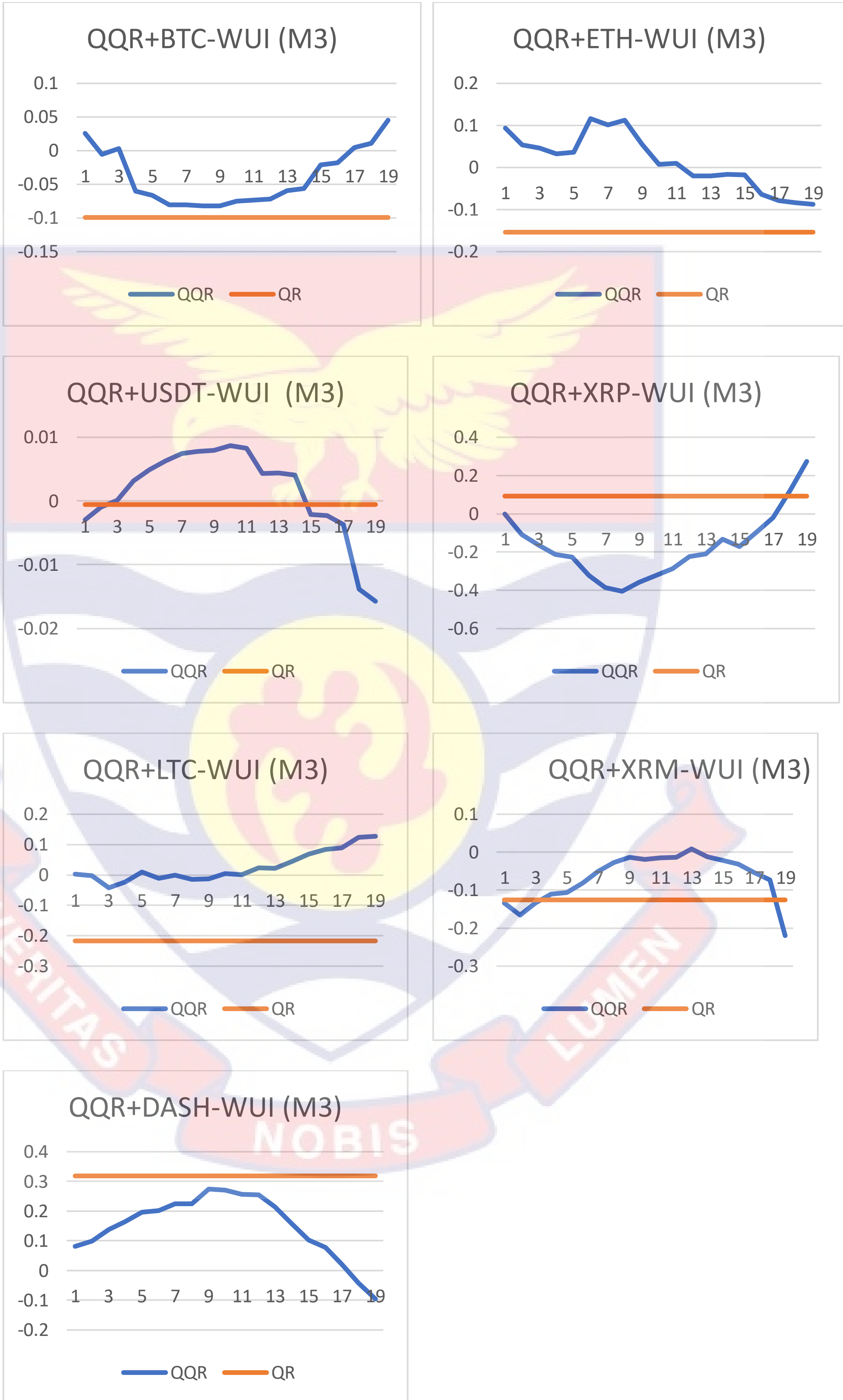


Figure 10:QQR for M3 of Cryptocurrency and WUI

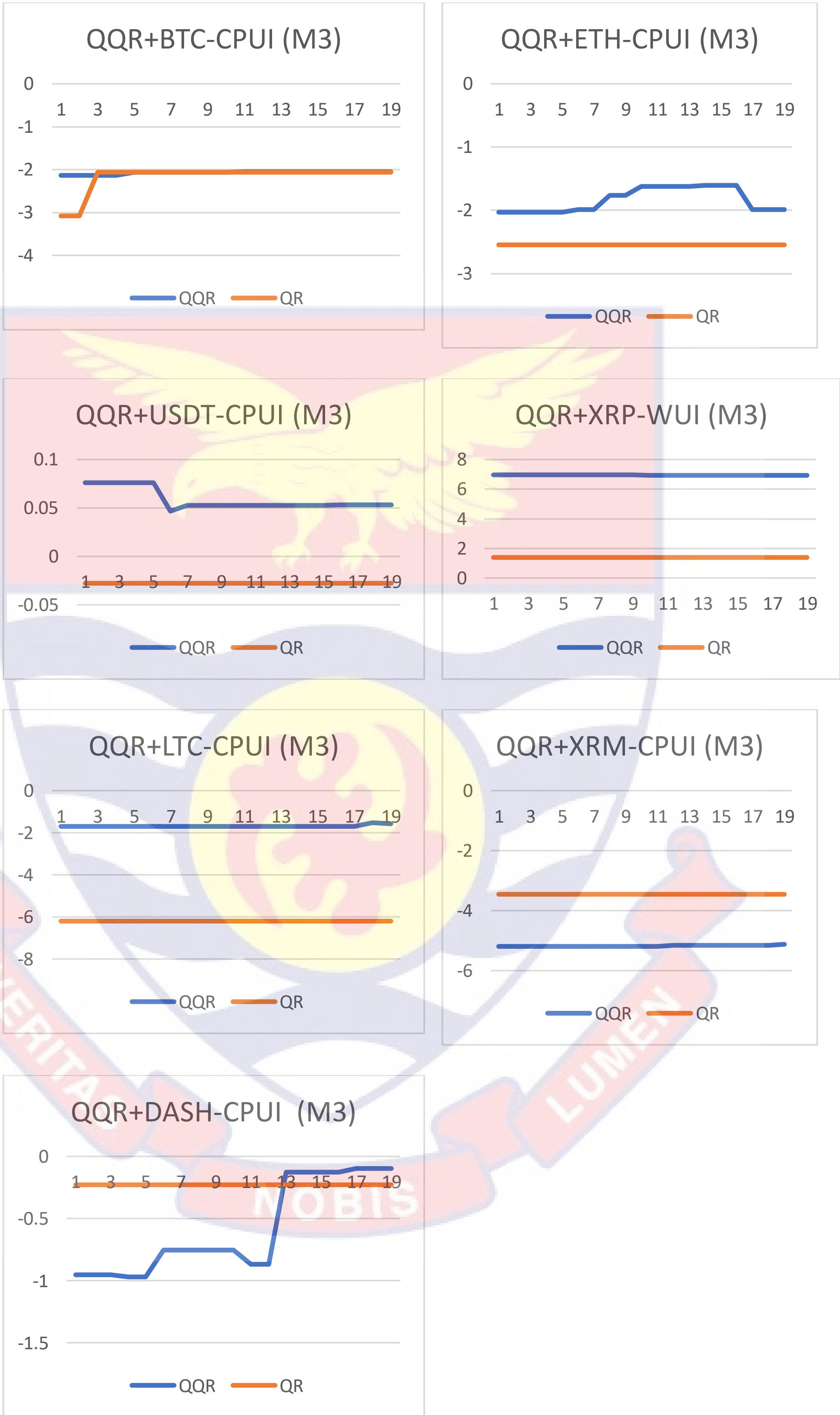
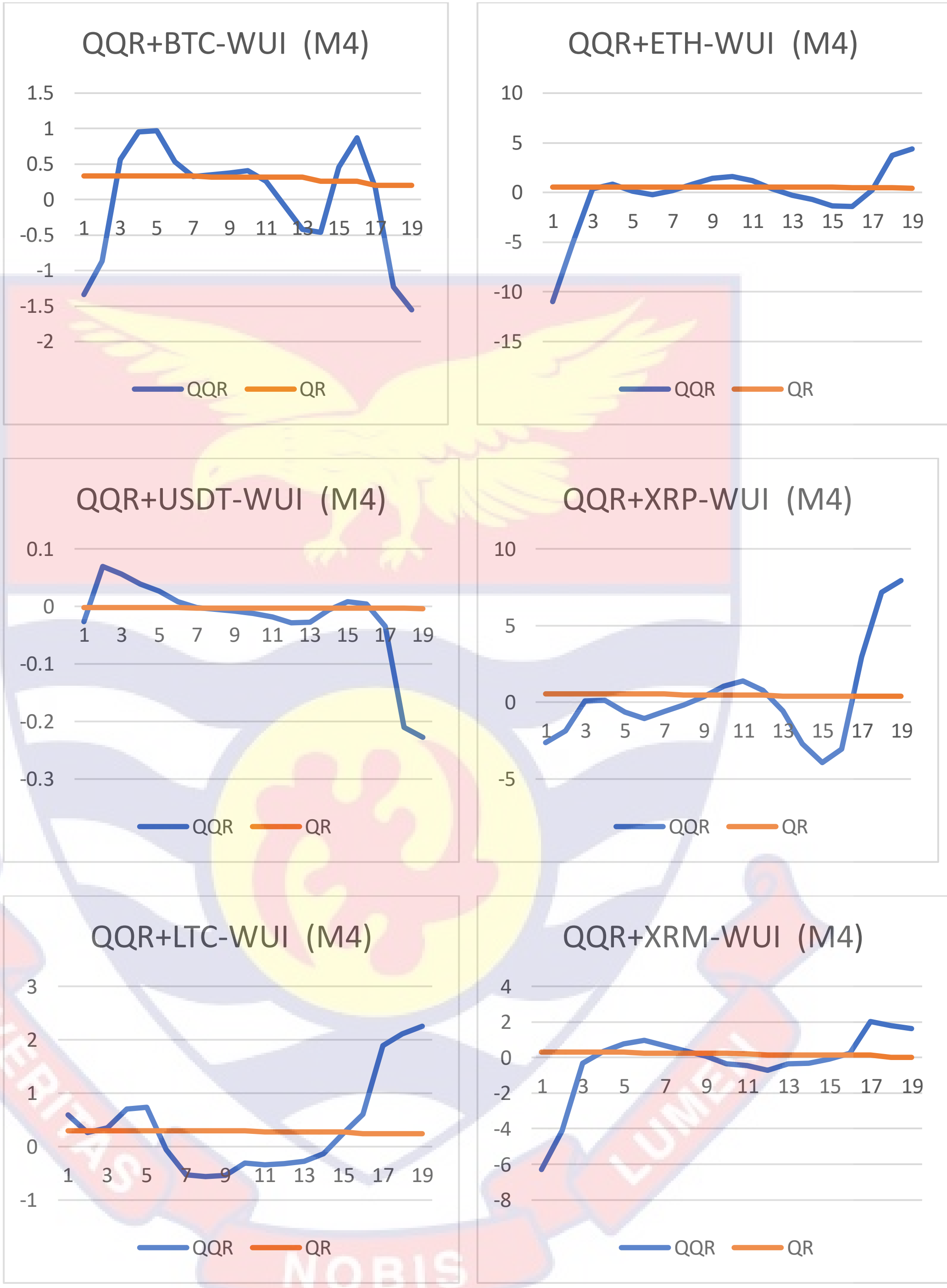
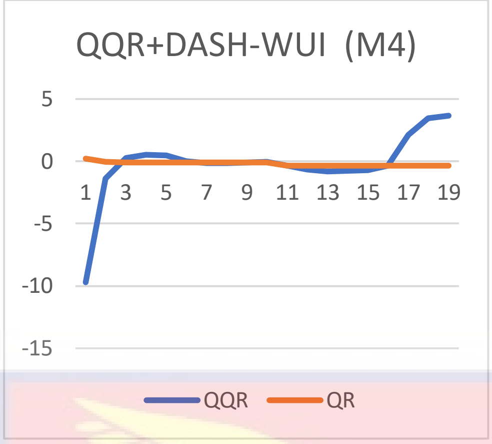
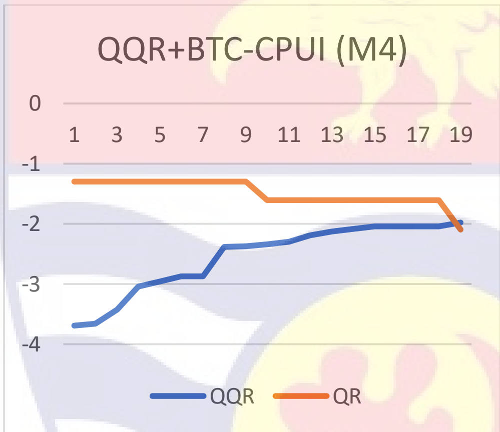


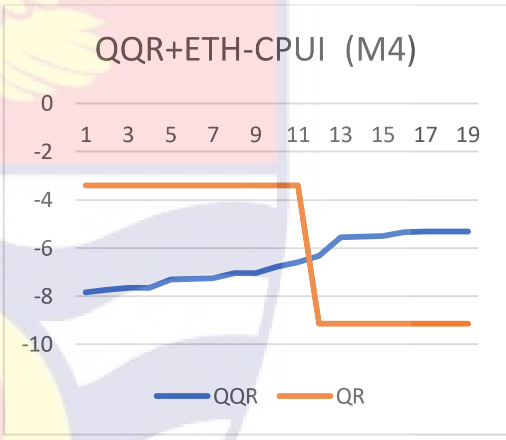
Figure 11:QQR for M3 of Cryptocurrency and CPUI

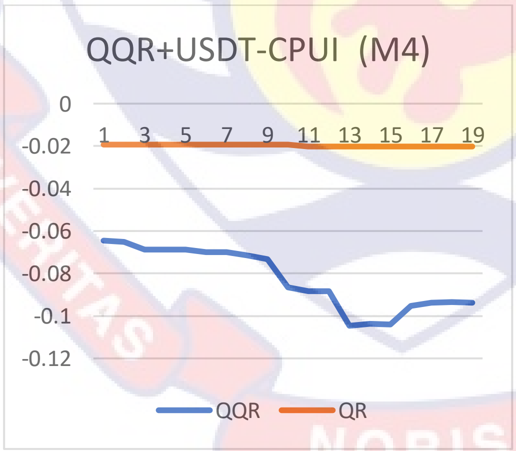
Quantile on quantile of M4

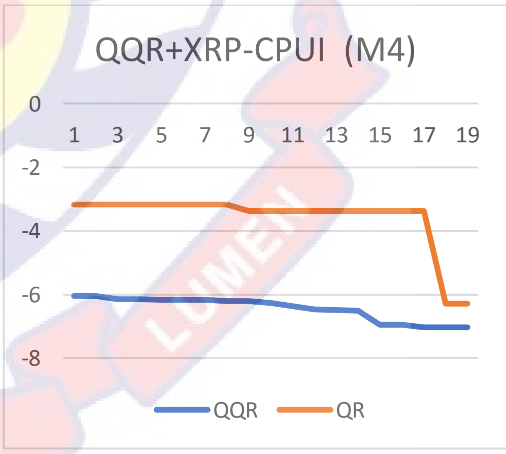



QQR+DASH-WUI (M4)
5
0
-5
-10
-15
1 3 5 7 9 11 13 15 17 19
QQR
QR


QQR+BTC-CPUI (M4)
0
-1
-2
-3
-4
1 3 5 7 9 11 13 15 17 19
QQR
QR


QQR+ETH-CPUI (M4)
0
-2
-4
-6
-8
-10
1 3 5 7 9 11 13 15 17 19
QQR
QR


QQR+USDT-CPUI (M4)
0
-0.02
-0.04
-0.06
-0.08
-0.1
-0.12
1 3 5 7 9 11 13 15 17 19
QQR
QR


QQR+XRP-CPUI (M4)
0
-2
-4
-6
-8
1 3 5 7 9 11 13 15 17 19
QQR
QR

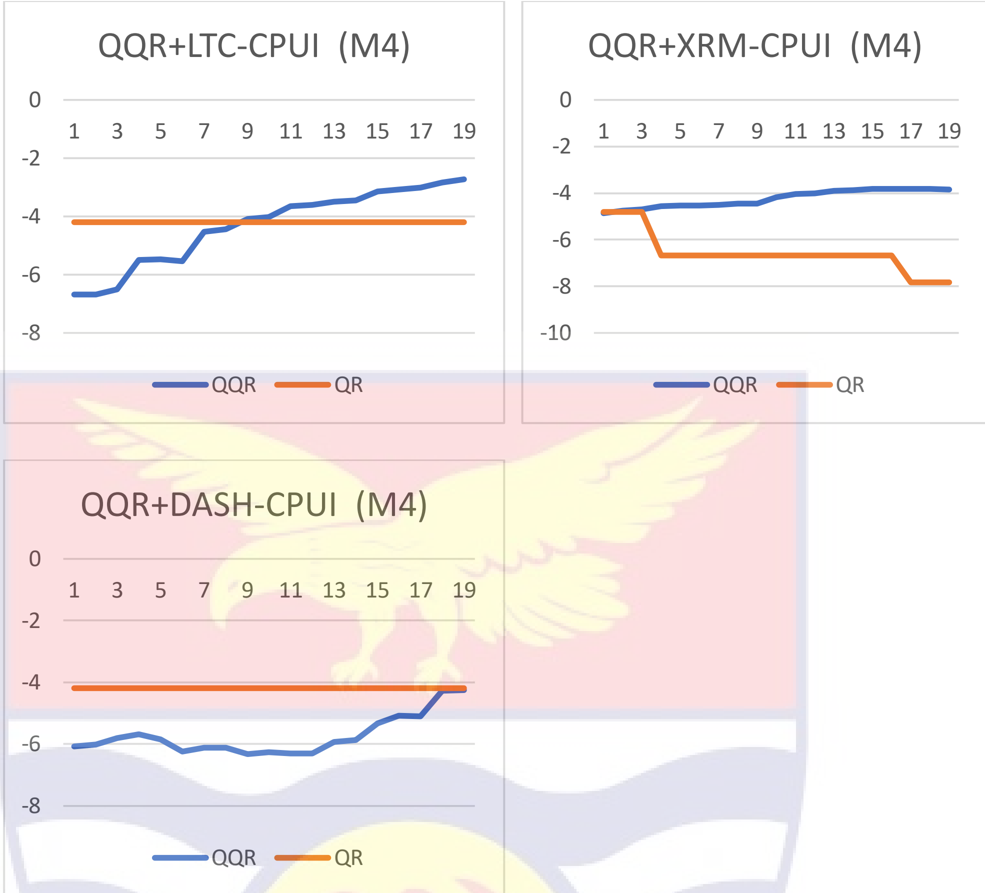


Figure 12: QQR for M4 of cryptocurrency and WUI and CPUI

Figures 4-12 illustrate the reliability of QQR approximations by comparing the gradient of factors derived from conventional quantile regression to the averaged quantile on quantile regression. The QR coefficients are represented by orange lines, while the QQR coefficients are denoted by blue lines. The quantiles (0.05-0.95) are displayed on the horizontal axis, whereas the coefficients of the cryptocurrency estimated from QR & QQR are shown on the vertical axis. The chosen Cryptocurrency encompass BTC, ETH, USDT, XRP, LTC, XRM, and DASH.

The QQR findings are validated by the QR to enable the inference of connections provided by the QQR from those indicated by the QR. As the QQR operates as a non-parametric model, determining the significance of the coefficients it reveals becomes unfeasible. The QQR approach can be perceived as a method that deconstructs the outcomes of a conventional quantile regression, permitting the precise observations of results for different quantiles of the independent variable. In this research, the QQR model is applied to regress the θth quantiles of Cryptocurrency returns on τth quantiles of uncertainty, specifically WUI and CPUI. Therefore, the parameters will be indexed here by both θ and thus, compared to the conventional quantile regression (if employed), the QQR technique contains more localised information about the uncertainty-cryptocurrency relationship.

The QQR method considers the potential diversity in connections, considering different quantiles of cryptocurrency returns and uncertainty. This approach has a built-in attribute of decomposition, allowing it to recover standard quantile regression estimates using QQR estimates (Shahzad et al., 2017; Sim & Zhou, 2015). In particular, the quantile regression parameters, denoted by θ, are obtained by averaging the QQR parameters over τ, as presented in equation 12. Thus, a straightforward method to verify the validity of the QQR approach is by comparing the quantile regression parameters with the τ-averaged QQR parameters.

The coefficients of QQR estimates can be validated by comparing them to those of QR since they represent the decomposed estimations of QR into specific quantiles of the predictors (Bossman et. al., 2022; Adebayo & Acheampong, 2021; Ijasan et al., 2021). Fig. 4-12 displays line graphs of QR and QQR coefficients, demonstrating this correlation. These graphs serve two purposes: firstly, they visually depict the QR estimations, revealing the trends of increasing or decreasing uncertainty returns and the accompanying fluctuations in cryptocurrency returns. Second, when comparing it to the QR approximations, the graphs authenticate the QQR approach (Adebayo & Acheampong, 2021; Owusu Junior & Tweneboah, 2020). The averaged-QQR approximations for the slope coefficients seem akin to the estimates obtained through quantile regression for all the Cryptocurrency, as depicted in Fig. 4-12.

The primary disparity lies in the magnitude of the effect at specific quantiles, although the movements and trends of the QRR estimates are supported by those derived from the QR method where they do not supported by those derived from the QR method, the quantile-on-quantile regression approach might not be appropriate due to the following reasons; First, Violation of assumptions where QQ regression method assumes that the quantile estimates have a specific relationship, which may not hold true in all cases. If the data violates the assumptions of the QQ regression model, the estimates obtained may not be reliable. Second, Non-linear relationships where the QQ regression assumes a linear relationship between quantiles, but in reality, the relationship may be non-linear. This can lead to misleading results and inaccurate estimates. Lastly, Outliers and influential points where QQ regression can be sensitive to outliers and influential data points, leading to biased estimates that do not accurately represent the underlying relationship between quantiles (Chernozhukov et. al., 2013).

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CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

Introduction

This chapter addressed the study's summary, conclusions, and recommendations. The primary objective of the study is to investigate the connection between Cryptocurrency and global unpredictability. This chapter also provided a summary of the entire study, including the purpose, research objectives and hypothesis, overall conclusions, recommendations based on the study, and suggestions for future research.

Summary of the Findings

The purpose of this research was to examine the correlation between cryptocurrency and global uncertainty. To achieve this, the variational mode decomposition technique was employed to break down the data into variational mode functions (VMFs). These VMFs were categorised into four modes, namely short-term (M1), medium-term (M2 and M3), and long-term (M4). The measurement of uncertainty was conducted using two indices, namely the World Uncertainty Index (WUI) and the Cryptocurrency Policy Uncertainty Index (CPUI). The independent variables utilised in this study encompassed various Cryptocurrency, namely Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Ripple (XRP), Litecoin (LTC), Monero (XMR), and Dash (DASH) coins. The variational mode functions (VMF) was utilised alongside the signal to analyse the correlation between the two variables, namely uncertainty and cryptocurrency. This analysis was conducted using monthly data spanning from 2010 to 2022. The present study was undertaken with a theoretical framework that is grounded in the adaptive market hypothesis and modern portfolio theory.

The study's methodology employed an explanatory research design and a quantitative research approach, enabling the use of parametric statistical analysis to examine the relationship between the variables under investigation. The study was structured around three specific objectives and their corresponding hypotheses. The initial aim of the study focused on analysing the time and frequency-based association between cryptocurrency and global uncertainty. The second objective of this study aimed to examine the causal association between cryptocurrency and global uncertainty, with the null hypothesis stating that cryptocurrency does not have a causal relationship with global uncertainty. The third objective of this study aims to examine the potential safe haven and hedge properties of Cryptocurrency during periods of uncertainty. The null hypothesis for this objective posits that Cryptocurrency do not possess safe haven or hedge properties in times of uncertainty.

The study employed wavelet analysis to examine the time-frequency association between cryptocurrency and uncertainty. Additionally, the Diks and Panchenko test and the Granger causality test were employed to analyse the causal relationship between the variables. The quantile-on-quantile regression method was employed to ascertain the hedge and safe haven characteristics of cryptocurrency during periods of uncertainty. According to the study's first objective of the study, there was an identical or similar correlation with both cryptocurrency and uncertainty indices, namely WUI and CPUI. for short-term investment horizons, cryptocurrency returns outperform the Uncertainty indexes. However, for medium and long-term investment horizons, the co-movement is often negative, implying that Cryptocurrency lag the Uncertainty indexes, the uncertainty around Cryptocurrency is heightened by regulatory ambiguity, market volatility, security concerns, and limited acceptance. Understanding these variables is critical for addressing difficulties and promoting cryptocurrency growth and stability. Establishing clear and consistent rules, improving security measures, and encouraging wider acceptance are critical steps towards eliminating uncertainty and strengthening investor trust in the bitcoin industry.

In terms of the second objective and hypothesis, the null hypothesis that cryptocurrency has a causal relationship with global uncertainty is rejected, with the exception of XRP and XRM in the medium term with respect to WUI and CPUI, respectively. Using the Granger causality test, we can see that WUI is granger causing Bitcoin (BTC), Ethereum (ETH), Litecoin, and Dash in the short run. Furthermore, in the medium term, CPUI creates ETH and WUI causes LTC. The distinction between the outcomes of Granger causality and the Diks-Panchenko (2006) tests lies in their respective methodologies and objectives. Granger causality primarily examines the ability of one variable to predict future values of another, whereas the Diks-Panchenko framework aims to identify immediate causal relationships between variables. These approaches differ in terms of assumptions, testing procedures, temporal order, and model complexity, leading to potential disparities in their results (Granger, 1969; Diks & Panchenko, 2006).

Finally, the third objective and hypothesis, in the short run cryptocurrency serve could as a hedge and safe haven during uncertainty, in the medium term most Cryptocurrency were found to be insignificant except for ETH, XRP and LTC where these Cryptocurrency were found to pose some hedge and safe haven properties against WUI, XRM was the only cryptocurrency with some form of safe haven / hedge properties against CPUI in the medium term. In the long term BTC was significant against WUI in the upper quantiles with some sought of hedge ability whiles ETH, XRM and DASH was significant against CPUI, ETH was found to have some sought of safe haven properties against CPUI whiles XRM an DASH was found to have hedge properties against CPUI. cryptocurrency could serve as a hedge or a safe haven for both uncertainty indices from a dynamic and comprehensive perspective. cryptocurrency was found manly to be safe haven for WUI, and not a hedge in certain periods thus M1 and M3.

Conclusions

Based on the study's findings, the following conclusions have been established and summarised:

1. From the first objective the study concludes that cryptocurrency and uncertainty show bi-directional causality in the frequency interval from 1 – 3 months. Also, Cryptocurrency serve as a weak hedge in uncertainty in the medium- to long-term and Demir et al. 2018; Fang et al. 2019; Goodell and Goutte, 2020, provide evidence on the hedging role of cryptocurrency against uncertainty. From the study, hedging property is short-lived against increasing uncertainty and therefore investors need to design a timely hedging strategy to earn financial gains because it helps protect their investments from potential losses caused by market fluctuations and uncertainties. By employing such a

strategy, they can mitigate risks and enhance their chances of profiting in the financial markets.

2. With respect to the second objective the causality test indicates that uncertainty does not cause Cryptocurrency as shown in previous literature by (Aiken et. al., 2020; Bourassa & Lucey, 2021; Kotsiampa,2022) except XRP which is caused by WUI in the medium-term using Diks and Panchenko and BTC, ETH, LTC and DASH in the medium term using the granger test, this means uncertainty can create opportunities for investors to profit from fluctuations in cryptocurrency prices. For example, if there is uncertainty about the future of a particular cryptocurrency, investors may be able to buy it at a low price and then sell it at a higher price once the uncertainty is resolved. Overall, uncertainty about the future of Cryptocurrency can make it difficult for businesses to accept them as payment and for people to invest in them. This can limit the growth of the cryptocurrency market in the medium term because people become hesitant to invest or participate when they are unsure about what lies ahead for these digital assets. When there's a lack of clarity or predictability, potential investors and users may hold back, fearing potential risks or unfavorable developments. This hesitancy leads to a slower adoption rate and inhibits the market from reaching its full potential.

3. Based on the third objective, the heterogeneous nature of the market participants and the adaptive behaviour of markets are revealed by the asymmetric link between Cryptocurrency and uncertainty, the propensity of Cryptocurrency to hedge, diversify, or act as a safe haven

for uncertainty, and the degree of correlation. it was observed that most Cryptocurrency have strong safe haven and hedge properties in the short and medium term thus M1 and M2, this is in line with studies such as Brière et. al., 2020; Dimitrova & Wei,2019 and Corbet et. al.,2018. Cryptocurrency can provide safety and a buffer against instability in these times for people wishing to escape the effects of financial volatility. If traditional investment strategies fail, investors may use cryptocurrency as a powerful tool to secure their investments. Additionally, cryptocurrency has proven to be sturdy in times of uncertainty, making it a great option for reliable investments during times of uncertainty for both experienced and inexperienced investors alike. historically during the global financial crisis in 2008, when there was an upheaval towards safe havens such as gold, cryptocurrency could have been used to preserve wealth during that period.

The overall conclusion drown from the study is that that investing in Cryptocurrency might be a viable way for investors to hedge against uncertainty on a global scale. Cryptocurrency is more robust during periods of economic and political volatility and uncertainty in general, since it is not linked to any government or financial institution. Cryptocurrency are still a rather young and unstable asset class, nevertheless. So, before making an investment, it's crucial to exercise caution and perform the needed research. Before Cryptocurrency may be introduced on a larger scale, legislative and security issues must be resolved. Overall, even though Cryptocurrency may offer some benefits during an uncertain moment for the world, it is vital to approach them with prudence and a long-term investment plan. The conclusions drawn from this study has contributed towards bridging the gap in literature where evidence on the cryptocurrency uncertainty nexus has been provided in the short, medium and long term. Furthermore, the study has revealed that there is the existence of a relationship between cryptocurrency in the short, long and medium term but uncertainty does not cause cryptocurrency in general.

Recommendations

1. . Keeping up with legislative developments is crucial, as is making sure that adequate safeguards are in place to protect assets. In general, participants ought to approach Cryptocurrency cautiously and with a long-term investment plan. Even if it might have some advantages in a world of uncertainty, assessing the potential advantages and disadvantages is crucial before making financial decisions. Investors can decide whether or not to invest in Cryptocurrency as a hedge or safe haven against global uncertainty by being knowledgeable and exercising caution.
2. Investors of cryptocurrency should diversify their investments it's essential to gather information from a variety of reputable sources. Cryptocurrency is a rapidly evolving field, and global uncertainties can arise from various factors like geopolitical tensions, economic fluctuations, or technological advancements.

Diversifying simply means spreading funds across many asset classes, such as bonds, equities, and real estate, as opposed to investing them completely in one. This lessens risk and safeguards investments in the event that an asset class underperforms. By using this approach, investors can create a portfolio of investments that is more diversified and well-balanced, which can assist to reduce the risks associated with investing in Cryptocurrency.

Suggestions for Further Studies

This study examined the nexus between cryptocurrency and uncertainty by looking at the short, medium and long-term relationship between cryptocurrency and uncertainty and by using only two uncertainty indexes, future studies should consider using a number of these uncertainties to better understand cryptocurrency in times of uncertainty. Also, future research should consider using the copula model to capture the dependence between cryptocurrency and uncertainty, the copula model is used to understand how cryptocurrency and uncertainty are related. The copula model is a statistical tool that helps analyse the dependence between two variables, such as cryptocurrency prices and uncertainty levels.

By using this model, insight is gained into how changes in uncertainty might affect cryptocurrency prices and vice versa. It provides a way to study the relationship more accurately and make informed decisions based on their interdependence. Further research is needed on the benefits and dangers of diversifying cryptocurrency holdings in the face of global uncertainty and this can assist investors in making well-informed choices about how to diversify their holdings and control risk in their portfolios. Lastly, further studies should be conducted on how regulatory changes affect investor behaviour and how they impact the cryptocurrency market. Researchers can get substantial information on the advantages and dangers of investing in Cryptocurrency in times of global instability by undertaking this study and this can aid investors in making well-informed choices regarding their cryptocurrency investments and risk management strategies.

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