Risk and Uncertainty in Cryptocurrency Markets

By

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A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy

Norwich Business School
University of East Anglia
September 2023

Declaration

I confirm that this is my own work and that the use of all material from sources has been properly and fully acknowledged.

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Abdulrahman Alsamaani

Date: 09/29/2023

To

my amazing father (Abdulkarim) and my amazing mother (Latifa);

my brothers (Sultan, Abdulmalik, Abdulaziz)

sisters (Eman, Awatef, Nada);

brother-in-law (Abdulkarim);

my nieces (Yara, Shaden, Latifa, Maha, Shatha)

and my nephews (Tamim, Meshal)

Acknowledgements

"Man's mind, once stretched by a new idea, never regains its original dimensions."
Oliver Wendell Holmes

"The roots of education are bitter, but the fruit is sweet."
Aristotle

"the more I learn the more I realize how little I know."
Albert Einstein

These quotes have always touched an emotional chord with me, but as I approach the final chapter of my Ph.D., their profound meaning has taken on new importance in my life. When I started my Ph.D. journey five years ago, I had no idea about the profound experiences that lay ahead. As I pursued my long-held desire to obtain a Ph.D., I realized the excitement and enjoyment of gaining new knowledge. As Oliver Holmes expressed, new dimensions will be unlocked. All praise to Allah!

I am extremely grateful for the opportunity to be a part of Norwich Business School and work with its brilliant staff, who provide deep insights and support. Mainly, I extend my heartfelt appreciation to my supervisors, Dr. Apostolos Kourtis and Prof. Raphael Markellos, who kindly share their extensive academic knowledge and play an essential role in helping me establish myself within the academic community. I am genuinely thankful for their firm yet compassionate guidance, which unlocked new thinking dimensions I never thought I would acquire.

I sincerely appreciate my university in Saudi Arabia, Imam Mohammad Ibn Saud Islamic University (IMSIU), for granting me the scholarship and trusting and believing in me to pursue my Ph.D. journey. Also, I am very grateful to my friends, colleagues, loved ones, and family for their endless support and encouragement throughout my journey.

A special indebtedness and gratitude go to my Father, Mother, Brothers, Sisters, Nieces, and Nephews. They were and have been my soul fuel and ultimate motivators. Without their support, encouragement, and pride, I would not reach this chapter of my Ph.D. journey. I will be in great admiration and appreciation for them.

Access Condition and Agreement

Chapter One: Introduction

Over the last two decades, financial technology, sometimes known as Fintech, has emerged as a disruptive force in the world of business and finance. The dynamic convergence of cutting-edge technology and financial services reshapes established business structures and financial transactions. Because of its potential to transform the financial landscape, this phenomenon has attracted the interest of scholars, legislators, and corporations alike. Therefore, Fintech refers to a wide range of innovative products and services that use technology to improve and optimize financial operations. Mobile banking applications and digital payment systems, as well as blockchain-based cryptocurrency and automated investment advising services, are examples of these solutions. Its importance in business cannot be understated since Fintech has impacted conventional financial institutions and opened new channels for firms to acquire money, manage finances, and communicate with consumers. The link between Fintech and business is complex and ever-changing, causing scholars to investigate many elements of this phenomenon. A great deal of published research shines a light on the complicated relationship between Fintech and business, giving insights into the potential and problems this dynamic industry brings.

Furthermore, regarding the impact of Fintech on Business, the influence of Fintech on firms is extensively established in the study literature. Fintech solutions have considerably boosted financial inclusion by providing access to financial services to underserved and unbanked people. According to a World Bank analysis (2022), Fintech has played a critical role in closing the financial inclusion gap, allowing firms to enter previously unreachable areas. Fintech has also transformed company funding. Crowdfunding platforms, online marketplace financing, and peer-to-peer lending have offered start-ups and small enterprises alternate sources of money. One of the most important results in fintech research in improving efficiency and customer focus is its capacity to improve corporate operational efficiency. Accounting and payroll administration have been automated, which has not only eliminated human mistakes but also optimized resource allocation. Different case studies and industry reports illustrate that this results in cost savings and increased organizational competitiveness. Furthermore, businesses may now acquire more profound insights into consumer behaviour, preferences, and trends thanks to artificial intelligence and data analytics. As a result, personalized marketing methods, product suggestions, and customized financial advice have grown more widely available, resulting in higher consumer satisfaction and loyalty.

Also, Fintech has changed the way people think about money, payments, and financial services. Cryptocurrency, a digital and decentralized currency, is at the heart of this change. Since the turn of the millennium, cryptocurrency has been regarded as one of the most inventive financial trading vehicles. Nakamoto introduced Bitcoin as a new financial asset in 2008. Bitcoin, according to Nakamoto (2008), is a peer-to-peer transaction that employs an electronic currency system to allow users to transfer online payments to each other directly without the involvement of intermediary financial organizations.

Furthermore, cryptocurrencies have no connection to regulators or political entities, and Bitcoin has no physical presence. Cryptocurrencies enable consumers to send payments online by building a secure electronic currency system (Cheah and Fry, 2015). In 2009, Bitcoin was first traded. Since then, Bitcoin has been the most renowned digital money on the cryptocurrency market. Therefore, traditional banking systems have been challenged by Fintech and cryptocurrencies, which provide efficient and borderless alternatives. Blockchain technology is used by fintech businesses to generate cryptocurrencies such as Bitcoin and Ethereum, revolutionizing the way individuals transact, invest, and store value. Fintech and cryptocurrency have a complicated connection since these digital assets serve as both a crucial application and a driver for innovation in the financial field. New possibilities and challenges develop on a regular basis in this restricted environment, changing the future of finance.

Likewise, Bitcoin and cryptocurrencies have developed as critical financial innovations, providing significant benefits to businesses and society as a whole. They simplify cross-border transactions while lowering costs and time delays, making them especially useful for global business and financial inclusion. The security characteristics of the blockchain technology that underpins cryptocurrencies improve supply chain transparency and prevent fraud, both of which benefit businesses. Furthermore, cryptocurrencies have revolutionized fundraising through Initial Coin Offerings and Security Token Offerings, making capital raising more accessible. Smart contract implementation automates complicated business procedures, increasing operational efficiency and confidence in business interactions. Cryptocurrencies, as decentralized digital assets, also function as hedges against traditional financial instability and provide new investment options. These developments, however, carry with them problems such as regulatory uncertainty and security dangers, demanding cautious navigation while maximizing their transformational potential.

In addition, several new cryptocurrencies have entered the financial markets. Consequently, several academics have attempted to simplify and clarify their actions. Cryptocurrencies were separated from other traditional financial assets by Kyriazis, Daskalou, Arampatzis, and Prassa (2019). Cryptocurrencies have also been employed as new financial tools for creative investments. Therefore, many individuals are interested in investing in cryptocurrencies. The popularity of cryptocurrencies continues to expand, attracting the interest of academics, financial market participants, and professionals in high-frequency data processing techniques. Given its novel characteristics and unpredictable swings, Bitcoin has also generated considerable literature.

For example, Corbet, Lucey, and Yarovaya (2018), Cheah and Fry (2015), and Cheung, Roca, and Su (2015) all found bubbles in the Bitcoin market. According to their findings, Bitcoin values are prone to speculative bubbles. Some researchers have argued that Bitcoin is a money or an asset. As a result, Luther and White (2014) believe Bitcoin has the potential to become a means of exchange. However, Wu and Pandey (2014) determined that, while Bitcoin is not beneficial as a currency, it may be useful and play an essential role in boosting the efficiency of an investor's portfolio. Baur, Hong, and Lee (2018) validated that study by demonstrating that Bitcoin accounts are predominantly utilized as an investment tool rather than an alternative currency. Furthermore, Kristoufek (2015) discovered that Bitcoin exhibits characteristics of both traditional and speculative financial assets. Therefore, Bitcoin and cryptocurrencies have strongly altered the financial sector, enclosing two characteristics of digital currency and new investment tools.

Nevertheless, throughout their history, Bitcoin and cryptocurrencies have been characterized by high price volatility. This volatility results from several causes, including speculation, market sentiment, and a lack of thorough regulation. Speculative trading, driven by investors looking for quick returns, frequently results in rapid and unpredictable price movements. Furthermore, the sensitivity of the cryptocurrency market to news, social media trends, and market emotion can result in significant price movements in response to excellent or flawed occurrences. The lack of comprehensive regulation in cryptocurrency makes it vulnerable to manipulation and market abuse, exacerbating volatility. Furthermore, many cryptocurrencies have shallow trading volumes compared to traditional financial markets, making them more disposed to excessive price changes. Because cryptocurrencies are a relatively new technology with little mainstream use, their value is speculative and prone to a fast shift as the technology evolves and becomes more broadly recognized. Price volatility gets worse by external variables such as regulatory declarations, security breaches, and macroeconomic developments. Despite their development and promise of growth, addressing and reducing volatility remains a concern, providing dangers and possibilities for investors, firms, and regulators equally.

As a result, unlike traditional currencies, cryptocurrencies are characterized by a high amount of volatility, which has drawn the attention of academics to developing reliable assessment and prediction models. These models best capture the most recent and exact findings for the variables of interest. The volatility GARCH model is most commonly used by researchers in conditional variance studies, which are directly relevant to the cryptocurrency market. When analyzing IBM returns, Hansen and Lunde (2005) verified the model's effectiveness by comparing GARCH to superior predicting ability (SPA) and the reality check (RC) for data snooping, which showed to be less accurate in evaluations. Their investigation of currency rates found no indication that more complicated models outperform a GARCH(1,1). Nonetheless, in their research of IBM returns, the GARCH(1,1) is inferior to models that can handle a leverage effect.

Furthermore, Caporale and Zekokh (2019) highlighted the idea of utilizing over 1,000 different GARCH models to discover the most effective model for volatility for four cryptocurrencies: Bitcoin, Ethereum, Ripple, and Litecoin. According to the study findings, the Model Confidence Set approach for the loss functions provided the best support for the Value-at-Risk and Expected Shortfall projections. Caporale and Zekokh (2019) stated that traditional GARCH models provide mistaken VaT and ES forecasts and inadequate risk management. The findings of Caporale and Zekokh (2019) contradict Hansen and Lunde's (2005) work, suggesting the applicability of GARCH models to forecast the volatility of cryptocurrency returns. In contrast, Caporale and Zekokh (2019) proposed adopting models that allow asymmetries and regime shifts. The conflicting findings regarding the efficiency of various models indicate a gap between researchers concerning which model is most suitable and applicable to forecast the volatility analysis of cryptocurrencies, implying a potential inefficiency of GARCH models applied to volatility estimation for cryptocurrencies.

These studies and findings clearly outlined the potential gap found in the literature to investigate and answer the question of the best-fitted model to predict the volatility of cryptocurrency returns. The previous literature suggested conflicting findings on which model can accurately forecast the volatility of cryptocurrency market. Therefore, Chapter Two aims to answer that question by applying six models on twelve cryptocurrency returns. The cryptocurrency returns span from the most dominant cryptocurrency to less dominant cryptocurrencies in terms of market capitalization. Not only that, but also different frequencies have been examined to understand better which model is the best-fitted model to predict the volatility of cryptocurrency returns in terms of each frequency: daily, weekly, and monthly.

The findings of the univariate regressions utilizing the Mincer and Zarnowitz (1969) regressions with the Newey-West (1987) heteroskedasticity and autocorrelation consistent standard errors are shown in Chapter Two. It analyses the outcomes of six models: GARCH, EGARCH, IGARCH, GJR-GARCH, LRE, and HAR. Each model has its justifiable reason to be applied in Chapter Two. For example, the Lagged Realized Volatility model assumes that volatility occurs within a Markov process, which signifies that its period is predictive of future data (Kourtis et al. 2016). Also, the GARCH model can capture the clustering in volatility (Bollerslev, 1986).

Furthermore, the EGARCH model can tolerate the asymmetric effects of negative and positive innovations (Nelson, 1991). Too, the IGARCH model accounts for the influences of past squared shocks with persistent data that remain essential to forecasting future time horizons (Bentes, 2015). Moreover, the GJR-GARCH model's main advantage of this model rests on its ability to analyze asymmetric behaviours (Nugroho et al., 2019). Lastly, the Heterogeneous Autoregressive model can estimate the long memory behaviour and describe the sign and size asymmetries (McAleer and Medeiros, 2008).

The univariate regressions results of Chapter Two for 1-day horizons show that the HAR model outperforms the other models. However, the univariate regressions for 7-day horizons, on the other hand, demonstrate that the EGARCH model has the best explanatory power of all the investigated models. Furthermore, the univariate regressions for 30-day horizons show that the EGARCH model has the most significant explanatory power of all the study models. In addition, the study reported the outcomes of the encompassing regressions. The encompassing regressions enable a direct comparison of two sets of predictions to determine if one's beneficial information dominates the other, making it redundant (Cook, 2014). The HAR + EGARCH models have the best explanatory power among the different pairings of models, according to the comprehensive regressions with Newey-West Standard Errors for a 1-day prediction horizon.

Similarly, for the 7-day prediction horizon, the encompassing regressions with Newey-West Standard Errors show that the HAR + EGARCH pair has the best explanatory power among the other pairings of models. Furthermore, the encompassing regressions with Newey-West Standard Errors for the 30-day prediction horizon demonstrate that the HAR + EGARCH models have the most significant explanatory power of the other pairings of models. The out-of-sample analysis was performed.

Shifting the focus on which is the best-fitted model to predict the volatility of cryptocurrency retunes to examining the exogenous factors that might affect the returns of the cryptocurrency market. One of the critical elements for investors to consider when making investment decisions has been the economic uncertainty affecting the cryptocurrency market. The economic uncertainty has a tremendous impact on investors, affecting both ordinary market participants and cryptocurrency investors. Also, risk aversion rises among investors during times of uncertainty, causing a shift towards secure assets such as government bonds or gold while decreasing exposure to risky assets such as equities. Therefore, diversification is becoming increasingly important as investors attempt to spread risk across several asset classes, including alternative assets such as real estate and cryptocurrency. Economic uncertainty also influences corporate decision-making, causing companies to postpone investments or slash expenses. Likewise, central banks frequently modify interest rates in response to such uncertainty, which can influence the returns on fixed-income assets.

Economic uncertainty can push cryptocurrency supporters to head to safety, with some investors perceiving cryptocurrencies, particularly Bitcoin, as "digital gold" and a store of value resistant to government manipulation. However, the volatile nature of cryptocurrencies might increase during economic instability, providing difficulties for investors. During difficult economic times, regulatory monitoring of cryptocurrencies may increase, possibly impacting market stability and investor trust. Also, because of their limited supply, some cryptocurrency investors see these digital assets as hedges against economic instability and inflation. However, the association between cryptocurrencies and traditional markets is not always stable, and they may not always act as a solid hedge during extreme market shocks. For instance, Bouri et al. (2017) investigated whether Bitcoin may be used to hedge global uncertainty, as assessed by the first primary component of the VIXs of 14 established and emerging equities markets. After decomposing Bitcoin returns into multiple frequencies, they used quantile regression and provided evidence of heavy tails. They show that Bitcoin functions as a hedge against uncertainty, responding favourably to uncertainty at higher quantiles and shorter frequency fluctuations of Bitcoin returns.

Nevertheless, Mokni et al. (2021) examined Bitcoin, contradicting the aggregate and categorical EPU in the United States. They utilized monthly data from September 2011 to December 2019. The empirical findings demonstrate that Bitcoin is not a way to hedge against the aggregate US EPU. Furthermore, Bitcoin's hedging behaviour may be seen at the bottom and top of the Bitcoin return curve. Similarly, Balcilar et al. (2017) used a quantile-based model to assess the predictability of cryptocurrency (Bitcoin). With the exception of bear and bull market conditions, their statistics suggest that trade volume has predictive potential over cryptocurrencies. Demir et al. (2018) show that the EPU index positively impacts Bitcoin returns and can predict Bitcoin price returns. According to Demir et al. (2018), uncertainty regarding government policies may cause investors to lose trust in their fiat currencies or be anxious about the larger economy, especially in the aftermath of the 2008 financial crisis. As a result, a change in the EPU may cause investors to review their portfolios to reduce future value loss. The effect and connectedness of the uncertainty indices on cryptocurrency returns have not been thoroughly investigated.

Therefore, economic uncertainty throws a wide net across traditional and cryptocurrency investors, impacting risk tolerance, diversification tactics, and investment decisions. While some investors consider cryptocurrencies a potential safe haven, their volatility and complicated connection with traditional assets show the multiple nature of economic uncertainty's influence on the financial landscape. Managing the consequences of economic uncertainty remains a top priority for investors in various financial markets. Therefore, nowadays, economic uncertainty factors have contributed directly and indirectly to investors' behaviours and shaped their investment decisions. These economic uncertainty factors vary between economy, policy, price, attention, and environmental attention uncertainty indices. Consequently, the relationship between cryptocurrency and various uncertainty indices, such as geopolitical risk (Aysan et al., 2019), the volatility index (Akyildirim et al., 2020), news implied volatility (Manela and Moreria., 2017), and sentiment index (Corbet et al., 2020), has already been studied in the current finance literature.

Some studies aim to determine the hedging and forecasting capabilities of certain assets. For example, Hasan et al. (2022) used the Quantile-on-Quantile approach to explore the hedging and safe-haven qualities of cryptocurrency policy uncertainty (UCRY). According to their results, the UCRY index hedges against gold and the DJ Islamic Index. The UCRY index, on the other hand, does not hedge Bitcoin returns in different quantiles. Furthermore, Shang et al.'s (2022) research analyzed and compared the UCRY Policy's predictive potential with numerous standard predictors for the gold market using a newly created cryptocurrency policy uncertainty index (UCRY Policy) and an efficient forecasting approach called Dynamic Occam's Window (DOW). Their empirical findings show that the UCRY Policy has a significant predictive capacity in estimating weekly gold returns, surpassing several commonly used predictors from 2014 to 2022. Lucy et al. (2022) created the UCRY Policy index that they employed. Furthermore, in forecasting weekly gold returns, the DOW approach with different thresholds beats dynamic model averaging/selection (DMA/DMS) and other standard econometric models.

Shaikh (2020) examined the Bitcoin market and EPU. His study assessed the economic policy uncertainty (EPU) in the US, the UK, Japan, China, and Hong Kong, equity market-specific uncertainty (EMPU), and the global MPU indices of other vital economies. Furthermore, the model incorporates control variables, such as VIX and SPX returns. The robust assessments from the quantile regression and Markov regime-switching models reveal that EPU affects Bitcoin returns. This effect can be described by one of the study's critical conclusions that Bitcoin returns are more sensitive to EPU in the United States, China, and Japan, while the uncertainty in the Bitcoin returns and equity market are negatively associated.

Focusing on EPU indices on cryptocurrency returns only, Nguyen and Nguyen (2023) also evaluated the short- and long-term effects of crypto-specific policy uncertainty and overall economic policy uncertainty (EPU) on Bitcoin exchange inflows. Their study found that crypto-specific policy uncertainty has short-term and long-term effects on BTC exchange inflows, but the general EPU explains these inflows only in the short run. The authors also found that BTC "Granger" exchange inflows exacerbate price volatility. Furthermore, the authors demonstrate that BTC volatility responds strongly and persistently to shocks to its exchange inflows.

Xia et al. (2023) further explored the relationship between the Economic Policy Uncertainty (EPU) and Cryptocurrency Uncertainty (UCRY) indices and BTC volatility. According to their findings, in-sample calculations reveal that the worldwide EPU index significantly negatively impacts long-term Bitcoin volatility. The UCRY indexes, on the other hand, have a beneficial impact on long-term Bitcoin volatility. Out-of-sample validation reveals that the One-Side Asymmetric GARCH-MIDAS with UCRY price index is the best-performing model, and forecasting models, including the UCRY indices, outperform models with global and national EPUs. Despite their restricted breadth, UCRY indices have emerged as a credible data source for driving Bitcoin trading behaviours.

These researches and findings outlined the potential gap in the literature that need to be investigated. The questions of which uncertainty index can strongly affect the returns of the cryptocurrency market? Which uncertainty indices pair can strongly affect the returns of the cryptocurrency market during bear market periods? Which uncertainty indices pair can strongly affect the returns of the cryptocurrency market during bull market periods? have been picked to be explored to bridge the gap in the literature. Chapter Three aims to answer those questions by measuring the relationships between cryptocurrency's returns with multiple indices. Each index has its measurement and concentrates on a different aspect of possible linkages that might affect the returns of the cryptocurrency market. The first and second indices are the Cryptocurrency Policy Uncertainty Index (UCRY Policy) and the Cryptocurrency Price Uncertainty Index (UCRY Price). The two indices have been generated from 726.9 million data text mining. The third index is "the Cryptocurrency Environmental Attention (ICEA) Index, which aims to capture the relative extent of media discussion around the environmental impact of cryptocurrencies based on 778.2 million data". The fourth and fifth indices are "Based on 663.9 million news stories from LexisNexis News & Business, we provide two new indices for central bank digital currency (CBDC) analysis: the CBDC Uncertainty Index (CBDCUI) and CBDC Attention Index (CBDCAI)".

The sixth index is the Economic Policy Uncertainty Index for Europe, an indicator created using newspaper stories about policy uncertainty from major newspapers. It calculates the number of newspaper stories containing uncertain or uncertain, economic or economy, and one or more policy-relevant words. The seventh index is the Twitter Economic Uncertainty (TEU) index, derived from tweets from June 2011 to the present. Thomas Renault (University Paris 1 Panthéon-Sorbonne) created it with the help of Scott R. Baker (Northwestern), Nicholas Bloom (Stanford), and Steve Davis (University of Chicago). The models applied in this research will be the Quantile Regression and the Granger Causality model.

In this chapter, the analysis results show that the daily and weekly data of the Twitter-based Economic Uncertainty (TEU) index has insignificant effects on cryptocurrency returns across all quantiles, which are consistent with Aharon et al. (2022) study findings. Therefore, the Twitter-based Economic Uncertainty (TEU) index exhibits a lack of short and long-term effects on cryptocurrency returns. However, the weekly data of the Cryptocurrency Policy Uncertainty index significantly affects bear periods for cryptocurrency returns across some quantiles, which contradicts the results of Karaömer (2022) research findings. On the other hand, the Cryptocurrency Price Uncertainty index exhibited less effects on cryptocurrency returns. The findings During the crisis period supported these results by revealing more evidence of the effect of the Cryptocurrency Policy Uncertainty index on cryptocurrency returns for the 10%, 80%, and 90% quantiles. Although they study only BTC volatility, these results support the research findings of Xia et al. (2023) study that the UCRY indices have positive effects on long-term Bitcoin volatility.

Correspondingly, the Central Bank Digital Currency Uncertainty Index, the Central Bank Digital Currency Attention Index, the Cryptocurrency Environmental Attention (ICEA) index, and the monthly data of the Economic Policy Uncertainty Index for Europe index have an insignificant relationship on most cryptocurrency returns across most of the quantiles. These results support the research findings of Ayadi et al. (2023) for the first two indices. However, the result of the ICEA index contradicts the findings of Wang et al. (2022) 's study. Also, the results of the EPUIE index contradict the findings of Shaikh's (2020) research findings. During the crisis period, the findings confirm the full sample results of an insignificant relationship between those indices and the returns for almost all cryptocurrency returns. Therefore, investors in the cryptocurrency market have trust concerns with some uncertainty indices and shape their investment decisions based on other external and internal factors.

The Multivariate Quantile Regression model was applied as well. Unexpected results have been obtained. The results of the multi-indices effect on cryptocurrency returns showed that the early quantile (quantile = 5) exhibits insignificant impact across most cryptocurrency returns, which means that these indices have less effect when the market experiences a bull period wave. These results supported the findings of (Aharon et al. 2022, Xia et al. 2023, Ayadi et al. 2023, and Shaikh, 2020). For the rest of the quantiles, the results show no evidence of a significant impact of the indices on most of the returns of cryptocurrencies, except for the 95% quantiles for The UCRY Price Index and the Cryptocurrency Environmental Attention (ICEA) index.

Also, the pairs effects approach has been applied, and it has been found that the UCRY Policy Index + Central Bank Digital Currency Attention Index pair was the most influential pair when the bull period wave hit the market. These results contradict the results of Karaömer (2022) research findings that reveal that the UCRY Policy negatively influences cryptocurrency returns throughout significant events. At the same time, the UCRY Policy Index + the Central Bank Digital Currency Attention Index pair is the least influential pair on cryptocurrency returns when the bear period wave hits the market. Nonetheless, when accounting for only the bear period wave, the UCRY Policy Index + the Cryptocurrency Environmental Attention (ICEA) index pair is the most influential on cryptocurrency returns under study. At the same time, the UCRY Policy Index + the Cryptocurrency Environmental Attention (ICEA) index pair is the least influential pair on cryptocurrency returns when the bull wave period hits the market.

Moreover, the Granger Causality Test was performed and applied. The results of the daily data of the Twitter-based Economic Uncertainty (TEU) index and cryptocurrency returns at lagged order (LO) = 1 reveal an insignificant relationship. This result is consistent with Aharon et al. (2022) study. In contrast, the weekly data show significant and strong relationships between the index and all the cryptocurrency returns except for XLM returns, which contradict the results of the Aharon et al. (2022) study. Also, for the LO = 6, there is a significant relationship for all cryptocurrency returns except for EOS, XLM, and ETC returns in the full sample results and except for XRP, LTC, EOS, XLM, DASH, and ETC returns during crisis period results while the weekly data show there is a significant relationship for all cryptocurrency returns. These results indicate the long-term effect of the daily and weekly data of the Twitter-based Economic Uncertainty (TEU) index on cryptocurrency returns.

The UCRY Policy Index and the UCRY Price Index Granger Causality Test results significantly affect all cryptocurrency returns except for BTC returns at LO =1, which support the results of Karaömer (2022) research findings. Also, there is no evidence of a significant impact of cryptocurrency returns on the UCRY Policy Index and UCRY Price Index. Still, XRP, LTC, and ETC returns significantly affect the UCRY Policy Index, and BCH and DASH returns significantly affect the UCRY Price Index. During the crisis period, results confirmed these results. Too, there is no evidence of a significant impact of cryptocurrency returns on the UCRY Policy Index and the UCRY Price Index.

Nevertheless, for the UCRY Policy Index, XRP, LTC, and ETC returns significantly affect the UCRY Policy Index, while BTC and XMR returns showed no evidence of any impact from the UCRY Policy Index at LO = 6. Also, for the UCRY Price Index, BCH and DASH returns significantly affect the UCRY Price Index, while all cryptocurrency returns showed strong evidence of impact from the UCRY Price Index at LO = 6. This result supports Xia et al.'s (2023) study that the UCRY indices positively affect long-term Bitcoin volatility.

The Central Bank Digital Currency Uncertainty Index (CBDCUI) Granger Causality Test results show a significant effect between the CBDCU Index and ETH, XRP, BCH, EOS, XLM, DASH, ETC, and the rest of the cryptocurrencies reveal no evidence of a significant effect at the LO = 1. Also, there is no evidence of a significant impact of cryptocurrency returns on the CBDCU Index. Nevertheless, there are significant effects for the CBDCU Index on all the cryptocurrency returns at LO = 6, and there are significant effects from BTC, LTC, EOS, DASH, and ETC returns on the CBDCU Index, and the rest of the cryptos show no effect at all. The results during the crisis period confirmed most of the full sample results.

The Central Bank Digital Currency Attention Index and the Cryptocurrency Environmental Attention (ICEA) index Granger Causality Test results reveal significant effects between the indices index and all the cryptocurrency returns except for BTC. This result supports the findings of Wang et al. (2023) 's study. They found that CBDC attention significantly influences cryptocurrency markets. Similarly, the result supports the findings of Wang et al. (2022) 's study. The ICEA shows stronger correlations between environmental attention, Bitcoin, and UCRY indexes during big events that significantly affect the values of digital assets.

Furthermore, there is no evidence of a significant impact between cryptocurrency returns and the two indices at LO =1. Likewise, there is a significant effect on all cryptocurrency returns from the Central Bank Digital Currency Attention Index. Correspondingly, there is a significant effect from XRP, LTC, BCH, EOS, and ETC returns on the CBDCA Index. Similarly, the ICEA index significantly affects all cryptocurrency returns. Only XRP, LTC, and EOS significantly affect the ICEA index. The results during the crisis period confirmed most of the full sample results.

The Monthly data of the Economic Policy Uncertainty Index for Europe index and Cryptocurrencies returns Granger Causality Test results show no evidence of a significant impact from the index on cryptocurrencies returns, which contradicts the findings of Shaikh's (2020) research findings. However, there is an apparent significant effect from the cryptocurrency returns on the Economic Policy Uncertainty Index for Europe index. After considering the LO = 6, the results show that there is still a limited effect on some cryptocurrency returns, such as the LTC, XLM, and DASH. The rest of the cryptocurrency returns show no effect from the Economic Policy Uncertainty Index for Europe index. Also, cryptocurrency returns significantly affect the Economic Policy Uncertainty Index for Europe index at a 1% significant level. The results during the crisis period confirmed the full sample results.

It is crucial also to consider the risk in the cryptocurrency market. Therefore, covariance forecasting is becoming increasingly crucial in cryptocurrency funds and portfolios as the digital asset market becomes more complicated. With cryptocurrencies infamous for their high volatility and varied array of assets, there is an obvious need for accurate risk management and diversification measures. Hence, accurate covariance analysis enables investors to assess the risk of owning numerous cryptocurrencies in their portfolios, allowing them to build portfolios that strike an optimal balance of risk and return. In addition, investors may limit the effect of significant price changes in individual portfolios by diversifying based on covariance insights, enhancing portfolio stability and resilience.

Additionally, covariance forecasts are critical in optimizing asset allocation techniques, allowing investors to adapt their cryptocurrency mix to specific risk-return objectives. This strategy discovers assets with low or negative correlations, which might provide considerable hedging benefits during periods of market turmoil. Covariance analysis may also help with the effective management of volatility, which is a feature of cryptocurrency markets and may contribute to enhanced portfolio performance by directing asset selection and rebalancing choices.

Furthermore, these forecasts are useful in analyzing risk-adjusted returns, an essential criterion for measuring portfolio performance in the cryptocurrency industry. Covariance analysis enables bespoke methods linked with individual risk tolerance and financial goals, becoming increasingly important as investors seek personalized investment strategies. Accurate covariance forecasting is the foundation of successful risk management, portfolio optimization, and navigating the complex and unexpected world of digital assets in the ever-changing cryptocurrency market.

Therefore, based on the literature on the cryptocurrency connectedness within the cryptocurrency market, Bouri et al. (2019) employ a frequency domain Granger causality approach to discover that Bitcoin is not the only source of volatility, emphasizing the importance of other prominent cryptocurrencies in the network of volatility spillovers. Koutmos (2018) reveals that spillovers change over time and point to the increasing interconnection of cryptocurrencies, implying a higher level of contagion risk. The report also emphasizes Bitcoin's critical role in the return and volatility spillover network. Corbet et al. (2018) investigate the volatility and return spillovers of three prominent cryptocurrencies (Bitcoin, Ripple, and Litecoin). Using time-domain connectivity measures, they discover that Bitcoin returns significantly influence Ripple and Litecoin returns, whereas the response impact is negligible. This result reveals Bitcoin's dominance in the return connectedness network. However, the authors' conclusions about volatility spillovers differ from those of Koutmos (2018). They found that Litecoin and Ripple influence Bitcoin, but Bitcoin has limited influence on Litecoin and Ripple. Furthermore, Ripple and Litecoin are inextricably connected through return and volatility channels. Corbet et al. (2018) go on to demonstrate that the three digital assets are distinct from traditional assets, signalling that they have the potential to function as diversifiers.

The literature on interrelationships and volatility dynamics in bitcoin markets is still in its early stages. Return and volatility spillovers measure intermarket links, which are essential in international finance and have considerable implications for portfolio and hedging decisions. This topic has received much attention in empirical studies, including increased market integration due to market openness, globalization, financialization, and technological improvements. Any evidence of high return and volatility spillovers between Bitcoin and other asset classes has the potential to affect asset selection and allocation, as well as regulators' policies to maintain the global financial system's stability. Bouri et al. (2018a) investigated the return and volatility spillover among Bitcoin, equities, currencies, stocks, bonds, and commodities. They found empirical evidence that Bitcoin is mainly associated with the commodities market and not isolated, while Ji et al. (2018) showed that the Bitcoin market is disconnected from other assets; as such, no asset plays an essential role in the Bitcoin market. Still, there appears to exist lagged and significant correlations. Bouri et al. (2018b) argued that Bitcoin price movements can be correctly predicted using data from the aggregate commodities index and gold prices. However, according to these researchers, Bitcoin is connected to some investment possibilities, such as commodities, but it is not linked to other investment opportunities, such as bonds and shares. Ji et al. (2019b) investigated commodities linkages with prominent cryptocurrencies and observed that cryptocurrency connectivity fluctuates over time and becomes increasingly intertwined in the system. They also noted that cryptocurrency price dynamics influence energy commodities.

Similarly, Hayes (2017) showed a significant connection between cryptocurrencies and the energy market (electricity market) in terms of the requirement for electricity for cryptocurrency mining. Furthermore, Adebola et al. (2019) report significant degrees of mean reversion movements in the values of Gold and some Cryptocurrencies with cointegrations. Gold prices and aggregate commodity price information can be used to forecast Bitcoin prices (Bouri et al., 2018a, 2018b). However, according to Shahzad et al., 2019, Bitcoin, gold, and the commodities index could be better safe-haven assets for investors, although their performance fluctuates over time across stock market indices. Bitcoin not only exhibited these traits, but it also has hedging potential with stocks, according to Okorie (2019).

Furthermore, Al-Yahyaee et al. (2019) revealed that when paired with crude oil and the S&P GSCI, Bitcoin and gold are capable of diversifying and hedging a portfolio, whilst Okorie (2019) highlighted the relevance of Bitcoin and the S&P500 for portfolio balance and diversification. As a result, Guesmi et al. (2019) demonstrate significant volatility spillovers between Bitcoin and other financial instruments such as gold and stocks and that an investment portfolio composed of gold, oil, Bitcoin, and equities can reduce portfolio risk. Furthermore, Cebrian-Hernandez and Jimenez-Rodriguez (2021) used Engle's (2002) Dynamic Conditional Correlation (DCC) model on a varied portfolio that included Bitcoin and ten other assets. The obtained findings demonstrate some variation in the fit of the various variables, emphasizing the uncorrelation concerning classic safe-haven assets such as gold and oil. When the CC-MGARCH model is used, the dynamic conditional correlation behaves better than the constant conditional correlation.

The emphasis on predicting the covariance matrix for equities market returns has received much attention. Many types of research have lately been published. Multivariate GARCH models are commonly used to model and forecast covariance matrices for any market, particularly equities markets. Scholars' primary attention has yet to be on exploiting high-frequency data. Forecasting the covariance matrix is critical to portfolio design and strategy. Chou et al. (2009) proposed a range-based dynamic conditional correlation (DCC) model, which is a hybrid of the return-based DCC model and the conditional autoregressive range (CARR) model. According to them, a considerable improvement in volatility estimation efficiency can enhance the accuracy of estimating time-varying covariances. They examined the in-sample and out-of-sample results for six models, including MA100, EWMA, BEKK, CCC, range-based DCC, and return-based DCC, using the S&P 500 stock index and 10-year government bond futures.

The range-based DCC model surpasses all other models regarding the estimation and forecasting of covariance matrices. However, Fiszeder et al. (2019) noted that Engle's (2002) dynamic conditional correlation (DCC) model is exclusively dependent on closing prices. Consequently, they suggested a model incorporating high and low pricing into the DCC framework. They applied the novel approach to currency, equity, and commodity exchange-traded fund datasets. Their findings reveal that the novel model approach outperforms the standard DCC and range-based DCC models in three tests: in-sample fit, covariance predictions, and value-at-risk forecasts.

In addition, Bauwens et al. (2012) developed a similar DCC approach for realizing covariance modelling with the Wishart density. The proposed technique's mechanism to update the time-varying parameters differs. However, Vassallo et al. (2021) incorporated the conditional density score that defines the update rule into their system (Creal, Koopman, & Lucas, 2013). In the case of the Wishart density, scaling the score by the inverse of the Fisher information matrix produces the same updating algorithm as Bauwens et al. (2012). On the other hand, the two-scale sub-sampler proposed by Zhang et al. (2005), the multi-scale version proposed by Zhang (2006), the realized kernel introduced by Barndorff-Nielsen et al. (2008), which depends on autocovariance-based corrections, and the pre-averaging estimator proposed by Podolskij and Vetter (2009) and Jacob et al. (2009) are the main univariate approaches that the damage triggered by the noise is fixed.

On the other hand, Callot et al. (2017) used penalized vector autoregressive models to describe and forecast large realized covariance matrices. They applied Lasso-type estimators to reduce dimensionality. They suggested that the dynamics were unstable when the data was aggregated from daily to lesser frequency. Furthermore, BEKK-GARCH models were utilized by Katsiampa, Corbet, and Lucey (2019) to demonstrate the existence of bi-directional positive shock transmission impacts between Bitcoin and both Ether and Litecoin as well as uni-directional shock transmission from Ether to Litecoin. It was discovered that a cryptocurrency's historical shocks and volatility have a major impact on its current conditional variance. However, they discovered evidence of bi-directional shock transmission effects throughout Bitcoin and Ether, as well as throughout Bitcoin and Litecoin, as well as uni-directional shock spillover from Ether to Litecoin. Furthermore, they discovered bi-directional volatility spillover effects between all three cryptocurrency pairings. At last, it was demonstrated that time-varying conditional correlations exist, with positive correlations predominating.

Also, Katsiampa et al. (2019) tested eight cryptocurrencies using the Diagonal BEKK (Engle and Kroner 1995) and its asymmetric variation. Although it was discovered that all of the examined cryptocurrencies exhibit high levels of persistence of volatility over time, diagonal BEKK and asymmetric diagonal BEKK models revealed that cryptocurrency investors pay attention to news concerning Neo and the least attention to news relating to Dash. Meanwhile, Shocks in OmiseGo remain the most minor shocks, while shocks in Bitcoin remain the most shocks. Using both methodologies, identical results were obtained for conditional covariances, which were heavily influenced by cross-products of earlier error terms and previous conditional covariances, showing high dependency across cryptocurrencies. Because of its greater log probability value and lower information criteria values, the Asymmetric Diagonal BEKK model was also proved to be a superior strategy.

These studies and findings drew the potential new gap in the literature to investigate the forecasting of the covariance matrix of cryptocurrency returns. Chapter Four aims to answer the question of the best-fitted model to forecast the covariance matrix of cryptocurrency returns by using five models on ten cryptocurrency returns to forecast the covariance matrices. Then, forecast evaluation criteria are applied to evaluate each model's forecast by applying three loss functions as the first phase: the Euclidean distance (Le), the Frobenius distance (Lf), and the multivariate quasi-likelihood loss function (LQ). Then, a statistical comparison of the forecast approach is applied by evaluating the forecast and determining the best model to provide accurate forecasting ability. The Mean Squared Error (MSE) and Mean Absolute Error (MAE) were used in this approach as the second phase. The cryptocurrency returns span from the most dominant cryptocurrency to less dominant cryptocurrencies in terms of market capitalization. Not only that, but also different frequencies have been examined to understand better which model is the best-fitted model to forecast the covariance of cryptocurrency returns in terms of daily and weekly frequency.

The results of the first phase reveal that the Lagged Realized Volatility model is the best-fitted model across all three multivariate loss functions for the daily and weekly cryptocurrency returns. The results of this phase support the findings of Huang et al. (2019) study. Also, The result is supported by most of the second-phase findings. The second phase findings reveal that the best-fitted model to forecast the daily covariance matrix is the Lagged Realized Volatility model when applying the Mean Squared Error measures, which support the findings of Huang et al. (2019) study. Also, it supports the fact obtained from several empirical evidence that historical volatility estimators derived from daily data are inferior to their high frequency-based data (Andersen and Bollerslev, 1998; Andersen, Bollerslev, and Diebold, 2007; Blair et al., 2001). However, when using the Mean Absolute Error measures, only the multivariate quasi-likelihood loss function endorses the finding of the forecast evaluation criteria results for the daily returns. The other two loss functions reveal that the Asymmetric DCC model is the best-fitted model to forecast the daily covariance matrix, supporting Asai and McAleer, (2015) 's study.

Also, when applying the Mean Squared Error measures, the best-fitted model to forecast the weekly covariance matrix is the Lagged Realized Volatility model based on the LE and LF loss functions. This finding supports the forecast evaluation criteria results for the weekly returns. However, the LQ loss function reveals different results than the forecast evaluation criteria for weekly returns. It shows that the Asymmetric DCC model is the best-fitted model. However, when applying the Mean Absolute Error measures, the Asymmetric DCC model is the best-fitted model to forecast the covariance matrix for weekly returns. This finding does not support the weekly results of the forecast evaluation criteria across all three multivariate loss functions. Instead, the Asymmetric DCC is the best-fitted model to forecast the covariance matrix for weekly cryptocurrency returns.

Overall, this thesis is designed to predict the volatility of cryptocurrencies using high-frequency data, examine the relationships and effects of diverse economic policy uncertainty indices on cryptocurrency market returns, and forecast the covariance matrices in the cryptocurrency market. Different models have been used, and various robustness checks have been applied to validate the empirical findings of each stage of this thesis. Finally, the conclusion summarizes the results and the suggested potential areas for future scholars to study and explore.

Chapter Two: Predicting the Volatility of Cryptocurrencies Using High Frequency Data

1. Abstract

This study seeks to identify the best model for forecasting the volatility of cryptocurrency returns that can predict the volatility of dominant and less prominent cryptocurrencies using high-frequency data. The GARCH, IGARCH, EGARCH, GJR-GARCH, HAR, and LRE models have been examined, and the univariate and encompassing regression have been applied. For the univariate regression findings, the HAR model outperformed the other models when aiming to forecast one day ahead while the EGARCH model outperformed the rest of the models when forecasting the seven and thirty days ahead. Also, the HAR + EGARCH pair outperformed the rest of the model pairs when forecasting the one, seven, and thirty days ahead. The out-of-sample analysis revealed mixed results apart from the primary analysis. These findings will significantly help investors, portfolio managers, and financial firms.

2. INTRODUCTION

Cryptocurrencies are often considered among the most innovative financial trading instruments since the turn of the millennium. In 2008, Nakamoto proposed Bitcoin as a new financial asset. According to Nakamoto (2008), Bitcoin is a peer-to-peer transaction that uses an electronic cash system permitting users to send online payments to each other directly without the need for intermediate financial institutions. Also, cryptocurrencies are not linked to regulators or authorities, and Bitcoin has no material representation. Bitcoin was first traded in 2009. Since then, Bitcoin has been the most prominent digital currency on the cryptocurrency market.

Also, a massive number of new cryptocurrencies have been introduced in the financial markets. As a result, many scholars have sought to simplify and clarify their behavior. By forming a secured electronic cash system, cryptocurrencies permit people to transfer payments online (Cheah and Fry, 2015). Kyriazis, Daskalou, Arampatzis, and Prassa (2019) distinguished cryptocurrencies from other traditional financial assets. The cryptocurrency's value is not based on tangible assets or the country's economy, but instead, its value relies on the security of an algorithm that tracks all transactions. The low transaction costs, peer-to-peer cash system, and not being associated with government authorities are the factors that have contributed to the growth in the use of cryptocurrencies. Digital currencies have been used as a new medium of payment yet fully digitalized. Although the initial perception of cryptocurrencies has been digital, they have different characteristics than traditional currencies. Not only that, but also cryptocurrencies have been used as new financial instruments for innovative investments.

Focusing on its essential and rapid use as a new investment tool by investors and financial institutions, this chapter aims to evaluate the capability of six models to forecast the volatility of twelve cryptocurrency returns. Also, it focuses on examining these models in three horizons, daily, weekly, and monthly, to see if they might impose different results when they experience or examine more extended periods as inputs.

3. LITERATURE REVIEW

Interest in cryptocurrencies is not fading, which, in turn, triggers the attention of scholars, financial market agents, and experts in high-frequency data analysis techniques. Also, a significant body of literature on Bitcoin has been developed, given its innovative features and massively volatile swings. To illustrate, Corbet, Lucey, and Yarovaya (2018); Cheah and Fry (2015); and Cheung, Roca, and Su (2015) identified the existence of bubbles in the Bitcoin market. Their studies concluded that Bitcoin prices are disposed to speculative bubbles. Some authors have focused on whether Bitcoin is a currency or an asset. As such, Luther and White (2014) contend that Bitcoin can become a medium of exchange. However, Wu and Pandey (2014) concluded that although Bitcoin is not valuable as a currency, it can be useful and play an essential role in increasing an investor's portfolio's efficiency. That study was supported by Baur, Hong, and Lee (2018), who demonstrated that Bitcoin accounts are primarily used as an investment tool rather than an alternative currency. Also, Kristoufek (2015) found that Bitcoin reveals properties of both traditional and speculative financial assets. Therefore, it is essential to investigate cryptocurrencies' volatility and portfolio selection to benefit investors to make wise and clever decisions when investing in cryptocurrency markets.

Moreover, unlike traditional currencies, cryptocurrencies are characterized by a high level of volatility, which has attracted scholars' attention to identifying accurate estimation and prediction models. These models are used to best capture the most available and accurate results with regard to the chosen variables. Researchers most frequently employ the volatility GARCH model in the context of studies into conditional variance, which is directly correlated to the cryptocurrency market. Hansen and Lunde (2005) confirmed the efficiency of the model when analyzing IBM returns, comparing GARCH against superior predictive ability (SPA) and the reality check (RC) for data snooping, which proved to be less accurate in assessments. On the other hand, aiming to identify the most effective model for volatility for four cryptocurrencies, namely Bitcoin, Ethereum, Ripple, and Litecoin, Caporale and Zekokh (2019) mentioned the possibility of using over 1,000 diverse GARCH models. Based on the study findings, the Value-at-Risk and Expected Shortfall predictions were best supported by the Model Confidence Set procedure for the loss functions. Caporale and Zekokh (2019) concluded that standard GARCH models tend to yield incorrect VaT and ES predictions and ineffective risk management. Caporale and Zekokh (2019) findings contradict Hansen and Lunde (2005) 's study indicating the applicability of GARCH models for cryptocurrencies. Instead, Caporale and Zekokh (2019) suggested using models that allow asymmetries and regime-switching. Hypothesizing the potential inefficiency of GARCH models applied to volatility estimation for cryptocurrencies, the conflicting findings for the efficiency of diverse models demonstrate a lack of agreement among researchers regarding which model is most suitable and applicable to the volatility analysis of cryptocurrencies.

Similarly, Chu, Chan, Nadarajah, and Osterrieder (2017) evaluated several models and concluded that the combination of IGARCH and GJRGARCH models provided the optimal fit. One of the observations reported by Chu, Chan, Nadarajah, and Osterrieder (2017) is the varying scope of the robustness of different models when applied to different cryptocurrencies. This finding implies that there is no universal model suitable for all cryptocurrencies. For example, with regard to Bitcoin, Dash, Litecoin, Maidsafecoin, and Monero, Chu, Chan, Nadarajah, and Osterrieder (2017) found that the IGARCH (1, 1) model offers the best fit. Nevertheless, GJRGARCH (1, 1) is the best-fitted model for Dogecoin, and GARCH (1, 1) is Ripple's best-fitted model. However, in terms of goodness-of-fit, Katsiampa (2017) found that the AR-CGARCH was the best-fitted model for Bitcoin. Katsiampa (2017) applied the optimal conditional heteroskedasticity model and provided evidence that the AR-CGARCH model was effective in conditional variance analysis for both short-run and long-run components for Bitcoin.

A closer analysis of studies focusing on high-frequency data for cryptocurrencies revealed a lack of consistency among researchers regarding the use of specific methodologies and prediction tools. The diversity of instruments researchers and scholars use indicates the relative absence of agreement and solid evidence of the most efficient tools. For example, Katsiampa, Corbet, and Lucey (2019) applied Diagonal BEKK and Asymmetric Diagonal BEKK methodologies to intra-day data for eight cryptocurrencies. The researchers assessed conditional volatility dynamics and co-movements among the cryptocurrencies. With a few studies exploring cryptocurrencies other than Bitcoin and Ethereum, the report revealed that investors are paying increasing attention to news related to less popular cryptocurrencies, namely Neo. In line with the findings reported by Catania and Sandholdt (2019), Katsiampa, Corbet, and Lucey (2019) provided evidence of the high level of persistence of volatility over time for cryptocurrencies. Katsiampa, Corbet, and Lucey (2019) concluded that the Asymmetric Diagonal BEKK methodology is the superior model but did not specify the other models with which this method was compared.

Also, Mensi, Al-Yahyaee, and Kang (2019) studied the long memory and structural breaks and their impact on Bitcoin and Ethereum price returns. The study applied four different GARCH models: ARFIMA-GARCH, ARFIMA-FIGARCH, ARFIMA-FIAPARCH, and ARFIMA-HYGARCH. The study results explained the dual long memory property of Bitcoin and Ethereum, along with contrasting the market efficiency and random walk hypothesis. The study also found that the long memory in the mean and variance decreases significantly when accounting for structural breaks indicating shifts in mean and variance. The study concludes that not taking into account the long memory and structural breaks when using GARCH model estimations would lead to volatility persistence overestimating the Bitcoin market and delaying the prediction process. Also, in the out-of-sample analysis, the FIGARCH model with structural breaks variables provides a superior forecasting accuracy performance compared to the other models. The study findings would greatly benefit investors when accounting for future volatility and implementing hedging strategies.

Another study by Abakah, Gil-Alana, Madigu, and Romero-Rojo (2020) analyzed the volatility persistence in 12 leading cryptocurrencies with accounting for the possibility of structural breaks. The study findings indicate that both squared and absolute returns exhibit long memory features. Nevertheless, when taking into account the structural breaks, it appeared that there was a reduction in the degree of persistence in the cryptocurrency market. Furthermore, Catania and Grassi (2022) provide a novel dynamic model that takes into account long memory and asymmetries in the volatility process, as well as time-varying skewness and kurtosis. The empirical research conducted on 606 cryptocurrencies demonstrates that an accurate screening for cryptocurrency volatility is essential. Forecasting results show that incorporating time-varying skewness improves density, volatility, and quantile projections over a range of time horizons. Mensi, Sensoy, Aslan, and Kang (2019) also used the asymmetric volatility model to trace similarities between the volatility of Bitcoin and major precious metal markets. Using high-frequency data, Mensi, Sensoy, Aslan, and Kang (2019) confirmed the presence of significant volatility spill-over effects between cryptocurrency and metals. With these studies and findings, scholars could explore cryptocurrencies further using the recent best-fitted models that have been identified and recognized.

Researchers have discussed Other factors shaping cryptocurrency returns volatility: the central bank monetary policy announcements, the uncertainty of future values, high inflation, significantly high risks, fear of sizeable losses, and tax treatment lifts. In a study of central bank monetary policy announcements, Corbet, McHugh, and Meegan (2017) relied on the GARCH estimation model and confirmed the direct but insignificant correlation between monetary policy and cryptocurrency returns. Researchers concluded that cryptocurrencies are subject to the same economic factors as traditional fiat currencies. Using the GARCH-MIDAS framework to forecast the daily, weekly, and monthly volatility of Bitcoin, Ethereum, Litecoin, and Ripple, Walther, Klein, and Bouri (2018) concluded that the most powerful driver of volatility is the Global Real Economic Activity factor. However, researchers admitted that the average forecast combination results are necessary for lower loss functions. Focusing on Bitcoin and Ether in investigating the volatility dynamics, Katsiampa (2019) provided evidence of the interdependencies of these two principal cryptocurrencies using the bivariate Diagonal BEKK model. Another important finding by Katsiampa (2019) is the significant effect of major news on conditional volatility and correlation.

Despite the common opinion among scholars that cryptocurrency volatility follows the patterns of more traditional currencies, an increasing number of studies suggest the opposite and advocate an atypical analysis of cryptocurrency volatility. In particular, Baur and Dimpfl (2018) analyzed asymmetric volatility effects for 20 cryptocurrencies and revealed different asymmetries compared to equity markets. Specifically, it was reported that positive shocks tend to increase volatility to a greater extent than negative shocks. Similarly, Conrad, Custovic, and Ghysels (2018) relied on the GARCH-MIDAS model to extract cryptocurrencies' long-term and short-term volatility elements. The researchers confirmed the negative and significant effect of the S&P 500 on the long-term volatility of the principal cryptocurrencies. This finding is irregular for volatility co-movements in financial markets. The atypical movement further suggested a close correlation between Bitcoin volatility and global economic activity, which provides a rationale for constructing improved forecasts of cryptocurrency volatility, which supports the findings of Walther, Klein, and Bouri (2018)' study. Although Corbet, Meegan, Larkin, Lucey, and Yarovaya (2018) provided evidence for the relative isolation of cryptocurrencies from traditional economic and financial assets and suggested that cryptocurrencies offer a short-term diversification benefit for investors. Other studies discuss the importance of the choice of analysis when predicting the volatility of cryptocurrencies. For example, Gurrib, Kweh, Nourani, and Ting (2019) analyzed returns associated with leading capitalized digital currencies. The researchers advised paying attention to the distinction between currency movements and world macroeconomic news because one of these factors could affect the behavior of cryptocurrencies. They also compared the efficacy of various models, concluding that autoregression models were more effective than vector autoregressive models in predicting one day ahead, whereas random walk approaches were the least effective.

Additionally, Trucíos (2019) explained that few researchers had questioned the predictability of risk measures. The study demonstrated that robust methods are more likely than non-robust ones to predict volatility and estimate the value at risk. The study emphasized that in forecasting and modelling Bitcoin risk measures, the presence of outliers plays an essential role that needs to be considered. Thus, identifying and recognizing the exogenous factors that affect cryptocurrencies will result in precise conclusions and findings.

Focusing on the predictability of volatility, Hafner (2018) applied time-varying volatility principles to cryptocurrencies and correlated volatility to the recent nature of ICO. In particular, Hafner (2018) discovered that more mature cryptocurrencies tend to be less volatile than those that have been launched relatively recently. Hafner (2018) assumed that cryptocurrencies have stochastic volatility changes that are typical for financial markets, even though high volatility alternates with low volatility in a random manner. The hypothesis tested by Hafner (2018) was based on a spline-GARCH model using the long-return of cryptocurrencies for analysis.

Additionally, using high-frequency data (thirty-minute returns), Akyildirim et al. (2019) analyzed the relationship between the price volatility of cryptocurrencies and the implied volatility of financial markets. The results confirmed the existence of strong correlations during periods of heightened financial market stress. However, in terms of informational efficiency, Bariviera, Zunino, and Rosso (2018) used high-frequency data to test whether cryptocurrencies have different unobservable dynamical structures compared to more traditional financial assets. Using permutation information theory quantifiers, Bariviera, Zunino, and Rosso (2018) noted the different dynamical structures of cryptocurrencies.

Correspondingly, the literature review revealed results relating to multifractality and financial environments. Mensi, Lee, Al-Yahyaee, Sensoy, and Yoon (2019) contributed to the existing scholarly knowledge by exploring high-frequency asymmetric multifractality, long memory, and the weak-form efficiency of Bitcoin and Ethereum. They adapted and combined the generalized Hurst exponent with the asymmetric multifractal detrended fluctuation analysis that took into account different market conditions. They used high-frequency data at 5, 10, and 15 minutes. The study findings suggested that Bitcoin and Ethereum markets have structural breaks and asymmetric multifractality for upward and downward-trending. In turn, Zhang, Chan, Chu, and Sulieman (2020) offered an interesting perspective on the functioning of cryptocurrencies in the complex bull and bear market. They employed specific algorithms to locate turning points associated with bull and bear phases in high-frequency environments. The researchers explained that market efficiency and the liquidity of cryptocurrencies play a role during turbulent periods in the market. Detrended-fluctuation analysis was one of the frameworks of choice for the researchers to arrive at their conclusions. The study emphasized the importance of the efficiency of cryptocurrency markets to determine the profit potential of trading strategies. Hence, considering the efficiency of cryptocurrency markets, structural breaks, and asymmetric multifractality enhances the scholar's understanding of the functioning of cryptocurrency markets.

A separate field of research on cryptocurrency volatility focuses on the correlation among specific cryptocurrencies and how they shape the volatility of each other. Using the three digital currencies with the highest capitalization (Bitcoin, Ethereum, and Ripple), Kyriazis, Daskalou, Arampatzis, Prassa (2019) observed and modeled the impact on other virtual currencies for the bearish market conditions from 1st January 2018 to 16th September 2018. The findings confirmed the complementarity of the majority of cryptocurrencies with Bitcoin, Ethereum, and Ripple. Furthermore, Katsiampa (2019) confirmed that Ether offers an effective hedge against Bitcoin.

Bitcoin is the main cryptocurrency of interest for researchers and scholars, as evidenced by the largest number of studies devoted to this digital asset (Catania & Sandholdt, 2019; Aysan et al., 2019). In a recent study, Catania and Sandholdt (2019) explored the behavior of Bitcoin returns at different sample frequencies. They concluded that high-frequency returns are accompanied by a smooth intra-daily seasonality pattern and abnormal trade/volatility intensity on Thursdays and Fridays. Reflecting on high-frequency data analysis, the researchers found no evidence to predict Bitcoin returns at or above one day, even though the researchers succeeded in tracing patterns for frequencies up to 6 hours. Among the important conclusions reached, the researchers mentioned that cryptocurrency volatility has a long memory, leverage effect, and lagged jumps have no impact. Catania and Sandholdt (2019) emphasized that Bitcoin volatility has become easier to predict since 2017, but prediction accuracy strongly depends on the length of the forecast horizon. They relied on several heterogeneous autoregressive specifications to build models on three different types of volatility. The results showed that long-term volatility had a significant impact on short-term traders. Also, seasonality has been explored in other research studies describing the field of cryptocurrencies. Specifically, Petrov, Golub, and Olsen (2019) study took seasonality into account to detail the newly developed intraday instantaneous volatility measure. The instantaneous volatility measure is based on draw-downs and draw-ups that serve as indicators of high-frequencies functioning within financial markets. Relying on weekly data, the study applied the described assessment to detect the volatility seasonality patterns of EUR/USD, EUR/JPY, and EUR/GBP rates, Bitcoin exchange rates, and the S&P 500 index. Computed in directional-change intrinsic time, the study demonstrates evidence of long memory related to instantaneous volatility. Exploring new patterns in cryptocurrency trading encourages scholars to investigate and focus on the factors that affect or influence cryptocurrency volatility.

3.1.REALIZED VOLATILITY:

Using the realized GARCH model to estimate Bitcoin returns' volatility better, Hung, Liu, and Yang (2020) provided some new exciting findings. Their first finding is that the jump-robust realized measure is more relevant and efficient in estimating Bitcoin volatility, and the realized measures deliver additional information on future volatility. Second, the Rational GARCH (RGARCH) model generates superior forecasting performance than the Standard GARCH (SGARCH) model for most cases, regardless of the volatility proxies. This finding supports Caporale and Zekokh (2019) 's study findings. Third, the RGARCH model leads to a substantial forecast error reduction relative to the GARCH model. Since the Mean Squared Error penalizes under/over predictions heavily, the forecast gains (benefit) of RGARCH models linked with the Mean Squared Error are marginally lower than those with the Mean Absolute Error. Fourth, the superior predictive ability test shows that the RGARCH model with tri-power variation generates a recovering performance in forecasting out-of-sample for Bitcoin volatility, especially during the increasing and decreasing markets. Fifth, because of the Bitcoin markets' recurrent jumps during the bearish market, the RGARCH model with jump-robust realized measures could provide stable forecasting performance. With these findings, it can be concluded that RGARCH with Mean Absolute Error can forecast better than the standard GARCH model when accounting for a better forecast for Bitcoin volatility.

Catania, Grassi, and Ravazzolo (2019) forecasted the prices of many cryptocurrencies, including Bitcoin, Litecoin, Ripple, and Ethereum, by evaluating the predictive abilities of several univariate and multivariate models. The study results show significant gains in forecasting two cryptocurrencies (Bitcoin and Ethereum) using combinations of univariate models and density predictions for all four cryptocurrencies depending on the time-varying multivariate models used.

Ma, Liang, Ma, and Wahab (2020) used the MRS-MIADS model to increase the prediction accuracy of Bitcoin's realised variance and validate whether or not the relevance of leaps for realised variance forecasting varies over time. The researchers wanted to improve the conventional Mixed-data sampling model (MIADS) by characterising distinct jump volatility regimes. They also wished to offer a time-varying jump-driven transition probability between the two regimes. In the in-sample estimate, their analysis indicated that the leaps had another predictive capacity for the future realised variance (RV) of Bitcoin for the Time-Varying Transition Probability-MIDAS-LCJ model. The predictive power shows high and low volatility regimes. The leverage effect has a detrimental impact on the one-step-ahead of Bitcoin realised variance in the low volatility regime.

Furthermore, in the out-of-sample evaluation, the Markov Regime-Switching-MIDAS model exhibits statistically significant improvement in forecasting the RV of Bitcoin. The researchers discovered that the jump-volatility predictive link had high and low volatility. Furthermore, the frequent occurrence of jumps considerably increases the persistence of the high-volatility regime and the transition between high and low-volatility regimes. As a result, while analysing cryptocurrency volatility, the jump-volatility predictive connection has to be accounted for and taken into account. They tested numerous multistep-ahead out-of-sample predictions and discovered that the suggested model significantly improved for 10-day-ahead (2 weeks) and 22-day-ahead (1 month) horizons. Furthermore, at the 5-day and 66-day timeframes, the FTP-MRS-MIDASLCJ model provides more precise out-of-sample forecasting performance.

Using five models, namely HAR-RV, HAR-CJ, LHAR-CJ, HAR-CJ-EPU, and LHAR-CJ-EPU, Yu (2019) found that the leverage effect has significantly impacted future Bitcoin volatility. Simultaneously, the jumps and economic policy uncertainty (EPU) did not influence the future volatility in-sample period. As a consequence, the Model Confidence Set (MCS) test findings show that the leverage effect outperforms jump components in forecasting Bitcoin volatility. As a result, the leverage effect offers useful predictive information for forecasting Bitcoin volatility.

Furthermore, incorporating the leverage effect and EPU into the benchmark model can boost prediction ability greatly. Thus, taking into account both the leverage impact and EPU can aid in forecasting Bitcoin volatility.

Another study that relied on realized volatility to evaluate the Bitcoin market's predictability has been conducted by Hattori (2019). The study relied on mean squared predictive error (MSE) and QLIKE measures to make forecast accuracy robust to noise in the imperfect volatility proxy. In contrast, different standards such as Mean Absolute Error (MAE), Theil Inequality Coefficient (TIC), and R-square (R2) are also used for the robustness check. The study findings show that asymmetric volatility models such as APARCH and EGARCH have additional predictive power, and the normal distribution is likely to fit the Bitcoin data better. Nevertheless, to improve the prediction accuracy, analysis of other models, such as the Heterogeneous Autoregressive (HAR) model, is essential in future research to predict cryptocurrency volatility.

Jha and Baur (2020) separated the realized volatility into good and bad volatility and a continuous and jump component within a HAR–QR framework. The researchers found that bad volatility is less significant than good volatility in predicting future volatility on average but not in all volatility regimes in 1-day ahead forecast horizons. However, in 7-day ahead forecast horizons, the bad volatility increases volatility more than good volatility. Also, the strength of the asymmetry increases with volatility as well. Moreover, the unstable asymmetric volatility and the relatively poor predictive power of the models compared with the equity market indicates that the excess volatility is an incomplete characterization of Bitcoin. The researchers also addressed that excess volatility is less of a problem if it is persistent and predictable. Still, they found that volatility is too high and volatile, and the drivers of volatility do not have a stable influence over different volatility regimes.

Soylu, Okur, Çatıkkas, and Altintig (2020) study took into consideration the long-memory properties of these cryptocurrencies and examined the market efficiency. The study findings show that the cryptocurrency market has a long memory. Therefore, long memory indicates inefficiency in the cryptocurrency market, where the estimated memory in volatility can help investors capture speculative profits. The study also found that the HYGARCH model appears to be the best-fitted model for Bitcoin, as testified by the AIC, SW, SB, and H-Quinn criteria and Log-likelihood. Moreover, to improve the performance of modelling cryptocurrencies with GARCH models, long memory should be considered. On the other hand, for Ethereum, the FIGARCH model with skewed student distribution delivers better estimations. Also, the excellent fit for Ripple returns is the FIGARCH model with student distribution. As a result, the models that consider volatility clustering, asymmetry, and long memory in the cryptocurrency volatilities can more accurately predict the VaR and ESF for short and long trading positions.

Wang, Liu, Chiang, and Hsu's (2019) study used realised volatility derived from high-frequency data to evaluate model performance as a proxy for Bitcoin volatility rather than daily squared returns. The researchers next investigated the models' capacity to anticipate rolling sample volatility for Bitcoin returns using ARJI, GARCH, EGARCH, and CGARCH. According to the study results, the ARJI model with jump dynamics delivers comparatively improved in-sample goodness-of-fit and out-of-sample predictive performance. However, the GARCH-employed models can marginally explain the Bitcoin prices' realized volatility because of the exceptionally volatile swings in the cryptocurrency market. Moreover, by applying Bayesian VAR, Bayesian VAR-SV, Bayesian VAR-GARCH, and Bayesian VAR-SVt models, Bohte and Rossini (2019) found that using a combination of stochastic volatility and a Student-t distribution, there are statistically significant improvements in point of forecasting for all the cryptocurrencies. Also, the stochastic volatility model provides the best predictability in density forecasting for all cryptocurrencies.

3.2.PORTFOLIO SELECTIONS:

Cryptocurrencies have exhibited remarkable performance in financial markets due to their main advantages: the investors control them exclusively of any regulatory rules in transactions. Also, third-party costs on transactions can be significantly reduced. That has been the main reason for the rapid development of the cryptocurrency market over the past ten years. Therefore, cryptocurrencies have gained enormously in market value through enormous inflows of capital and strong price fluctuations. Thus, cryptocurrency markets have become gradually attractive to investors considering cryptocurrencies as a novel class of alternative investments. In fact, as mentioned before, Wu and Pandey (2014) concluded that although Bitcoin is not useful as a currency, it can be useful and play an essential role in increasing an investor's portfolio's efficiency. That study was supported by Baur, Hong, and Lee (2018), who demonstrated that Bitcoin accounts are primarily used as an investment tool rather than an alternative currency. Also, Kristoufek (2015) found that Bitcoin reveals properties of both traditional and speculative financial assets. Nevertheless, the potential role of Cryptocurrencies in investors' portfolios has not been fully understood and remains controversial.

Petukhina, Trimborn, Härdl, and Elendner (2020) consider the benefit for different types of investors when adding cryptocurrencies to a well-diversified portfolio of conventional financial assets. At different frequencies, namely daily, weekly, and monthly, the researchers have considered risk-averse, return-maximizing, and diversification-seeking investors. In their study, the researchers aimed to analyze standard asset allocation models' performance based on historical prices and trading volumes of 52 cryptocurrencies combined with 16 traditional assets. The researchers found that traditional risk-minimizing strategies, such as minimum-variance and minimum-CVaR, did not significantly improve investment performance because of the volatility structure of cryptocurrencies. On the other hand, approaches with high target returns, such as diversification-seeking portfolios, reach higher expected returns for investors through broader cryptocurrency exposure.

Moreover, the study shows that constraints mitigating liquidity risks of cryptocurrencies (LIBRO) can significantly affect strategies that rely on a larger cross-section of cryptocurrencies. Similarly, the out-of-sample performance drops considerably for portfolios as small as USD 10. Simultaneously, the diversification benefits persist coherently across all frameworks.

Mba, Edson, and Koumba (2018) stated that It is essential to develop portfolio optimization methods to assist cryptocurrency investors in controlling their exposure risk while maximizing their returns. The researchers applied two approaches that were obtained from the traditional Differential Evolution (DE) method: the GARCH Differential Evolution (GARCH-DE) and the GARCH Differential Evolution t-copula (GARCH-DE-t-copula). The researcher then contrasts these two models with the Differential Evolution (DE) method (benchmark) in single and multi-period optimization on a portfolio containing five crypto-assets under the coherent risk measure CVaR constraint. The study findings show that GARCH-DE-t-copula outperforms the Differential Evolution and GARCH-DE approaches in single and multi-period frameworks. The researchers also used the GARCH Differential Evolution t-copula method (GARCH-DE-t-copula) to confirm the power of regular rebalancing of portfolio assets to adapt to market changes. Also, the tail dependence modeling through t-copula and extreme value distribution (GPD) has revealed a significant positive impact on the portfolio returns across all multi-period optimization periods and in the control of the risk because of the high volatility that illustrates cryptocurrencies.

By analyzing the daily returns of the common cryptocurrencies: Bitcoin, Ethereum, Bitcoin Cash, XRP, Litecoin, and NEM, Hrytsiuk, Babych, and Bachyshyna (2019) confirm cryptocurrency returns are not subject to normal distribution, yet the Cauchy distribution can describe their returns. The study aimed to use the Cauchy distribution function to get the analytical expressions for VaR risk measures and performed calculations of cryptocurrency risk assessment utilizing the VaR approach. Therefore, sets of optimal cryptocurrency portfolios were built. Also, using the modified Markowitz model, the efficient frontiers of cryptocurrency portfolios were constructed. Bitcoin prearranges its dominance in the cryptocurrency portfolio due to its high return and low risk.

Liew, Li, Budavári, and Sharma (2019) have examined the most extensive 100 cryptocurrency returns ranging from 2015 to early 2018. They focused on analyzing daily returns and found several interesting stylized facts. The first fact is that principal components analysis provides a complicated daily return-generating process. Surprisingly, The researchers found that more than one principal component explains the cross-sectional variation. The second fact is that cryptocurrency returns suffer from the "beta-in-the-tails" hidden risk similar to hedge fund returns. Third, the researchers found that using machine learning and artificial intelligence algorithms to predict cryptocurrency movements is slightly attractive with the disparity in predictability power for each cryptocurrency. Fourth, cryptocurrencies with lower volatility are marginally more predictable than cryptocurrencies with higher volatility. Fifth, predictability might be more complicated given a set of machine learning algorithms when the ability of distinct information sets differs across machine learning algorithms. Finally, near-term cryptocurrency markets are semi-strong form efficient because the predictability is very weak for the short term. Therefore, trading cryptocurrencies would be challenging for investors lacking experience in investing and evaluating investment opportunities.

Yang and Zhao (2020) employed ten criteria, including the Log of the last day of market capitalization, to analyze daily data from the 100 biggest cryptocurrencies. To construct the efficient sorting portfolios and the quantile-based sorting portfolios, the previous day's low price, the maximum price during the previous week, one-week momentum, two-week momentum, three-week momentum, one-month momentum, Log of average daily volume during the previous week, Log of average daily volume times price, and Log of average daily volume times price scaled by market capitalization were used. The researchers discovered that just two criteria, the most outstanding price over the previous week and the close price of the previous day, adequately capture cross-sectional variations and anticipate future returns.

Liu (2019) aimed to examine the inevitability and the role of diversification in cryptocurrencies as an alternative investment asset class. The researcher also applied the portfolio selection theory to determine if there is an advantage in the cryptocurrency market. The study findings show that diversification among cryptocurrencies significantly improves the Sharpe ratio and utility. By comparing the out-of-sample performance of six classical asset allocation models, namely the 1/N rule, Minimum variance, Risk parity, Markowitz, Maximum Sharpe, and Maximum utility, it is found that the minimum variance model is less risky with the most negligible maximum drawdown. Also, the maximum utility model holds higher returns and utility. However, most models cannot outperform the naïve 1/N rule under the Sharpe ratio criterion. These findings can be an excellent help for investors to make more informed decisions.

Using daily data from September 2015 to June 2018, Boako, Tiwari, and Roubaud (2019) applied vine copula approaches to model six cryptocurrencies' co-dependence and portfolio value-at-risk (VaR), namely Bitcoin, Ethereum, Litecoin, Dash, Ripple, and Stellar. The study findings show that using the efficient frontier, Ethereum provides the best optimal and economically risk-reward trade-off dependent on a no-shorting constraint for portfolio investors. Also, the study findings show strong dependencies between Bitcoin and Ethereum. Additionally, the study shows that the most connected cryptocurrencies to Bitcoin are Litecoin, Ripple, and Dash. Essentially, Litecoin has the only direct dependence on Bitcoin. The researchers modelled the portfolio VaR based on the dependencies obtained from depending on the R-vine copula's ability and the majority of the Student-t copula family in modelling dependence. The results show that the Value at Risk forecasts closely follow the daily returns with limited violations.

Moreover, the researchers conclude that their vine copula models are the best-suited models to compute the portfolio VaR during the considered period. The study analysis proposes the best optimal and economically risk-reward trade-off dependent on portfolio investors' shorting limitation using the efficient frontier. The study also offers new useful insights for investors willing to speculate or hedge positions using cryptocurrencies, not only for investors but also for regulators such as financial market authorities, central banks, or policymakers willing to reduce the systemic risks.

Platanakis and Urquhart (2019) compared the performance of naive diversification, Markowitz diversification, and the advanced Black–Litterman model and variance-based constraints that control estimation errors in a cryptocurrency portfolio. The study findings show that using the advanced Black–Litterman model with variance-based constraints yields superior out-of-sample risk-adjusted returns with lower risks. This finding indicates that when managing cryptocurrency portfolios, applying sophisticated techniques that control estimation errors is prioritized, especially with transaction costs and short-selling.

By using six optimization strategies, namely MinVar, MinCVaR, MaxSR, MaxSTARR, MaxUT, and MaxMean, TOMIĆ (2020), study findings show limited exposure to changes in the value of BTC presented as a systematic factor can lead to having higher returns and Sharpe Ratios in four of the six implemented optimization strategies. However, in terms of absolute risk, five of the six portfolios reached an overall lower risk. Therefore, achieving a higher cumulative return, lower risk, and better overall portfolio performance is possible by controlling the portfolio exposure based on the systematic factor represented by Bitcoin cryptocurrency. From that result, it is possible to conclude that it would be perfect for portfolio managers to hedge their position at negative returns and make the most of the factor's dependence during its positive momentum.

Kurosaki and Kim (2020) investigate four major cryptocurrencies' portfolio optimization: BTC, ETH, LTC, and XPR. In their study, the researchers applied generalized autoregressive conditional heteroscedasticity (GARCH) model with multivariate normal tempered stable (MNTS). Also, they have optimized the portfolio in terms of Foster-Hart risk. The study findings show that introducing the multivariate normal tempered stable (MNTS) distribution enhances the illustrative power of the GARCH-type model for cryptocurrency return and risk forecasting. As a result, the multivariate normal tempered stable (MNTS) distribution GARCH model fits better with cryptocurrency returns than the competing GARCH-type models. The study findings confirm that combining the multivariate normal tempered stable (MNTS) distributed GARCH model and Foster-Hart risk aims at desirable portfolio optimization concerning risk-return balance and cumulative returns.

4. RESEARCH GAP AND CONTRIBUTION

Because cryptocurrencies are still relatively new compared to traditional financial instruments, there remains limited empirical research concerning their trading and volatility. Although some research studies emphasize the additional risk such investments might pose to investors in developing economies, numerous researchers recognize the various benefits cryptocurrencies offer. Thus, understanding and predicting the volatility of cryptocurrencies using high-frequency data will reveal the usefulness and benefits for potential investors. Therefore, this research will examine the capability and accuracy of forecasting and prediction abilities of six different models. These models have been selected based on the recommendations of previous literature and studies. Each model captures and accounts for different aspects. It sets out to confirm which models offer the best fit to forecast the volatility of cryptocurrencies. This study's contribution focuses on applying the most prominent volatility forecasting models based on previous studies, where the study compares models across models to identify the models that outperform in predicting the volatility of cryptocurrency returns. Also, more contributions go towards high-frequency data of the dominant cryptocurrency returns that have the highest market cap and less dominant cryptocurrency returns to provide valuable insights to investors, portfolio managers, financial firms, and regulators.

Additionally, the research field has a gap in the scientific literature because insufficient attention has been devoted to cryptocurrencies other than Bitcoin, Ethereum, Litecoin, and Ripple. As such, there is inadequate knowledge about the volatility of less dominant cryptocurrencies. Therefore, the current research will strive to contribute to the literature by testing the less dominant cryptocurrencies. It provides significant insights into possible price movements, allowing investors and traders to make more educated decisions and efficiently manage risk. Also, it contributes to boosting market efficiency by increasing awareness of the underlying dynamics of less dominant cryptocurrencies, resulting in better price discovery. Not only that but also it contributes to enabling the development of risk management techniques customized to the specific features of these cryptocurrencies, which improves overall portfolio performance. Finally, anticipating volatility in less dominant cryptocurrencies leads to a more mature and stable crypto-system, attracting a broader spectrum of investors and promoting long-term sustainability. This will help scholars with future investigations and assist investors and corporations in shaping their investment decisions.

4.1.Research Question

What is the best-fitted model to predict the volatility of cryptocurrencies?

4.2. Research objectives

1. Identify the best-fitted model to predict cryptocurrency volatility.
2. Predict the volatility of both the dominant and less dominant cryptocurrencies.
3. Predict cryptocurrency volatility using high-frequency data.

5. METHODOLOGY

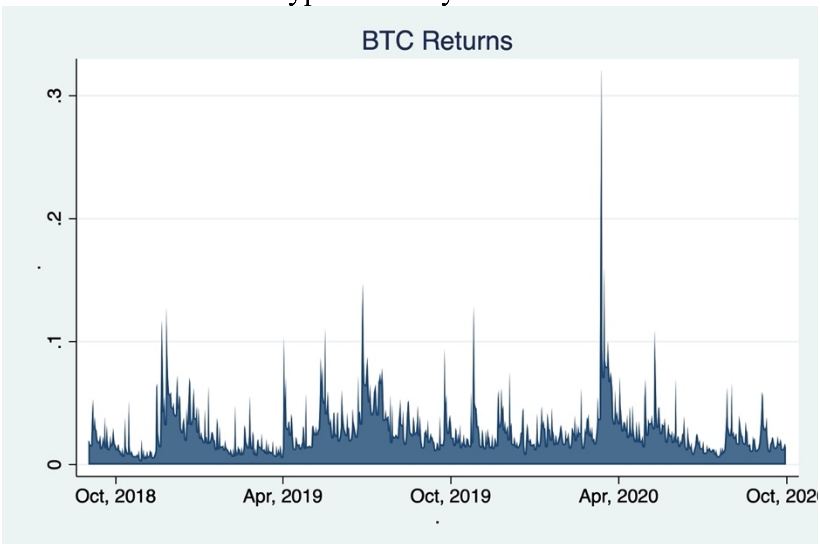
5.1. RESEARCH DESIGN

Predicting cryptocurrency volatility using high-frequency data depends on selecting a suitable methodology that produces valuable and accurate findings. The extensive use of academic resources that support analytical approaches contributes to producing and communicating results that can be used in the real world. Specifically, lagged realized volatility (LRE), the GARCH model, the IGARCH model, the EGARCH model, the GJR-GARCH model, and the heterogeneous autoregressive (HAR) model are the frameworks applied in the current study. These models have been chosen based on previous literature and the contribution of Kourtis, Markellos, and Symeonidis's (2016) study. Their study has inspired the research's methodology design. Although their study has been applied to 13 international equity indices, some of the models they used apply to the research dataset and field. Some models they used do not apply to our study since they used option prices. Some models they used do not apply to our study since they used option prices. Therefore, three models have been adapted and inspired by different studies such as the GARCH and IGARCH models from Chu, Chan, Nadarajah, and Osterrieder (2017) research and the EGARCH model from Petrică and Stancu's (2017) research. Each model has advantages and characteristics that improve the research's primary aim to find the best-fitted model to forecast the volatility of cryptocurrency returns. Each model will be explained in detail in the following sections.

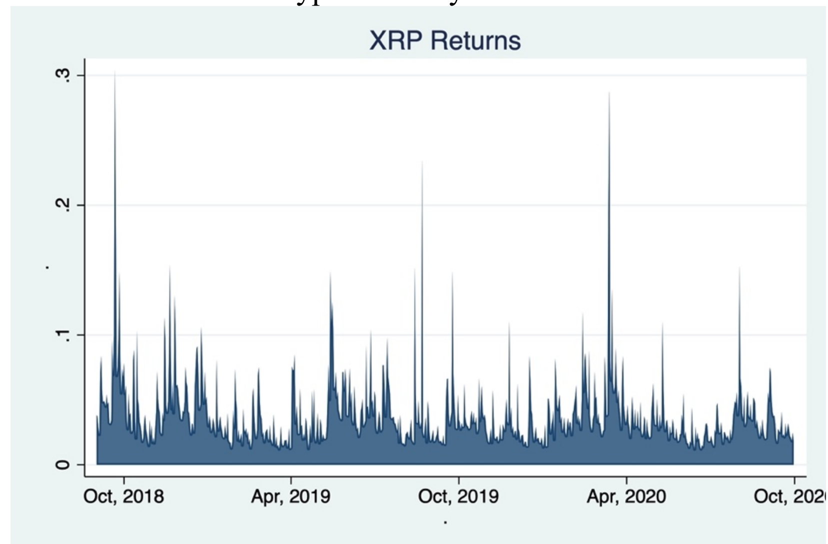
5.2. DATA COLLECTION

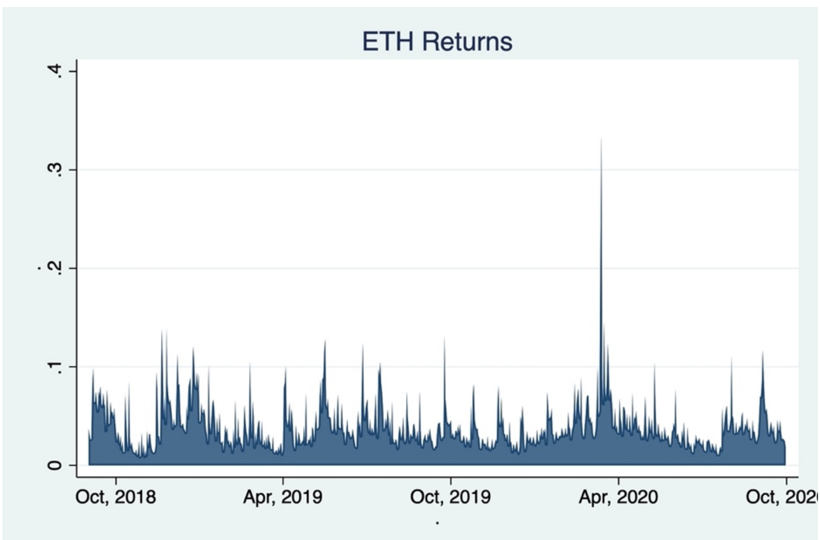
This research uses daily, weekly, and monthly historical data computed from 5-minute log returns for the following 10 cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), Bitcoin Cash (BTH), Eos (EOS), Monero (XMR), Stellar (XLM), Dash (DASH), and Ethereum Classic (ETC) between 1st September 2018 to 30th September 2020 (Table A). These cryptocracies have chosen based on market capitalizations that vary from dominant to less dominant cryptocurrencies. The data were obtained from https://www.kraken.com. Here are the cryptocurrency returns figures.

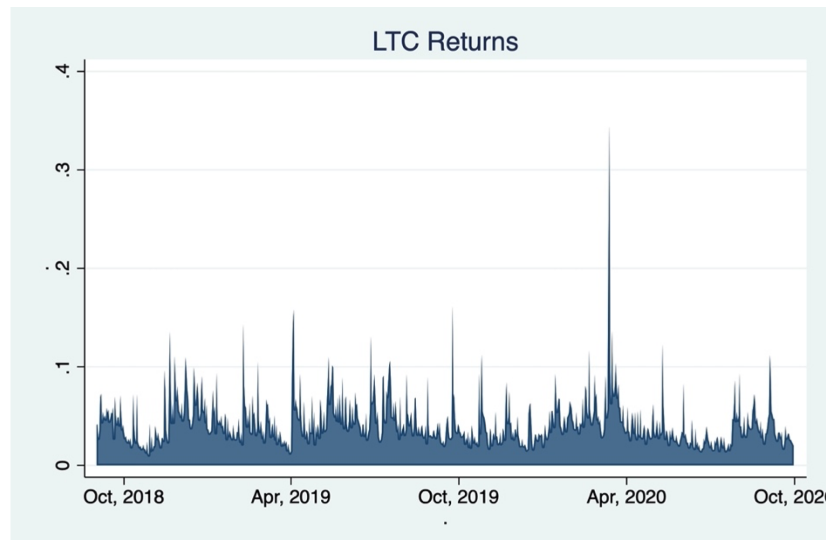
Cryptocurrency Returns



Cryptocurrency Returns

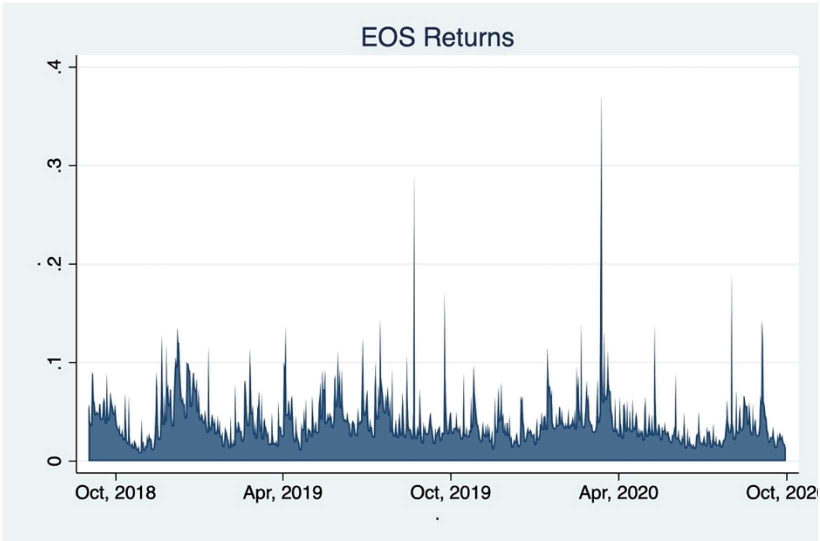


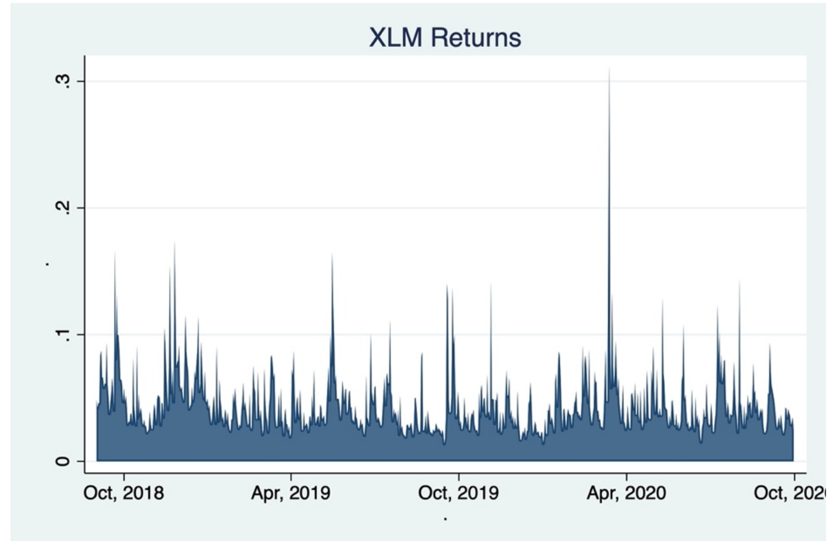


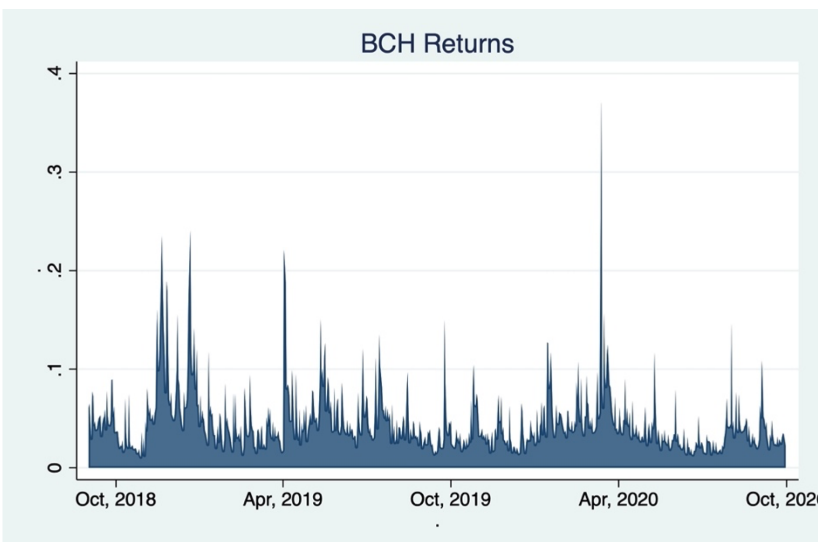


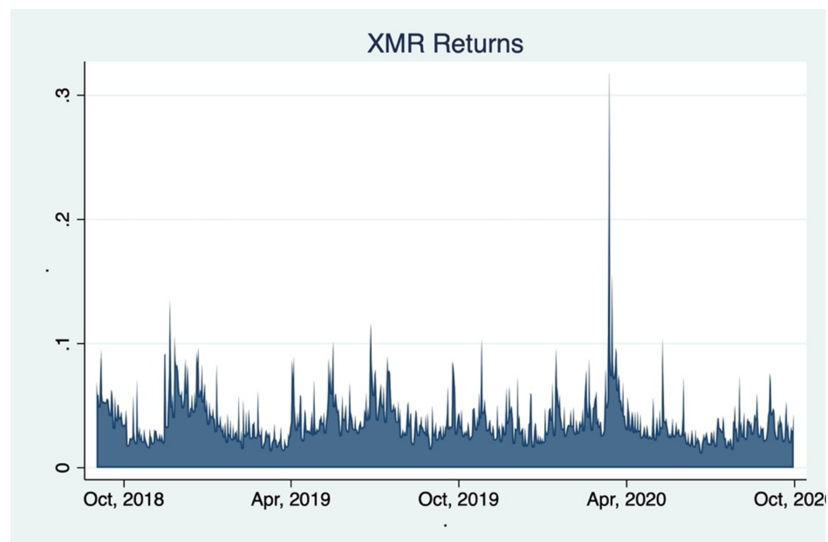
Cryptocurrency Returns

Cryptocurrency Returns

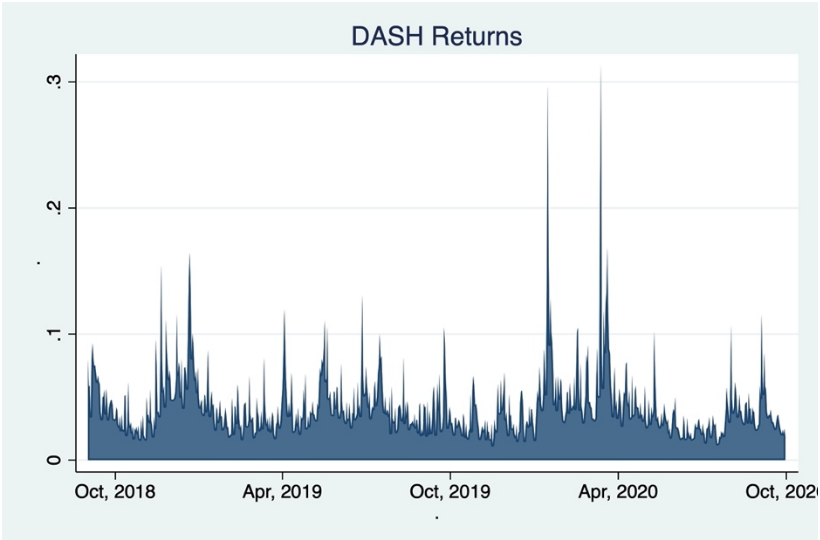




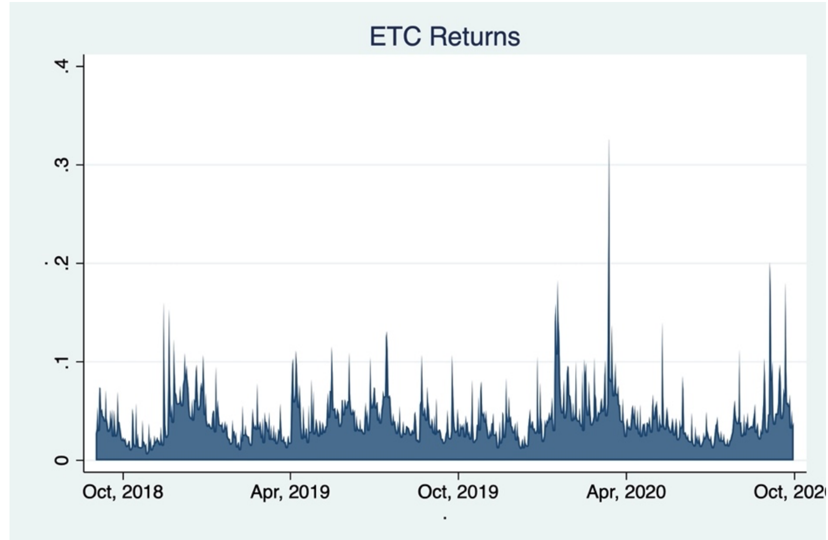




Cryptocurrency Returns



Cryptocurrency Returns



5.3. VOLATILITY FORECAST MODELS

5.3.1. Lagged Realised Volatility (LRE) Model

LRE is one of the methods used for financial instrument predictions. For this reason, its consideration in the present research is justified by the necessity to predict the volatility of cryptocurrencies. Kaminska and Roberts-Sklar (2018) explained that the LRE model considers the regular array of short-term predictive aspects, including a variable representing volatility persistence. Also, Sensoy and Omole (2018) point out that volatility becomes persistent when lagged realized volatility is significant.

Moreover, the ability of LRE to explain high-frequency data has been confirmed in recent academic research. Huang, Tong, and Wang (2019) emphasized that the findings of their study supported the hypothesis that taking into account realized volatility contributes to producing superior predictions. In particular, quarterly and yearly data on lagged realized volatility describe the long-term dynamics of volatility. Periods of high volatility are particularly well explained with the help of the LRE framework. Given that the model is gaining momentum among financial academics, its use for analyzing cryptocurrency behavior will likely improve our understanding of innovative currencies. Because the cryptocurrency market experiences high levels of volatility, the capacity of LRE to analyze such data makes the model a relevant and justifiable approach to employ. According to Kourtis, Markellos, and Symeonidis (2016), the realized volatility is calculated as follows:

$$RV_t = \sqrt{\sum_{j=1}^{m} r_{tj}^{2}} \tag{1}$$

Therefore, the lagged realized volatility can be calculated:

$$LRE = \sqrt{\sum_{j=1}^{m} r_{t-1}^{2}} \tag{2}$$

As Kourtis, Markellos, and Symeonidis (2016) explained, these variables are crucial because they are based on the assumption that volatility occurs within a Markov process, which signifies that its period is predictive of future data.

5.3.2. GARCH Model

The Autoregressive Conditional Heteroskedasticity (GARCH) model can capture the clustering in volatility. Although the GARCH model has been criticized by many studies, as mentioned in the literature review section, it would be wise to consider it when comparing the research models since we are using the GARCH models. The GARCH model equation is as follows (Bollerslev, 1986):

$$\sigma_t^2 = \omega + \alpha_1 Z_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (3)$$

The $\alpha_1 + \beta_1$ coefficients accounts for the sum of volatility clustering that is captured by the model. Also, when considering the $\alpha_1 + \beta_1 < 1$, that means there is a weak stationarity.

5.3.3. EGARCH Model

The development of the GARCH model created a foundation for similar frameworks to appear as financial scientists sought to avoid the limitations of the original model. In particular, Nelson (1991) proposed the Exponential Generalised Autoregressive Conditionally Heteroscedastic (EGARCH) model to tolerate the asymmetric effects of negative and positive innovations, make the conditional variance positive by construction and include exogenous variables in the volatility equation. Also, the development of the EGARCH equation was required due to restrictions related to non-negativity found in the original model because EGARCH could provide information about the volatility of currencies from the perspective of asymmetry. Brandt and Jones (2006) emphasized that the EGARCH model has important features capable of capturing the negative correlation with returns, time-series clustering, lognormality, and under certain specifications, long memory. Whereas some equational processes generate data based on symmetry, EGARCH specifically uses asymmetrical concepts. Petrică and Stancu (2017) explained that the exponential nature of this GARCH model creates the logarithm of conditional variance that considers asymmetric information related to good news and bad news. The EGARCH model equation is expressed as follows (Petrică and Stancu, 2017):

$$\log(\sigma_t^2) = \omega + \sum_{i=1}^{q} \alpha_i \frac{|\varepsilon_{t-i}|}{\sigma_{t-i}} + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} + \sum_{j=1}^{p} \beta_j \log(\sigma_{t-j}^2) \qquad (4)$$

The γ_k signifies the asymmetry parameter which is the leverage effect. If the γ_k do not equal to zero that indicates the presence of asymmetry. However, if the $\gamma_k < 0$ that means the volatitiy increases more after bad news that is represented in ($\varepsilon_{t-1} < 0$) and good news represented in ($\varepsilon_{t-1} > 0$)

5.3.4. Integrated GARCH Model

The Integrated GARCH (IGARCH) model offers additional insights into forecasting the behavior of cryptocurrencies with the help of high-frequency data. Like EGARCH, the IGARCH framework relies on the original GARCH model, and the unit-root nature of GARCH models is seen in IGARCH. Also, Bentes (2015) emphasized that IGARCH accounts for the influences of past squared shocks with persistent data that remain essential to forecasting future time horizons. Chu, Chan, Nadarajah, and Osterrieder (2017) state that structural changes, such as policy changes, have not been accounted for, which might justify why the IGARCH model can be a good fit for several cryptocurrencies. Moreover, Kumar and Anandarao (2019) used the IGARCH model in their study to capture the persistence in volatility for cryptocurrency returns.

Mikosch and Starica (2004) express the IGARCH equation as follows:

$$\begin{aligned} &\alpha_t = \sigma_t Z_t \\ &\sigma_t^2 = \alpha_0 + \alpha_1 \alpha_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (5) \\ &t \in \mathbb{Z}, \end{aligned}$$

5.3.5. GJR-GARCH Model

The GJR-GARCH model is another approach capable of predicting the cryptocurrency market's volatility using high-frequency data. The framework assumes that forecasts should depend on time-conditional variance. The original use of GJR-GARCH focused on multiple functions, including the volatility of stock returns. Innovations in the financial field require future studies to embrace the applicability of GJR-GARCH for the cryptocurrency market. Typically, investors use the GJR-GARCH to explore compensation opportunities for holding volatile assets. The original GARCH model underwent multiple alterations to meet the needs of financial researchers, whereas GJR-GARCH created a platform for the current variance with a different response to the returns of the past (Nugroho et al., 2019). GARCH models have been extensively used to examine the behaviour of volatile markets.

Furthermore, the main advantage of this model rests on its ability to analyze asymmetric behaviours (Nugroho et al., 2019). Asymmetric volatility may play a role in cryptocurrency markets. Klein, Thu, and Walther (2018) claimed that the property occurs when negative and positive returns are connected to upward and downward revisions of conditional volatility, respectively. Also, Klein, Thu, and Walther (2018) observed that although cryptocurrencies (specifically Bitcoin) exhibit a low leverage effect, an inverse leverage effect, and substantial long memory are typical of the leading digital currencies. Importantly, exploring the property of asymmetric volatility will be possible based on applying the GJR-GARCH model..

The GJR-GARCH model is as the following equations by Kourtis, Markellos, and Symeonidis (2016):

$$h_t = \omega + \alpha e_{t-1}^2 + \gamma I_{\{e_{t-1}<0\}e_{t-1}^2} + \beta h_{t-1} \quad (6)$$

The e_t is the residuals from the mean equation $r_t = u + e_t$. Also, u is the unconditional mean of the return series. The conditional variance of the residuals is h_t. The $I_{\{e_{t-1}<0\}}$ is marker function that equivalents to 1 if the prior period innovation is negative and zero otherwise.

5.3.6. Heterogeneous Autoregressive Model

Ultimately, using the HAR model could also make a valuable contribution to efforts to reveal the future outlook for cryptocurrencies. Audrino and Knaus (2016) pointed out that the HAR model can estimate long memory and highlight good out-of-sample performance. Also, McAleer and Medeiros (2008) emphasized that the HAR model can estimate the long memory behavior and describe the sign and size asymmetries. These qualities have made the model popular among financial researchers. The ease with which the approach can be applied is its primary advantage when researching volatile markets. Correspondingly, the HAR model has succeeded in exploring realized volatility.

Researchers can employ multiple datasets when studying volatility based on Kourtis, Markellos, and Symeonidis (2016) work. The results can potentially model the long-term behaviour of volatility that confirms the success of forecasting properties. Kourtis, Markellos, and Symeonidis (2016) used the HAR model to apply additive elements created by utilizing high-frequency data for daily, weekly, and monthly volatilities. This approach ensures that long-memory behaviours are noted. While the model has been used to analyze stock markets, its insightful use in volatile fields makes the model a feasible option for exploring cryptocurrency markets. At the same time, the HAR model is known for using historical high-frequency data for model specification, while its simplicity can also be considered a limitation. Other models provide comprehensive data to address this limitation because focusing on three methods would constitute a holistic approach. The daily HAR-RV model is expressed as the following equation by Kourtis, Markellos, and Symeonidis (2016):

$$RV_{t:t+k} = \omega + \beta_d RV_t + \beta_w RV_{t-7:t} + \beta_m RV_{t-30:t} + e_{t+k} \tag{7}$$

6. Information Content of The Volatility Forecasts

6.1. Univariate Regressions

In the univariate regressions, the Mincer and Zarnowitz (1969) regressions have been applied to the 10 cryptocurrencies using the total sample for each research model to evaluate each model's ability to forecast the volatility accurately. Also, Mincer and Zarnowitz (1969) regressions can evaluate the information content of individual volatility forecasts (Kourtis, Markellos, and Symeonidis, 2016). The Mincer and Zarnowitz (1969) regressions formula can be as follows:

$$RV_{t:t+k} = \alpha + \beta \hat{F}_{t:t+k} + e_t \tag{8}$$

The $\hat{F}_{t:t+k}$ stands for the k-day ahead forecast from the respective volatility forecasting model to evaluate the in-sample fit. If the regression Equation (8) coefficient is statistically different from zero, a forecast is instructive about future volatility. With Mincer and Zarnowitz (1969) regressions, the Newey–West (1987) heteroskedasticity and autocorrelation consistent standard errors have been used for all forecast horizons.

Table 1 shows the results of the Mincer-Zarnowitz Regression with Newey-West Standard Errors for a 1-day forecast horizon. In the table, the $\alpha + \beta + adj.R^2$ coefficient estimates, which are presented along with the t-statistic in parenthesis. The aggregate estimations for each model's coefficient are presented at the table's end.

The results of the 1-day horizon regression table show that all slope coefficient estimates for the 10 cryptocurrency returns are statistically significant at the 5% level. Hence, it can be indicated that all forecasts have informative information about future volatility. Also, the results show different coefficient values for each cryptocurrency. Three different models outperformed and fit several cryptos, namely GARCH, EGARCH, and HAR models. When considering only the adjusted R^2 values, it can be noticed that only three models dominated the explanatory power for different cryptos. The HAR model has the most explanatory power among the three models, with 4 out of 10 cryptocurrency returns (40%). That means the HAR model has superiority over the remaining models. this result supports the results of the 1-day forecast of Kourtis et al., 2016 study. However, their study examined the equity indices.

Subsequently, the GARCH model has explanatory power for 2 of the 10 cryptocurrency returns (20%). Finally, the EGARCH and GJR-GARCH models have explanatory power for the remaining cryptos, 2 out of 10 cryptocurrency returns (20%), respectively. These results support the outcome that many studies have emphasized the need for more agreement among researchers regarding which model is most suitable and applicable to the volatility analysis of cryptocurrencies.

Table 2 displays the results of the Mincer-Zarnowitz Regression with Newey-West Standard Errors for a 7-days forecast horizon. In the table, the $\alpha + \beta + adj.R^2$ coefficient estimates, which are presented along with the t-statistic in parenthesis. The aggregate estimations for each model's coefficient are presented at the table's end.

The results of the 7-day horizon regression table show that all slope coefficient estimates for the 10 cryptocurrencies are statistically significant at the 5% level. Therefore, it can be indicated that all forecasts have informative information about future volatility. Also, the results show different coefficient values for each cryptocurrency in terms of the $adj.R^2$. Only three of the six models have outperformed and fit several cryptos: EGARCH, GJR-GARCH, and HAR. To illustrate, when considering only the adjusted R^2 values, it can be observed that three models dominated the explanatory power for all the cryptocurrencies. The EGARCH model has the most explanatory power among the three models for 7 out of 10 cryptocurrency returns (70%). That means the EGARCH has superiority over the remaining models. This result challenge the study' findings of Kourtis et al., 2016. They have found that the an implied models are more accurate for longer periods when forecasting the volatility of equity indices. Then, the HAR model lies second with 2 out of 10 cryptocurrency returns (20%). Finally, the GJR-GARCH model has explanatory power for only 1 out of 10 cryptocurrency returns (10%).

Table 3 reveals the results of the Mincer-Zarnowitz Regression with Newey-West Standard Errors for a 30-day forecast horizon. The coefficient estimates are presented in parentheses along with the t-statistic. The aggregate estimations for each model's coefficient are presented at the table's end.

Unlike the 1-day and 7-day horizons, the 30-day horizon regression table results show that most slope coefficient estimates for the 10 cryptocurrencies are statistically significant at the 5% level. Thus, it can be indicated that all forecasts have informative information about future volatility. Also, the results show different coefficient values for each cryptocurrency in terms of the $adj.R^2$. Only three out of six models outperformed and fit several cryptos, namely EGARCH, IGARCH, and HAR models. To demonstrate, when accounting only for the adjusted values, it can be noticed that three models controlled the explanatory power for different cryptos. The EGARCH model has the most explanatory power among the three models, with 8 out of 10 cryptocurrency returns (80%). That means the EGARCH has superiority over the remaining models. This result contradict the study' findings of Kourtis et al., 2016. They have found that the an implied models are more accurate for longer periods when forecasting the volatility of equity indices. Then, the HAR model lies second with 1 out of 10 cryptocurrency returns (10%). Lastly, the IGARCH model has the explanatory power for only 1 out of 10 cryptocurrency returns (10%).

6.2. Encompassing Regressions

The encompassing regression is an extension of the univariate regression equation. The encompassing regressions replace the individual forecasts on the right side of Equation (8) to have a duo of forecasts from two different volatility models in these regressions. The encompassing regression equation can be expressed as follows:

$$RV_{t:t+k} = \alpha + \beta_1 \hat{F}_{t:t+k} + \beta_2 \hat{F}_{t:t+k} + e_t \tag{9}$$

The $\beta_1 \hat{F}_{t:t+k}$ stands for the k-day ahead forecast for the first model from the respective volatility forecasting models in the research to evaluate the in-sample fit. Also, The $\beta_2 \hat{F}_{t:t+k}$ stands for the k-day ahead forecast for the second model from the separate volatility forecasting models. As Cook (2014) stated, forecasting encompassing allows a direct comparison of two sets of projections to see if one is informative content outweighs the other, making it redundant. The dominating set of projections is said to forecast the other in such circumstances. As a result, using forecast-encompassing regressions as a supplement to evaluation statistics gives an alternative and essential additional source of information. Whereas assessment statistics can provide a rating of predictions, forecast-encompassing tests can be used to determine the extent to which one group of projections is superior to another.

Table 4 shows the results of the encompassing regressions with Newey-West Standard Errors for a 1-day forecast horizon. In the table, the $\alpha + \beta_1 + \beta_2 + adj.R^2$ coefficients estimates are presented along with the t-statistic in parenthesis. The aggregate estimations for each model's coefficient are presented at the table's end. Table 4 contains two panels of models. The first panel combines the Lagged Realized Volatility model (LRE) with the rest except the HAR model. The LRE and HAR models are related to each other. The second panel combines the Heterogeneous Autoregressive (HAR) model with the rest except the LRE model. It can be observed from Table 4, encompassing regressions results for 1-day horizons, that most of the slope coefficient estimates are statistically significant at a 5% level.

Consequently, it can be indicated that all forecasts have informative information about future volatility. Furthermore, the results show different coefficient values for each combination of models in terms of $adj.R^2$. When considering only the adjusted R^2 values, it can be observed that model diversity dominated the explanatory power for all the cryptocurrencies. To illustrate, the HAR + EGARCH models have the most explanatory power among the other pairs of models, with 4 out of 10 cryptos (40%). That means the HAR + EGARCH pair has superiority over the remaining pairs of models. Then, LRE + GARCH models lay second with 2 out of 10 cryptos (20%). The HAR + GJR-GARCH rest third with 2 out of 10 cryptos (20%). Finally, LRE + EGARCH pair and LRE + GJR-GARCH pairs come last with 1 out of 10 cryptos each (10%). It is worth noticing that if the analysis were divided into two clusters and evaluated separately, the outcomes for the dominations pairs would be almost the same pairs across all cryptocurrency returns with 8 out of 10 cryptos (80%). For example, if the LRE + EGARCH pair is the dominant pair for BTC in terms of $adj.R^2$. The second group would also be HAR + EGARCH pair.

Table 5 shows the results of the encompassing regressions for 7-day horizons. Most slope coefficient estimates are statistically significant at the 5% level. Hence, it can be implied that all forecasts have informative information about future volatility. Besides, the results show different coefficient values for each combination of models in terms of $adj.R^2$. When considering only the adjusted R^2 values, it can be observed that model diversity dominated the explanatory power for all the cryptocurrencies. However, the variety in models that dominated the explanatory power is less than the results presented in Table 4 (1-day horizons). To illustrate, the HAR + EGARCH pair has the most explanatory power among the other pairs of models, with 7 out of 10 cryptocurrency returns (70%). That means the HAR + EGARCH pair has superiority over the remaining pairs of models. Then, LRE + EGARCH pair follows with 2 out of 10 cryptocurrency returns (20%). The HAR + GJRGARCH set third with 1 out of 10 cryptocurrency returns (10%).

Same as in Table 4, it is worth noticing that if the analysis were divided into two clusters and evaluated separately, the outcomes of the dominations of pairs would be almost the same across all cryptos, with 8 out of 10 cryptos (80%). For example, if the LRE + EGARCH pair is the dominant pair for BTC in terms of $adj. R^2$, the second group would also be HAR + EGARCH pair.

Table 6 shows the results of the encompassing regressions for 30-day horizons. Almost half of the slope coefficients are statistically significant at the 5% level. Therefore, it can be implied that all forecasts have instructive information about future volatility. Further, the results show different coefficient values for each combination of models in terms of the $adj. R^2$. When considering only the adjusted R^2 values, t can be seen that there is diversity in models that dominated the explanatory power for all the cryptocurrencies. However, the diversity in models that dominated the explanatory power is less than the results presented in Table 4 (1-day horizons) and the same as Table 5 (7-day horizons) with only one difference. To illustrate, the HAR + EGARCH pair has the most explanatory power among the other pairs of models, with 5 out of 10 cryptocurrency returns (50%). That means the HAR + EGARCH pair has superiority over the remaining pairs of models. Then, LRE + EGARCH and HAR + IGARCH pairs follow with 4 out of 10 cryptocurrency returns (40%) and 1 out of 10 cryptocurrency returns (10%), respectively.

Unlike Table 4 (1-day horizon) and Table 5 (7-day horizons) results, table 6 results have an interesting similarity in the dominating pairs across all cryptos if the analysis is divided into two clusters and evaluated separately. The outcomes of the dominations of pairs are the same across all cryptos, with 9 out of 10 cryptocurrency returns (90%). For example, if the LRE + EGARCH pair is the dominant pair for BTC in terms of the adjusted R^2, the second group would also be HAR + EGARCH pair.

7. Out of Sample Forecasts Evaluation:

The out-of-sample forecast evaluations will validate the results generated from the univariate and encompassing regressions. For this step, examining the competing models' out-of-sample predicting accuracy will be performed. In order to do so, the two commonly utilized loss functions are the root mean squared error (RMSE), and the quasi-likelihood loss function (QLIKE) will be used. These are described as follows:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(RV_{t:t+k} - \hat{F}_{t:t+k})^2} \tag{10}$$

$$\text{QLIKE} = \frac{1}{N}\sum_{t=1}^{N}\left[\log \hat{F}_{t:t+k} + \frac{RV_{t:t+k}}{\hat{F}_{t:t+k}}\right] \tag{11}$$

The N accounts for the number of out-of-sample volatility forecasts. These two-loss functions have been chosen based on previous studies. Patton (2011) stated that the Quasi-Likelihood (QLIKE) loss function can be robust to the existence of noise in the volatility proxy. Also, the root-mean-square error (RMSE) is a wide choice in an empirical application. The Diebold–Mariano (DM) predictive accuracy test has been applied to determine the forecast errors between the applied models and whether they are statistically significant (Diebold & Mariano, 1995).

In this analysis, the researcher applied the rolling window approach of 300 observations to forecast the out-of-sample volatility for all 10 cryptocurrencies. Table 7 shows the results of the out-of-sample forecasting performance for 1-Day Horizon. The table consists of two panels. The first panel is the root mean squared errors (RMSE) loss function, and the second is the Quasi-Likelihood (QLIKE) loss function. The lowest forecast error results for RMSE and QLIKE have been highlighted in bold. Also, based on the DM test, the models with higher forecast errors and are more statistically significant than the best models are signaled with one, two, and three asterisks (10%, 5%, and 1%). From the table, it can be observed that the Heterogeneous Autoregressive Model (HAR) is the superior model among the other models, with 6 out of 10 (10 out of 10) cryptocurrency returns for RMSE (QLIKE) loss functions. This result supports Bergsli, Lind, Molnár, and

Polasik (2021) study's findings. Based on daily data, they concluded that the HAR models based on realized variance outperform the GARCH models. The lowest forecast error results for RMSE and QLIKE have been highlighted in bold. All the models are inferior to the HAR model for LTC, BCH, EOS, XLM, DASH, and ETC cryptos. The HAR model yields the lowest forecast errors compared to the other models. However, for BTC, ETH, and XMR cryptos, the EGARCH model is the superior model among the different models and yields the lowest forecast errors. At the same time, the IGARCH model has the worst performance among the other models for both the RMSE and QLIKE performances, followed by LRE and GJR-GARCH models with equally divided between the 10 cryptos for RMSE and GJR-GARCH model for most of the cryptos in terms of QLIKE. It is worth noticing that when observing the worst models for RMSE, the dominant cryptos have the LRE as a common model that has the worst forecast errors after the IGARCH, while the less dominant cryptos have the GJR-GARCH as the common model that has the worst forecast errors after the IGARCH in terms of RMSE performance. Therefore, as a result of all of the above analysis, it can be observed that the HAR model yields the best forecast errors when predicting most of the less dominant cryptocurrencies, while the EGARCH model yields the best forecast errors when predicting the dominant cryptocurrencies such as the BTC, ETH, and XRP.

However, when comparing the results of Table 7 with Table 8, which presents out-of-sample forecasting performance: 7-Day Horizon, it can be seen that there is a slight change in the superior model among the other models for RMSE and QLIKE. To illustrate, the superior model for the RMSE is still a Heterogeneous Autoregressive Model (HAR). The HAR model is considered the best model when considering the lowest forecast errors for them. It has insufficient forecast errors for ETH, XRP, BCH, XLM, DASH, and ETC. The EGARCH model for LTC, EOS, XMR, and GARCH model for BTC follows them. In comparison, the IGARCH model has the worst performance among the other models for both the RMSE and QLIKE performances, followed by LRE (GJR-GARCH) for RMSE and GJR-GARCH (LRE) for QLIKE. It is worth noticing that when observing the worst models for RMSE, the LRE model dominated most of them. Therefore, it can be stated that when considering only the historical prices, the forecasting errors would be higher than the other model subject to this study regarding RMSE performance. These results primarily support the 1-day horizon performance for the RMSE and QLIKE.

Interestingly, the results for Table 9 show the Out-of-Sample Forecasting Performance: 30-Day Horizon, indicating similar outcomes as Tables 7 and 8 with a slight difference. All the models are inferior to the HAR model for BTC, ETH, XRP, XMR, XLM, DASH, and ETC cryptos. The HAR model yields the lowest forecast error compared to the other models for RMSE, followed by GJR-GARCH for BCH and EOS and EGARCH for LTC regarding the RMSE performance. With a slight change, the ETH, EOS, XRP, XMR, XLM, DASH, and ETC cryptos have the HAR model as the superior model in terms of QLIKE, followed by LRE for BCH, GJR-GARCH for LTC, and GARCH for BTC. Nonetheless, the IGARCH exhibits the lowest forecast error for both performance criteria, followed by LRE, GJR-GARCH, GARCH, and HAR for RMSE performance. Also, for QLIKE performance, the LRE, GJR-GARCH, GARCH, and EGARCH have the worst forecast errors. Therefore, it can be stated that the HAR model is the best model when forecasting the volatility for most of the cryptos in this research, with the lowest forecast errors for the RMSE and QLIKE.

8. Limitations

When examining the breadth of research, it is critical to recognize some limitations. While the dataset is extensive, it does not include data from the during-COVID-19 and post-COVID-19 periods. A dataset containing the COVID-19 pandemic would acquire a more thorough understanding of how the COVID-19 pandemic, as an external factor, affects the volatility of cryptocurrency returns. In addition, for analyzing realized volatility, the research focused on six models from the GARCH family. Future studies might go beyond this selection, perhaps revealing innovative methods for more accurate prediction of cryptocurrency return volatility. It is also worth noting that the research looked particularly at 10 cryptocurrency results only. The dataset should be expanded to cover a larger spectrum of cryptocurrency returns. Adding more cryptocurrency returns to the dataset offers the potential to improve the precision of our findings. The large amount of data, which exceeded 100 million observations, created considerable time limitations. As a consequence, we chose only 10 cryptocurrency returns for the research.

9. Conclusion

This study evaluates the performance of different models regarding the best-fitted model to predict the volatility forecasts of 10 cryptocurrencies with different Market capitalizations. The study presents the results of the univariate regressions using the Mincer and Zarnowitz (1969) regressions with the Newey–West (1987) heteroskedasticity and autocorrelation consistent standard errors. It compares the results of six different models: GARCH, IGARCH, EGARCH, GJR-GARCH, LRE, and HAR. The univariate regressions for 1-day horizons indicate the superiority of the HAR model over the remaining models. However, the univariate regressions for 7-day horizons show that the EGARCH model has the most explanatory power among all the research models. Also, the univariate regressions for 30-day horizons reveal that the EGARCH model has the most explanatory power among all the research models. Also, the study presented the results of the encompassing regressions. The encompassing regressions allow a direct comparison of two sets of projections to see if one is informative content outweighs the other, making it redundant (Cook, 2014). The encompassing regressions with Newey-West Standard Errors for a 1-day forecast horizon show that the HAR + EGARCH models have the most explanatory power among the other pairs of models. Similarly, the encompassing regressions with

Newey-West Standard Errors for the 7-day forecast horizon reveal that the HAR + EGARCH pair has the most explanatory power among the other pairs of models. Too, the encompassing regressions with Newey-West Standard Errors for the 30-day forecast horizon show that the HAR + EGARCH models have the most explanatory power among the other pairs of models.

The study also performed the out-of-sample regressions using the RMSE and QLIKE loss functions. The result of the out-of-sample regressions for 1-day horizons indicated that the HAR model has the lowest forecast errors among the research's models for both the RMSE and QLIKE loss functions. Also, the results are almost the same for 7-days horizons. Nevertheless, the out-of-sample regressions for 30 days revealed a slight difference from the daily and weekly results. The HAR model mostly outperformed the other models yielding the lowest forecast errors for RMSE and QLIKE loss functions. These findings support Bergsli, Lind, Molnár, and Polasik (2021) study's findings. Further studies should measure the prediction of cryptocurrency volatility and its effect on market performance.

References

Abakah, E.J.A., Gil-Alana, L.A., Madigu, G. and Romero-Rojo, F., 2020. Volatility persistence in cryptocurrency markets under structural breaks. *International Review of Economics & Finance*, *69*, pp.680-691

Akyildirim, E., Corbet, S., Lucey, B., Sensoy, A. and Yarovaya, L., 2019. The relationship between implied volatility and cryptocurrency returns. *Finance Research Letters.*

Audrino, F. and Knaus, S.D., 2016. Lassoing the HAR model: A model selection perspective on realized volatility dynamics. *Econometric Reviews, 35(8-10)*, pp.1485-1521.

Aysan, A.F., Demir, E., Gozgor, G. and Lau, C.K.M., 2019. Effects of the geopolitical risks on Bitcoin returns and volatility. *Research in International Business and Finance, 47,* pp.511-518.

Bariviera, A.F., Zunino, L. and Rosso, O.A., 2018. An analysis of high-frequency cryptocurrencies prices dynamics using permutation-information-theory quantifiers. *Chaos: An Interdisciplinary Journal of Nonlinear Science, 28(7),* p.075511.

Baur, D.G. and Dimpfl, T., 2018. Asymmetric volatility in cryptocurrencies. *Economics Letters, 173,* pp.148-151.

Bentes, S.R., 2015. Forecasting volatility in gold returns under the GARCH, IGARCH and FIGARCH frameworks: New evidence. Physica A: Statistical Mechanics and its Applications, 438, pp.355-364.

Bergsli, L.Ø., Lind, A.F., Molnár, P. and Polasik, M., 2021. Forecasting volatility of Bitcoin. *Research in International Business and Finance*, p.101540

Boako, G., Tiwari, A.K. and Roubaud, D., 2019. Vine copula-based dependence and portfolio value- at-risk analysis of the cryptocurrency market. *International Economics*, *158*, pp.77-90.

Bohte, R. and Rossini, L., 2019. Comparing the forecasting of cryptocurrencies by Bayesian time varying volatility models. *Journal of Risk and Financial Management*, *12*(3), p.150.

Bollerslev, Tim. 1986. Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics 31:* 307–27.

Brandt, M.W. and Jones, C.S., 2006. Volatility forecasting with range-based EGARCH models. Journal of Business & Economic Statistics, 24(4), pp.470-486.

Caporale, G.M. and Zekokh, T., 2019. Modelling volatility of cryptocurrencies using Markov Switching GARCH models. *Research in International Business and Finance, 48,*

Catania, L. and Sandholdt, M., 2019. Bitcoin at High Frequency. *Journal of Risk and Financial Management, 12(1),* p.36.

Catania, L., Grassi, S. and Ravazzolo, F., 2019. Forecasting cryptocurrencies under model and parameter instability. *International Journal of Forecasting*, *35*(2), pp.485-501.

Catania, L. and Grassi, S., 2022. Forecasting cryptocurrency volatility. *International Journal of Forecasting*, *38*(3), pp.878-894.

Cheah, E.T. and Fry, J., 2015. Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economics letters, 130*, pp.32-36.

Cheung, A., Roca, E. and Su, J.J., 2015. Crypto-currency bubbles: an application of the Phillips-Shi-Yu (2013) methodology on Mt. Gox bitcoin prices. *Applied Economics*, *47*(23), pp.2348- 2358.

Chu, J., Chan, S., Nadarajah, S. and Osterrieder, J., 2017. GARCH modelling of cryptocurrencies. *Journal of Risk and Financial Management, 10(4)*, p.17.

Conrad, C., Custovic, A. and Ghysels, E., 2018. Long-and short-term cryptocurrency volatility components: A GARCH-MIDAS analysis. *Journal of Risk and Financial Management, 11(2)*, p.23.

Cook, S., 2014. Forecast encompassing tests as a means of forecast comparison. *The Economic Network.*

Corbet, S., Lucey, B. and Yarovaya, L., 2018. Datestamping the Bitcoin and Ethereum bubbles. *Finance Research Letters*, *26*, pp.81-88.

Corbet, S., McHugh, G. and Meegan, A., 2017. The influence of central bank monetary policy announcements on cryptocurrency return volatility. *Investment management and financial innovations, (14, Iss. 4)*, pp.60-72.

Corbet, S., Meegan, A., Larkin, C., Lucey, B. and Yarovaya, L., 2018. Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters, 165,* pp.28-34.

Gurrib, I., Kweh, Q.L., Nourani, M. and Ting, I.W.K., 2019. Are cryptocurrencies affected by their asset class movements or news announcements? *Malaysian Journal of Economic Studies, 56(2),* pp.201-225.

Hafner, C., 2018. Testing for bubbles in cryptocurrencies with time-varying volatility. *Available at SSRN 3105251.*

Hansen, P.R. and Lunde, A., 2005. A forecast comparison of volatility models: does anything beat a GARCH (1, 1)? *Journal of applied econometrics, 20(7),* pp.873-889.

Hattori, T., 2020. A forecast comparison of volatility models using realized volatility: evidence from the Bitcoin market. *Applied Economics Letters*, *27*(7), pp.591-595.

Hrytsiuk, P., Babych, T. and Bachyshyna, L., 2019, September. Cryptocurrency portfolio optimization using Value-at-Risk measure. In *6th International Conference on Strategies, Models and Technologies of Economic Systems Management (SMTESM 2019) (pp. 385-389). Atlantis Press.*

Huang, Z., Tong, C. and Wang, T., 2019. VIX term structure and VIX futures pricing with realized volatility. *Journal of Futures Markets, 39(1),* pp.72-93.

Hung, J.C., Liu, H.C. and Yang, J.J., 2020. Improving the realized GARCH's volatility forecast for Bitcoin with jump-robust estimators. *The North American Journal of Economics and Finance*, *52*, p.101165.

Jha, K.K. and Baur, D.G., 2020. Regime-Dependent Good and Bad Volatility of Bitcoin. *Journal of Risk and Financial Management*, *13*(12), p.312.

Kaminska, I. and Roberts-Sklar, M., 2018. Volatility in equity markets and monetary policy rate uncertainty. *Journal of Empirical Finance, 45,* pp.68-83.

Katsiampa, P., 2017. Volatility estimation for Bitcoin: A comparison of GARCH models. *Economics Letters, 158,* pp.3-6.

Katsiampa, P., 2019. Volatility co-movement between Bitcoin and Ether. *Finance Research Letters, 30,* pp.221-227.

Katsiampa, P., Corbet, S. and Lucey, B., 2019. High frequency volatility co-movements in cryptocurrency markets. *Journal of International Financial Markets, Institutions and Money, 62,* pp.35-52.

Klein, T., Thu, H.P. and Walther, T., 2018. Bitcoin is not the New Gold–A comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis, 59,* pp.105-116.

Kourtis, A., Markellos, R.N. and Symeonidis, L., 2016. An international comparison of implied, realized, and GARCH volatility forecasts. *Journal of Futures Markets, 36(12),* pp.1164-1193.

Kristoufek, L., 2015. What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis. *PloS one*, *10*(4), p.e0123923.

Kumar, A.S. and Anandarao, S., 2019. Volatility spillover in crypto-currency markets: Some evidences from GARCH and wavelet analysis. Physica A: Statistical Mechanics and its Applications, 524, pp.448-458.

Kurosaki, T. and Kim, Y.S., 2020. Cryptocurrency portfolio optimization with multivariate normal tempered stable processes and Foster-Hart risk. *arXiv preprint arXiv:2010.08900*.

Kyriazis, N.A., Daskalou, K., Arampatzis, M., Prassa, P. and Papaioannou, E., 2019. Estimating the volatility of cryptocurrencies during bearish markets by employing GARCH models. *Heliyon, 5(8),* p.e02239.

Liew, J., Li, R.Z., Budavári, T. and Sharma, A., 2019. Cryptocurrency investing examined. *The Journal of The British Blockchain Association*, p.8720.

Liu, W., 2019. Portfolio diversification across cryptocurrencies. *Finance Research Letters*, *29*, pp.200-205.

Luther, W.J. and White, L.H., 2014. Can bitcoin become a major currency?.

Ma, F., Liang, C., Ma, Y. and Wahab, M.I.M., 2020. Cryptocurrency volatility forecasting: A Markov regime-switching MIDAS approach. *Journal of Forecasting*, *39*(8), pp.1277-1290.

Mba, J.C., Pindza, E. and Koumba, U., 2018. A differential evolution copula-based approach for a multi-period cryptocurrency portfolio optimization. *Financial Markets and Portfolio Management*, *32*(4), pp.399-418.

McAleer, M. and Medeiros, M.C., 2008. A multiple regime smooth transition heterogeneous autoregressive model for long memory and asymmetries. *Journal of Econometrics, 147(1),* pp.104-119.

Mensi, W., Al-Yahyaee, K.H. and Kang, S.H., 2019. Structural breaks and double long memory of cryptocurrency prices: A comparative analysis from Bitcoin and Ethereum. *Finance Research Letters*, *29*, pp.222-230.

Mensi, W., Lee, Y.J., Al-Yahyaee, K.H., Sensoy, A. and Yoon, S.M., 2019. Intraday downward/upward multifractality and long memory in Bitcoin and Ethereum markets: An asymmetric multifractal detrended fluctuation analysis. *Finance Research Letters, 31,* pp.19-25.

Mensi, W., Sensoy, A., Aslan, A. and Kang, S.H., 2019. High-frequency asymmetric volatility connectedness between Bitcoin and major precious metals markets. *The North American Journal of Economics and Finance, 50,* p.101031.

Mikosch, T. and Stărică, C., 2004. Nonstationarities in financial time series, the long-range dependence, and the IGARCH effects. Review of Economics and Statistics, 86(1), pp.378-390.

Mincer, J., & Zarnowitz, V. (1969). The evaluation of economic forecasts. In J. Zarnowitz (Ed.), Economic forecasts and expectations. New York: National Bureau of Economic Research.

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

Nelson, D.B., 1991. Conditional heteroskedasticity in asset returns: A new approach. Econometrica: Journal of the Econometric Society, pp.347-370.

Nugroho, D.B., Kurniawati, D., Panjaitan, L.P., Kholil, Z., Susanto, B. and Sasongko, L.R., 2019, August. Empirical performance of GARCH, GARCH-M, GJR-GARCH and log-GARCH models for returns volatility. *In Journal of Physics: Conference Series (Vol. 1307, No. 1, p. 012003).* IOP Publishing.

Patton, A. J. (2011). Volatility forecast comparison using imperfect volatility proxies. *Journal of Econometrics, 160, 246*–256.

Petrică, A.C. and Stancu, S., 2017. Empirical Results of Modeling EUR/RON Exchange Rate using ARCH, GARCH, EGARCH, TARCH and PARCH models. Romanian Statistical Review, (1).

Petrov, V., Golub, A. and Olsen, R., 2019. Instantaneous Volatility Seasonality of High-Frequency Markets in Directional-Change Intrinsic Time. *Journal of Risk and Financial Management, 12(2),* p.54.

Platanakis, E. and Urquhart, A., 2019. Portfolio management with cryptocurrencies: The role of estimation risk. *Economics Letters*, *177*, pp.76-80.

Sensoy, A. and Omole, J., 2018. Implied volatility indices: A review and extension in the Turkish case. *International Review of Financial Analysis, 60,* pp.151-161.

Soylu, P.K., Okur, M., Çatıkkaş, Ö. and Altintig, Z.A., 2020. Long Memory in the Volatility of Selected Cryptocurrencies: Bitcoin, Ethereum and Ripple. *Journal of Risk and Financial Management*, *13*(6), p.107.

Tomić, B., 2020, June. BITCOIN: Systematic Force of Cryptocurrency Portfolio. In *FEB Zagreb 2020 11th International Odyssey Conference on Economics and Business*.

Trucíos, C., 2019. Forecasting Bitcoin risk measures: A robust approach. *International Journal of Forecasting, 35(3)*, pp.836-847.

Walther, T. & Klein, T., Bouri, E., 2018. Exogenous Drivers of Cryptocurrency Volatility – A Mixed Data Sampling Approach to Forecasting. *SSRN Electronic Journal*.

Wang, J.N., Liu, H.C., Chiang, S.M. and Hsu, Y.T., 2019. On the predictive power of ARJI volatility forecasts for Bitcoin. *Applied Economics*, *51*(44), pp.4849-4855.

Wu, C.Y., Pandey, V.K., 2014. The value of Bitcoin in enhancing the efficiency of an investor's portfolio. *Journal of financial planning, 27(9),* pp.44-52.

World Bank Analysis, https://www.worldbank.org/en/publication/fintech-and-the-future-of finance.

Yang, Y. and Zhao, Z., 2020. Large cryptocurrency-portfolios: efficient sorting with leverage constraints. *Applied Economics*, pp.1-14.

Yu, M., 2019. Forecasting Bitcoin volatility: The role of leverage effect and uncertainty. *Physica A: Statistical Mechanics and its Applications*, *533*, p.120707.

Zhang, Y., Chan, S., Chu, J. and Sulieman, H., 2020. On the Market Efficiency and Liquidity of High-Frequency Cryptocurrencies in a Bull and Bear Market. *Journal of Risk and Financial Management, 13(1),* p.8.

Chapter Two Research Tables

Table A: List of the Cryptocurrencies: Start and End dates.

Cryptocurrency	**Symbol**	**Start Date**	**End Date**	**Number of observations in 5-min**	**Number of observations in days**
Bitcoin	BTC	9/1/2018	9/30/2020	219,200	761
Ethereum	ETH	9/1/2018	9/30/2020	219,200	761
Ripple	XRP	9/1/2018	9/30/2020	219,200	761
Litecoin	LTC	9/1/2018	9/30/2020	219,200	761
Bitcoin Cash	BCH	9/1/2018	9/30/2020	219,200	761
EOS	EOS	9/1/2018	9/30/2020	219,200	761
Monero	XMR	9/1/2018	9/30/2020	219,200	761
Stellar	XLM	9/1/2018	9/30/2020	219,200	761
Dash	DASH	9/1/2018	9/30/2020	219,200	761
Ethereum Classic	ETC	9/1/2018	9/30/2020	219,200	761

Table B: Descriptive Analysis of the Daily Data

	Mean	Median	SD	Kurtosis	Skewness	Range
BTC	0.030	0.024	0.024	35.91	4.20	0.32
ETH	0.041	0.035	0.025	25.36	3.30	0.32
XRP	0.040	0.032	0.028	23.31	3.74	0.29
LTC	0.044	0.038	0.025	28.44	3.53	0.33
BCH	0.049	0.039	0.034	15.66	3.07	0.36
EOS	0.045	0.037	0.029	28.50	3.78	0.36
XMR	0.041	0.035	0.022	37.80	4.00	0.31
XLM	0.046	0.039	0.025	19.16	3.09	0.30
DASH	0.045	0.038	0.027	24.06	3.59	0.30
ETC	0.046	0.039	0.028	16.30	2.88	0.32

Table C: Descriptive Analysis of the Weekly Data

	Mean	Median	SD	Kurtosis	Skewness	Range
BTC	0.086	0.075	0.054	12.26	2.74	0.43
ETH	0.115	0.103	0.055	8.18	2.09	0.42
XRP	0.115	0.099	0.060	6.50	2.12	0.41
LTC	0.124	0.116	0.053	9.18	2.05	0.43
BCH	0.137	0.120	0.078	5.05	2.05	0.46
EOS	0.128	0.113	0.061	7.01	1.91	0.46
XMR	0.112	0.099	0.047	11.80	2.59	0.38
XLM	0.129	0.115	0.052	5.34	1.81	0.38
DASH	0.125	0.109	0.061	7.06	2.27	0.41
ETC	0.129	0.113	0.061	4.43	1.67	0.39

Table D: Descriptive Analysis of the Monthly Data

	Mean	Median	SD	Kurtosis	Skewness	Range
BTC	0.188	0.169	0.092	3.05	1.55	0.51
ETH	0.246	0.226	0.087	2.50	1.29	0.53
XRP	0.246	0.223	0.090	1.15	0.96	0.50
LTC	0.264	0.256	0.085	2.33	0.89	0.53
BCH	0.297	0.255	0.129	0.55	1.06	0.63
EOS	0.275	0.269	0.094	1.48	0.71	0.55
XMR	0.236	0.219	0.079	2.83	1.44	0.47
XLM	0.274	0.261	0.077	1.07	0.74	0.46
DASH	0.265	0.243	0.103	1.00	1.08	0.55
ETC	0.277	0.256	0.097	0.11	0.76	0.50

Table 1: Mincer-Zarnowitz Regression with Newey-West Standard Errors for 1-day forecast horizon.

Cryptocurrency	GARCH	IGARCH	EGARCH	GJR-GARCH	LRE	HAR
BTC						
α	**-0.022** (-4.14)	**-0.007** (-1.99)	**-0.029** (-4.89)	**-0.0193** (-3.70)	**0.011** (4.81)	0.000 (-0.000)
β	**1.474** (9.14)	**0.955** (9.27)	**1.672** (9.46)	**1.394** (8.93)	**0.637** (7.56)	**1.000** (9.38)
$adj. R^2$	47.45%	48.53%	50.08%	47.51%	40.49%	43.74%
ETH						
α	**-0.028** (-3.59)	-0.004 (-0.92)	**-0.039** (-4.45)	**-0.024** (-3.05)	**0.016** (5.46)	0.000 (-0.000)
β	**1.464** (8.38)	**0.876** (8.25)	**1.701** (8.76)	**1.378** (7.86)	**0.606** (7.74)	**1.000** (8.48)
$adj. R^2$	41.04%	36.18%	40.89%	40.21%	36.60%	38.40%
XRP						
α	**-0.013** (-2.14)	0.000 (0.03)	**-0.015** (-2.48)	-0.010 (-1.68)	**0.018** (7.61)	0.000 (0.000)
β	**1.247** (8.07)	**0.867** (8.20)	**1.303** (8.43)	**1.183** (7.57)	**0.531** (7.95)	**1.000** (7.74)
$adj. R^2$	33.43%	31.99%	33.30%	32.05%	28.15%	26.50%
LTC						
α	**-0.029** (-2.80)	0.000 (0.07)	**-0.039** (-3.58)	**-0.026** (-2.55)	**0.019** (6.14)	0.000 (0.000)
β	**1.464** (6.73)	**0.809** (6.70)	**1.662** (7.35)	**1.406** (6.56)	**0.551** (7.02)	**1.000** (7.85)
$adj. R^2$	33.97%	20.31%	35.74%	34.29%	30.31%	32.58%
BCH						
α	**-0.029** (-3.06)	-0.003 (-0.60)	**-0.030** (-4.07)	**-0.029** (-3.09)	**0.015** (5.15)	0.000 (0.000)
β	**1.367** (7.64)	**0.823** (8.28)	**1.385** (9.68)	**1.372** (7.67)	**0.674** (9.66)	**1.000** (10.85)
$adj. R^2$	37.32%	34.33%	36.88%	37.62%	45.37%	47.43%
EOS						
α	**-0.048** (-3.68)	-0.003 (-0.50)	**-0.051** (-4.42)	**-0.047** (-3.28)	**0.023** (6.62)	0.000 (-0.000)
β	**1.767** (6.89)	**0.855** (6.81)	**1.841** (7.99)	**1.743** (6.25)	**0.482** (5.81)	**1.000** (6.66)
$adj. R^2$	23.75%	15.80%	22.90%	24.43%	23.11%	24.87%
XMR						
α	-0.005 (-0.91)	0.005 (1.32)	-0.007 (-1.17)	-0.004 (-0.70)	**0.015** (4.70)	0.000 (0.000)
β	**1.038** (7.52)	**0.732** (7.60)	**1.083** (7.54)	**1.010** (7.39)	**0.613** (6.94)	**1.000** (8.50)
$adj. R^2$	40.84%	40.63%	39.64%	41.10%	37.59%	40.37%
XLM						
α	-0.012 (-1.76)	**2.632** (2.51)	**-0.021** (-2.65)	**-0.014** (-1.98)	**0.020** (7.88)	0.000 (0.000)
β	**1.214** (7.85)	**-52.985** (-2.46)	**1.409** (7.98)	**1.257** (7.91)	**0.546** (8.90)	**1.000** (8.92)
$adj. R^2$	31.31%	1.11%	31.27%	31.56%	29.78%	30.72%

Table 1 (Continued)

Cryptocurrency	GARCH	IGARCH	EGARCH	GJR-GARCH	LRE	HAR
DASH						
α	0.001 (0.24)	0.006 (1.87)	-0.004 (-0.99)	0.000 (0.17)	**0.014** (5.20)	0.000 (-0.000)
β	**0.890** (9.51)	**0.729** (9.54)	**1.016** (9.90)	**0.900** (9.29)	**0.667** (9.33)	**1.000** (10.27)
$adj.R^2$	43.16%	40.99%	39.90%	41.39%	44.50%	45.86%
ETC						
α	**-0.013** (-2.09)	0.004 (1.19)	**-0.024** (-3.65)	**-0.013** (-2.17)	**0.018** (7.09)	0.000 (0.000)
β	**1.168** (8.95)	**0.730** (9.18)	**1.403** (9.92)	**1.177** (9.07)	**0.596** (9.69)	**1.000** (11.00)
$adj.R^2$	33.45%	33.83%	34.25%	33.14%	35.52%	38.29%
Aggregate Results						
Average α	-0.020	0.263	-0.026	-0.019	0.017	0.000
Average β	1.309	-4.561	1.448	1.282	0.590	1.000
Average $adj.R^2$	36.57%	30.37%	36.49%	36.33%	35.14%	36.88%

Table 1 shows the results from the Mincer-Zarnowitz (1969) Regression. The forecast horizon is 1 trading day. Each panel corresponds to a different cryptocurrency. Each column shows the estimation results for each forecasting model. α and β stands for the intercept and slope of the regression, while the row $adj.R^2$ shows the adjusted R^2 coefficient of the regression. t-statistics estimations are reported in parentheses. The average values of the intercepts, slopes, and adjusted R squared across cryptocurrencies for each forecasting model are reported at the end of the table. Significant coefficients at the 5% level are highlighted in bold. Newey–West (1987) heteroskedasticity and autocorrelation consistent standard errors was used for all the regressions. Forecasts are based on the GARCH model, the IGARCH model, the EGARCH model, the GJR-GARCH model, the lagged realized volatility (LRE), and the Heterogeneous Autoregressive (HAR) model.

Table 2: Mincer-Zarnowitz Regression with Newey-West Standard Errors for 7-day forecast horizon.

Cryptocurrency	GARCH	IGARCH	EGARCH	GJR-GARCH	LRE	HAR
BTC						
α	-0.012 (-1.43)	**0.014** (2.31)	**-0.026** (-2.94)	-0.007 (-1.12)	**0.042** (7.60)	0.000 (-0.000)
β	**1.047** (10.89)	**0.683** (10.98)	**1.200** (11.59)	**0.996** (14.59)	**0.499** (10.28)	**1.000** (14.32)
$adj. R^2$	32.13%	33.35%	34.62%	32.58%	24.54%	29.25%
ETH						
α	-0.006 (-0.48)	**0.034** (3.29)	-0.027 (-1.67)	0.001 (0.13)	**0.063** (9.53)	0.000 (0.000)
β	**0.963** (9.51)	**0.580** (7.31)	**1.138** (8.30)	**0.903** (10.37)	**0.443** (8.82)	**1.000** (11.05)
$adj. R^2$	26.42%	23.58%	27.18%	25.68%	19.50%	24.91%
XRP						
α	**0.026** (2.49)	**0.047** (5.51)	0.019 (1.83)	**0.030** (2.71)	**0.073** (10.35)	0.000 (-0.000)
β	**0.779** (8.00)	**0.547** (7.46)	**0.848** (8.26)	**0.745** (7.28)	**0.354** (6.82)	**1.000** (7.72)
$adj. R^2$	19.99%	19.50%	21.59%	19.45%	12.33%	14.93%
LTC						
α	0.005 (0.29)	**0.046** (2.89)	-0.016 (-0.78)	0.008 (0.57)	**0.077** (9.11)	0.000 (-0.000)
β	**0.885** (6.39)	**0.539** (4.61)	**1.047** (6.64)	**0.859** (7.43)	**0.373** (6.86)	**1.000** (8.56)
$adj. R^2$	19.64%	14.23%	22.45%	20.29%	13.58%	18.58%
BCH						
α	0.002 (0.09)	**0.044** (2.61)	-0.010 (-0.42)	0.001 (0.07)	**0.070** (7.56)	0.000 (-0.000)
β	**0.892** (4.73)	**0.553** (4.99)	**0.970** (5.68)	**0.896** (4.76)	**0.481** (7.28)	**1.000** (8.33)
$adj. R^2$	21.89%	21.41%	24.95%	22.11%	22.83%	30.58%
EOS						
α	-0.031 (-1.09)	**0.045** (2.38)	-0.058 (-1.92)	-0.029 (-0.97)	**0.083** (8.97)	0.000 (0.000)
β	**1.141** (5.46)	**0.553** (4.29)	**1.340** (5.94)	**1.127** (5.10)	**0.340** (5.65)	**1.000** (6.96)
$adj. R^2$	16.04%	10.70%	19.68%	16.53%	11.24%	15.20%
XMR						
α	**0.023** (2.44)	**0.043** (6.03)	0.016 (1.42)	**0.025** (2.96)	**0.056** (8.49)	0.000 (0.000)
β	**0.757** (8.53)	**0.536** (8.33)	**0.819** (7.47)	**0.738** (9.28)	**0.492** (9.15)	**1.000** (13.21)
$adj. R^2$	31.45%	31.54%	32.81%	31.76%	24.26%	29.38%
XLM						
α	**0.042** (3.46)	**8.498** (2.01)	**0.032** (2.24)	**0.039** (3.16)	**0.087** (10.07)	0.000 (-0.000)
β	**0.675** (6.76)	**-64.821** (-1.98)	**0.755** (6.20)	**0.701** (6.93)	**0.319** (5.26)	**1.000** (8.11)
$adj. R^2$	15.83%	2.92%	14.70%	16.06%	9.99%	15.36%

Table 2 (Continued)

Cryptocurrency	GARCH	IGARCH	EGARCH	GJR-GARCH	LRE	HAR
DASH						
α	**0.041** (3.76)	**0.050** (5.14)	**0.025** (1.98)	**0.040** (3.32)	**0.062** (7.64)	0.000 (0.000)
β	**0.636** (6.84)	**0.531** (6.61)	**0.769** (6.72)	**0.649** (6.31)	**0.491** (7.16)	**1.000** (11.12)
$adj. R^2$	30.66%	30.20%	31.79%	29.95%	23.88%	30.04%
ETC						
α	**0.026** (2.15)	**0.057** (6.43)	0.003 (0.23)	0.025 (1.92)	**0.069** (8.73)	0.000 (-0.000)
β	**0.765** (8.46)	**0.481** (8.47)	**0.943** (8.68)	**0.777** (8.03)	**0.454** (7.75)	**1.000** (10.35)
$adj. R^2$	21.80%	22.36%	23.54%	21.98%	20.42%	26.05%
Aggregate Results						
Average α	0.012	0.042	-0.006	0.012	0.065	0.000
Average β	0.820	0.554	0.989	0.843	0.442	1.000
Average $adj. R^2$	23.59%	23.84%	27.14%	25.21%	19.68%	24.83%

Table 2 shows the results from the Mincer-Zarnowitz (1969) Regression. The forecast horizon is 7 trading days. Each panel corresponds to a different cryptocurrency. Each column shows the estimation results for each forecasting model. α and β stands for the intercept and slope of the regression, while the row $adj. R^2$ shows the adjusted R^2 coefficient of the regression. t-statistics estimations are reported in parentheses. The average values of the intercepts, slopes, and adjusted R squared across cryptocurrencies for each forecasting model are reported at the end of the table. Significant coefficients at the 5% level are highlighted in bold. Newey–West (1987) heteroskedasticity and autocorrelation consistent standard errors was used for all the regressions. Forecasts are based on the GARCH model, the IGARCH model, the EGARCH model, the GJR-GARCH model, the lagged realized volatility (LRE), and the Heterogeneous Autoregressive (HAR) model.

Table 3: Mincer-Zarnowitz Regression with Newey-West Standard Errors for 7-day forecast horizon.

Cryptocurrency	GARCH	IGARCH	EGARCH	GJR-GARCH	LRE	HAR
BTC						
α	**0.097** (3.55)	**0.122** (5.52)	**0.079** (3.10)	**0.099** (4.05)	**0.158** (5.32)	0.000 (-0.000)
β	**0.464** (5.15)	**0.304** (5.38)	**0.557** (5.58)	**0.455** (6.36)	0.172 (1.80)	**1.000** (4.76)
$adj. R^2$	9.26%	9.75%	10.99%	10.03%	2.72%	8.16%
ETH						
α	**0.143** (4.72)	**0.178** (7.31)	**0.114** (2.80)	**0.150** (5.54)	**0.205** (7.13)	0.000 (0.000)
β	**0.394** (3.49)	**0.235** (2.87)	**0.507** (3.01)	**0.367** (3.74)	0.159 (1.50)	**1.000** (3.66)
$adj. R^2$	7.45%	6.52%	9.14%	7.15%	2.22%	8.95%
XRP						
α	**0.171** (6.05)	**0.189** (7.72)	**0.164** (5.56)	**0.177** (6.20)	**0.193** (6.40)	0.000 (0.000)
β	**0.319** (3.33)	**0.226** (3.13)	**0.354** (3.24)	**0.294** (3.16)	0.175 (1.74)	**1.000** (2.47)
$adj. R^2$	6.36%	6.33%	7.17%	5.75%	3.51%	5.77%
LTC						
α	**0.148** (3.24)	**0.178** (4.22)	**0.113** (2.26)	**0.151** (3.77)	**0.214** (5.27)	0.000 (0.000)
β	**0.418** (2.82)	**0.288** (2.24)	**0.545** (3.13)	**0.407** (3.15)	0.190 (1.35)	**1.000** (3.21)
$adj. R^2$	7.35%	6.84%	10.22%	7.63%	3.03%	9.50%
BCH						
α	**0.167** (2.83)	**0.200** (4.38)	**0.136** (2.15)	**0.166** (2.81)	**0.208** (3.98)	0.000 (0.000)
β	**0.416** (2.36)	**0.280** (2.38)	**0.513** (2.66)	**0.419** (2.37)	**0.298** (1.95)	**1.000** (3.19)
$adj. R^2$	7.27%	8.39%	10.70%	7.39%	8.10%	13.97%
EOS						
α	0.130 (1.92)	**0.209** (4.21)	0.078 (1.04)	0.120 (1.84)	**0.250** (6.52)	0.000 (0.000)
β	**0.501** (2.24)	0.212 (1.46)	**0.682** (2.63)	**0.535** (2.45)	0.089 (0.77)	**1.000** (2.82)
$adj. R^2$	5.46%	2.71%	9.08%	6.60%	0.56%	7.47%
XMR						
α	**0.152** (6.04)	**0.171** (8.48)	**0.135** (4.98)	**0.151** (6.32)	**0.199** (6.36)	0.000 (-0.000)
β	**0.342** (3.54)	**0.243** (3.53)	**0.415** (3.55)	**0.348** (3.85)	0.153 (1.30)	**1.000** (4.11)
$adj. R^2$	9.76%	9.92%	12.87%	10.74%	2.03%	11.10%
XLM						
α	**0.220** (8.46)	20.812 (1.92)	**0.212** (7.46)	**0.218** (8.20)	**0.276** (7.97)	0.000 (0.000)
β	**0.201** (2.20)	-76.83 (-1.90)	**0.232** (2.20)	**0.208** (2.21)	-0.021 (-0.20)	**1.000** (2.54)
$adj. R^2$	2.70%	8.44%	2.66%	2.73%	-0.10%	3.88%

Table 3 (Continued)

Cryptocurrency	GARCH	IGARCH	EGARCH	GJR-GARCH	LRE	HAR
DASH						
α	**0.164** (6.10)	**0.173** (6.99)	**0.138** (4.83)	**0.162** (5.77)	**0.198** (5.51)	0.000 (0.000)
β	**0.369** (4.46)	0.318 (4.45)	**0.474** (4.52)	**0.381** (4.31)	**0.248** (2.12)	**1.000** (4.20)
$adj. R^2$	15.58%	16.40%	18.23%	15.60%	5.50%	12.93%
ETC						
α	**0.175** (5.22)	**0.204** (8.05)	**0.146** (3.74)	**0.174** (5.05)	**0.238** (5.57)	0.000 (0.000)
β	**0.366** (3.48)	**0.233** (3.56)	**0.472** (3.58)	**0.368** (3.42)	0.151 (1.04)	**1.000** (3.56)
$adj. R^2$	8.35%	8.83%	9.93%	8.28%	2.11%	8.39%
Aggregate Results						
Average α	0.157	2.244	0.132	0.157	0.214	0.000
Average β	0.379	-7.449	0.475	0.378	0.161	1.000
Average $adj. R^2$	7.95%	8.41%	10.10%	8.19%	2.97%	9.01%

Table 3 shows the results from the Mincer-Zarnowitz (1969) Regression. The forecast horizon is 30 trading days. Each panel corresponds to a different cryptocurrency. Each column shows the estimation results for each forecasting model. α and β stands for the intercept and slope of the regression, while the row $adj. R^2$ shows the adjusted R^2 coefficient of the regression. t-statistics estimations are reported in parentheses. The average values of the intercepts, slopes, and adjusted R squared across cryptocurrencies for each forecasting model are reported at the end of the table. Significant coefficients at the 5% level are highlighted in bold. Newey–West (1987) heteroskedasticity and autocorrelation consistent standard errors was used for all the regressions. Forecasts are based on the GARCH model, the IGARCH model, the EGARCH model, the GJR-GARCH model, the lagged realized volatility (LRE), and the Heterogeneous Autoregressive (HAR) mod

Table 4: Encompassing regressions for volatility forecasts: 1-day forecast horizon with Newey-West Standard Error (1-lag)

CC	LRE+GARCH	LRE+IGARCH	LRE+EGARCH	LRE+GJR	HAR+GARCH	HAR+IGARCH	HAR+EGARCH	HAR+GJR
BTC								
α	**-0.015** (-2.85)	-0.004 (-1.30)	**-0.023** (-2.88)	**-0.013** (-2.14)	**-0.017** (-2.44)	-0.006 (-1.79)	**-0.025** (-2.55)	**-0.015** (-2.03)
β_1	**0.218** (2.38)	**0.188** (2.11)	0.140 (1.32)	0.206 (1.90)	0.329 (1.63)	0.281 (1.45)	0.199 (0.79)	0.332 (1.30)
β_2	**1.092** (5.48)	**0.741** (5.64)	**1.393** (4.53)	**1.047** (4.30)	**1.057** (3.01)	**0.727** (3.26)	**1.401** (2.86)	**1.000** (2.43)
$adj.R^2$	48.97%	49.57%	50.62%	48.80%	48.52%	49.34%	50.84%	48.72%
ETH								
α	**-0.016** (-2.02)	0.000 (0.14)	**-0.023** (-2.41)	-0.013 (-1.47)	-0.020 (-1.94)	-0.005 (-1.05)	**-0.027** (-2.05)	-0.017 (-1.58)
β_1	**0.264** (2.96)	**0.354** (4.26)	**0.266** (2.90)	**0.276** (2.80)	**0.439** (2.00)	**0.656** (3.88)	**0.454** (2.03)	**0.494** (2.05)
β_2	**0.988** (4.46)	**0.495** (4.86)	**1.143** (4.31)	**0.902** (3.67)	**0.920** (2.40)	**0.371** (2.27)	**1.052** (2.33)	**0.800** (1.97)
$adj.R^2$	43.60%	41.78%	43.48%	42.99%	42.06%	40.14%	41.93%	41.69%
XRP								
α	-0.006 (-1.10)	0.002 (0.76)	-0.008 (-1.34)	-0.004 (-0.73)	**-0.013** (-2.33)	-0.004 (-1.02)	**-0.014** (-3.10)	**-0.013** (-2.61)
β_1	**0.222** (3.49)	**0.253** (4.01)	**0.235** (3.39)	**0.256** (3.80)	**0.421** (2.55)	**0.496** (3.10)	**0.508** (3.32)	**0.489** (3.16)
β_2	**0.887** (4.81)	**0.585** (5.12)	**0.916** (4.91)	**0.798** (4.50)	**0.868** (3.60)	**0.532** (3.65)	**0.812** (4.82)	**0.803** (4.12)
$adj.R^2$	35.53%	34.92%	35.83%	35.12%	30.98%	30.21%	31.02%	30.68%
LTC								
α	-0.016 (-1.51)	0.005 (1.24)	**-0.026** (-1.99)	-0.014 (-1.21)	-0.022 (-1.82)	-0.004 (-0.82)	**-0.031** (-2.11)	-0.020 (-1.58)
β_1	**0.249** (3.19)	**0.435** (5.61)	**0.198** (2.31)	**0.238** (2.63)	**0.464** (2.38)	**0.875** (6.04)	0.350 (1.57)	0.447 (1.88)
β_2	**0.981** (3.85)	**0.367** (5.27)	**1.219** (3.87)	**0.958** (3.23)	**0.904** (2.41)	**0.181** (2.14)	**1.194** (2.54)	**0.889** (2.04)
$adj.R^2$	36.40%	33.09%	37.05%	36.40%	36.17%	33.00%	37.07%	36.32%
BCH								
α	-0.005 (-0.71)	0.004 (1.08)	-0.007 (-1.18)	-0.006 (-0.73)	-0.012 (-1.39)	-0.003 (-0.86)	-0.012 (-1.91)	-0.012 (-1.39)
β_1	**0.493** (5.01)	**0.521** (5.82)	**0.494** (5.12)	**0.490** (4.94)	**0.799** (5.13)	**0.864** (6.08)	**0.803** (5.08)	**0.794** (5.04)
β_2	**0.536** (2.67)	**0.297** (3.14)	**0.558** (3.38)	**0.543** (2.66)	0.385 (1.55)	0.165 (1.38)	0.388 (1.84)	0.394 (1.56)
$adj.R^2$	47.79%	47.48%	48.07%	47.83%	48.39%	47.87%	48.36%	48.43%

Table 4 (Continued)

CC	LRE+GARCH	LRE+IGARCH	LRE+EGARCH	LRE+GJR	HAR+GARCH	HAR+IGARCH	HAR+EGARCH	HAR+GJR
EOS								
α	**-0.026** (-2.47)	0.002 (0.63)	**-0.027** (-3.22)	**-0.025** (-2.02)	**-0.032** (-2.67)	-0.008 (-1.49)	**-0.033** (-3.42)	**-0.032** (-2.20)
β_1	**0.286** (3.88)	**0.376** (4.62)	**0.300** (3.78)	**0.274** (3.76)	**0.613** (3.84)	**0.826** (4.91)	**0.643** (3.75)	**0.585** (3.46)
β_2	**1.103** (4.97)	**0.443** (4.79)	**1.130** (5.91)	**1.105** (4.12)	**0.939** (3.23)	**0.296** (2.65)	**0.939** (3.76)	**0.961** (2.65)
$adj. R^2$	28.51%	26.18%	28.41%	28.57%	27.73%	25.92%	27.51%	27.85%
XMR								
α	-0.001 (-0.25)	0.005 (1.43)	-0.002 (-0.40)	-0.0005 (-0.10)	-0.006 (-1.14)	-0.0006 (-0.15)	-0.007 (-1.30)	-0.005 (-1.04)
β_1	**0.308** (3.08)	**0.310** (3.16)	**0.327** (3.42)	**0.302** (2.87)	**0.537** (2.54)	**0.541** (2.67)	**0.576** (3.05)	**0.524** (2.28)
β_2	**0.666** (3.80)	**0.468** (3.90)	**0.671** (3.87)	**0.654** (3.53)	**0.572** (2.09)	**0.401** (2.17)	**0.566** (2.16)	0.569 (1.95)
$adj. R^2$	45.12%	45.02%	44.60%	45.15%	44.06%	44.03%	43.79%	44.24%
XLM								
α	-0.003 (-0.39)	1.377 (1.84)	-0.008 (-1.00)	-0.004 (-0.53)	-0.013 (-1.87)	0.710 (0.96)	**-0.019** (-2.33)	-0.014 (-1.91)
β_1	**0.288** (3.50)	**0.541** (8.72)	**0.292** (3.88)	**0.283** (3.37)	**0.549** (3.34)	**0.998** (8.89)	**0.562** (3.86)	**0.539** (3.18)
β_2	**0.745** (3.30)	-27.792 (-1.81)	**0.865** (3.59)	**0.779** (3.28)	**0.707** (2.73)	-14.556 (-0.96)	**0.820** (3.07)	**0.740** (2.70)
$adj. R^2$	34.82%	30.02%	35.06%	34.90%	35.14%	30.71%	35.53%	35.19%
DASH								
α	0.004 (1.17)	**0.007** (2.35)	0.001 (0.40)	0.004 (1.20)	-0.002 (-0.68)	-0.001 (-0.22)	-0.005 (-1.36)	-0.002 (-0.75)
β_1	**0.391** (4.25)	**0.426** (4.82)	**0.441** (5.33)	**0.421** (4.78)	**0.642** (3.87)	**0.712** (4.56)	**0.724** (5.15)	**0.698** (4.52)
β_2	**0.464** (3.98)	**0.351** (4.10)	**0.486** (4.66)	**0.438** (4.02)	**0.378** (2.37)	**0.260** (2.23)	**0.363** (2.67)	**0.335** (2.30)
$adj. R^2$	48.63%	48.17%	48.49%	48.25%	47.81%	47.26%	47.46%	47.40%
ETC								
α	-0.002 (-0.37)	0.007 (1.82)	-0.009 (-1.37)	-0.002 (-0.44)	-0.010 (-1.58)	-0.002 (-0.67)	**-0.016** (-2.35)	-0.010 (-1.72)
β_1	**0.371** (4.54)	**0.366** (4.47)	**0.359** (4.60)	**0.376** (4.79)	**0.688** (4.58)	**0.678** (4.57)	**0.657** (4.72)	**0.695** (4.96)
β_2	**0.618** (3.57)	**0.390** (3.67)	**0.766** (4.29)	**0.620** (3.86)	**0.489** (2.20)	**0.313** (2.34)	**0.637** (2.86)	**0.489** (2.42)
$adj. R^2$	39.78%	39.82%	40.11%	39.83%	40.40%	40.51%	40.79%	40.41%

Table 4 (Continued)

Aggregate Results								
Average α	-0.009	0.141	-0.013	-0.008	-0.015	0.068	-0.019	-0.014
Average β_1	0.309	0.377	0.305	0.312	0.548	0.693	0.548	0.560
Average β_2	0.808	-2.366	0.915	0.784	0.722	-1.131	0.817	0.698
Average $adj.R^2$	40.92%	39.61%	41.17%	40.78%	40.13%	38.90%	40.43%	40.09%

Table 5 shows the results of the encompassing regressions for 1 trading day horizon with Newey-West Standard Error (1986). Each column represent the results generated from the encompassing regressions for each due of models. The LRE+GARCH column has the results of the lagged realized volatility model with GARCH model . LRE+IGARCH column has the results of the lagged realized volatility model with Integrated GARCH model . LRE+EGARCH column has the results of the lagged realized volatility model with Exponential GARCH model. LRE+GJR column has the results of the lagged realized volatility model with GJR-GARCH model . Also, the HAR+GARCH column has the results of the Heterogeneous Autoregressive (HAR) model with GARCH model. the HAR+IGARCH column has the results of the Heterogeneous Autoregressive (HAR) model with Integrated GARCH model. the HAR+EGARCH column has the results of the Heterogeneous Autoregressive (HAR) model with Exponential GARCH model. the HAR+GJR column has the results of the Heterogeneous Autoregressive (HAR) model with GJR-GARCH model. All the Significant coefficients at the 5% level are highlighted in bold. Also, the average values of the intercepts, slopes, and adjusted R squared across cryptocurrencies for each forecasting model are reported at the end of the table.

Table 5: Encompassing regressions for volatility forecasts: 7-day forecast horizon with Newey-West Standard Error (7-lag)

CC	LRE+GARCH	LRE+IGARCH	LRE+EGARCH	LRE+GJR	HAR+GARCH	HAR+IGARCH	HAR+EGARCH	HAR+GJR
BTC								
α	-0.012 (-0.99)	**0.014** (2.09)	-0.025 (-1.81)	-0.005 (-0.59)	-0.012 (-1.48)	0.010 (1.28)	**-0.026** (-2.66)	-0.009 (-1.29)
β_1	0.002 (0.02)	0.006 (0.05)	0.028 (0.26)	0.042 (0.35)	0.287 (1.21)	0.199 (0.85)	0.100 (0.34)	0.258 (0.83)
β_2	**1.045** (4.17)	**0.679** (4.41)	**1.156** (4.49)	**0.936** (4.31)	**0.788** (2.94)	**0.569** (3.28)	**1.109** (3.08)	**0.781** (2.63)
$adj.R^2$	32.13%	33.40%	34.73%	32.69%	32.58%	33.65%	35.10%	33.16%
ETH								
α	-0.008 (-0.55)	**0.035** (2.89)	-0.030 (-1.22)	0.004 (0.37)	-0.011(-0.88)	0.006 (0.57)	-0.024 (-1.36)	-0.007 (-0.63)
β_1	-0.024 (-0.27)	0.040 (0.35)	-0.026 (-0.23)	0.054 (0.59)	**0.475** (2.10)	**0.668** (3.28)	0.426 (1.61)	**0.550** (2.18)
β_2	**1.002** (5.17)	**0.539** (3.06)	**1.186** (3.85)	**0.822** (4.76)	**0.564** (2.44)	0.232 (1.58)	**0.722** (2.01)	**0.467** (2.00)
$adj.R^2$	26.42%	23.77%	27.14%	25.74%	26.71%	25.72%	27.08%	26.43%
XRP								
α	0.023 (1.89)	**0.046** (5.21)	0.018 (1.55)	**0.028** (2.37)	0.011 (0.81)	0.025 (1.76)	0.004 (0.30)	0.007 (0.53)
β_1	-0.068 (-0.64)	-0.078 (-0.68)	-0.028 (-0.31)	-0.034 (-0.34)	0.316 (1.43)	0.372 (1.76)	**0.355** (2.07)	**0.394** (2.15)
β_2	**0.879** (4.40)	**0.631** (3.91)	**0.888** (4.91)	**0.792** (4.35)	**0.588** (3.06)	**0.377** (2.84)	**0.610** (3.96)	**0.543** (3.37)
$adj.R^2$	20.09%	19.68%	21.57%	19.44%	17.80%	17.47%	18.67%	17.60%
LTC								
α	0.007 (0.31)	**0.052** (3.31)	-0.017 (-0.66)	0.010 (0.55)	-0.006 (-0.34)	0.002 (0.15)	-0.019 (-0.99)	-0.003 (-0.18)
β_1	0.021 (0.19)	0.192 (1.95)	-0.011 (-0.10)	0.023 (0.20)	0.443 (1.69)	**0.808** (5.05)	0.157 (0.49)	0.395 (1.29)
β_2	**0.851** (3.21)	0.329 (1.85)	**1.070** (3.65)	**0.825** (3.53)	**0.559** (2.18)	0.150 (1.15)	**0.925** (2.43)	**0.583** (2.15)
$adj.R^2$	19.56%	15.60%	22.40%	20.24%	20.53%	18.90%	22.57%	20.98%
BCH								
α	0.028 (0.98)	**0.064** (2.70)	0.008 (0.23)	0.024 (0.93)	-0.006 (-0.33)	0.000 (0.01)	-0.014 (-0.72)	-0.007 (-0.35)
β_1	**0.376** (3.95)	**0.461** (4.10)	**0.354** (3.78)	**0.363** (4.17)	**0.895** (4.51)	**0.938** (4.63)	**0.764** (3.24)	**0.888** (4.47)
β_2	0.424 (1.54)	0.059 (0.25)	0.597 (1.80)	0.465 (1.88)	0.136 (0.70)	0.050 (0.40)	0.307 (1.24)	0.146 (0.73)
$adj.R^2$	23.78%	22.77%	24.61%	24.19%	30.66%	30.54%	31.22%	30.68%

Table 5 (Continued)

CC	LRE+GARCH	LRE+IGARCH	LRE+EGARCH	LRE+GJR	HAR+GARCH	HAR+IGARCH	HAR+EGARCH	HAR+GJR
EOS								
α	-0.019 (-0.52)	**0.052** (2.85)	-0.060 (-1.36)	-0.021 (-0.50)	-0.035 (-1.35)	-0.004 (-0.20)	**-0.060** (-1.99)	-0.034 (-1.25)
β_1	0.072 (0.77)	**0.210** (2.70)	-0.005 (-0.05)	0.054 (0.47)	**0.515** (2.47)	**0.799** (4.58)	0.299 (1.40)	0.470 (1.76)
β_2	**0.989** (2.82)	0.318 (1.91)	**1.356** (3.29)	**1.019** (2.50)	**0.697** (2.20)	0.196 (1.36)	**1.075** (2.84)	0.730 (1.90)
$adj.R^2$	16.23%	13.07%	19.67%	16.66%	17.40%	15.82%	20.07%	17.62%
XMR								
α	**0.024** (2.15)	**0.042** (6.29)	0.017 (1.23)	**0.026** (2.58)	0.005 (0.56)	0.019 (1.53)	0.001 (0.17)	0.007 (0.69)
β_1	0.078 (0.51)	0.078 (0.52)	0.071 (0.45)	0.079 (0.50)	0.457 (1.83)	0.447 (1.80)	0.402 (1.45)	0.437 (1.57)
β_2	**0.666** (2.79)	**0.472** (2.78)	**0.734** (2.61)	**0.650** (2.83)	**0.472** (2.17)	**0.340** (2.18)	**0.562** (2.07)	**0.474** (2.11)
$adj.R^2$	31.47%	31.68%	32.90%	31.88%	32.74%	32.91%	33.97%	33.00%
XLM								
α	**0.042** (3.51)	6.358 (1.70)	**0.034** (2.41)	**0.039** (3.25)	0.008 (0.49)	4.119 (1.21)	-0.002 (-0.13)	0.007 (0.43)
β_1	0.121 (1.61)	**0.305** (5.54)	**0.147** (2.07)	0.115 (1.51)	**0.512** (2.73)	**0.994** (8.54)	**0.604** (3.53)	**0.494** (2.56)
β_2	**0.553** (4.29)	-48.557 (-1.68)	**0.590** (4.04)	**0.579** (4.34)	**0.425** (2.86)	-31.894 (-1.21)	**0.412** (2.52)	**0.450** (2.88)
$adj.R^2$	16.75%	11.52%	16.07%	16.88%	18.00%	15.94%	17.33%	18.07%
DASH								
α	**0.041** (3.79)	**0.050** (5.08)	0.026 (1.92)	**0.040** (3.39)	0.015 (1.25)	0.019 (1.47)	0.007 (0.60)	0.012 (1.07)
β_1	0.071 (0.59)	0.057 (0.40)	0.033 (0.21)	0.082 (0.64)	**0.514** (2.20)	**0.544** (2.37)	**0.457** (2.00)	**0.565** (2.60)
β_2	**0.562** (3.48)	**0.480** (3.05)	**0.724** (3.05)	**0.561** (3.14)	0.344 (1.80)	0.272 (1.68)	**0.468** (2.11)	0.320 (1.66)
$adj.R^2$	30.46%	29.98%	31.41%	29.75%	31.84%	31.67%	32.91%	31.56%
ETC								
α	**0.035** (2.59)	**0.053** (5.86)	0.016 (1.04)	**0.033** (2.46)	-0.002 (-0.18)	0.009 (0.69)	-0.012 (-0.88)	-0.003 (-0.24)
β_1	**0.232** (2.64)	**0.223** (2.60)	**0.205** (2.73)	**0.229** (2.69)	**0.748** (4.14)	**0.720** (3.99)	**0.656** (4.12)	**0.736** (4.39)
β_2	**0.480** (3.23)	**0.313** (3.41)	**0.650** (4.13)	**0.493** (3.34)	0.262 (1.63)	0.181 (1.78)	**0.424** (2.45)	0.279 (1.84)
$adj.R^2$	24.01%	24.48%	25.34%	24.14%	26.86%	27.07%	27.62%	26.99%

Table 5 (Continued)

Aggregate Results								
Average α	0.016	0.677	-0.001	0.018	-0.003	0.421	-0.014	-0.003
Average β_1	0.088	0.149	0.077	0.101	0.516	0.649	0.422	0.519
Average β_2	0.745	-4.474	0.895	0.714	0.483	-2.953	0.661	0.477
Average $adj.R^2$	24.09%	22.60%	25.58%	24.16%	25.51%	24.97%	26.65%	25.61%

Table 5 shows the results of the encompassing regressions for 7 trading days horizon with Newey-West Standard Error (1986). Each column represent the results generated from the encompassing regressions for each due of models. The LRE+GARCH column has the results of the lagged realized volatility model with GARCH model . LRE+IGARCH column has the results of the lagged realized volatility model with Integrated GARCH model . LRE+EGARCH column has the results of the lagged realized volatility model with Exponential GARCH model. LRE+GJR column has the results of the lagged realized volatility model with GJR-GARCH model . Also, the HAR+GARCH column has the results of the Heterogeneous Autoregressive (HAR) model with GARCH model. the HAR+IGARCH column has the results of the Heterogeneous Autoregressive (HAR) model with Integrated GARCH model. the HAR+EGARCH column has the results of the Heterogeneous Autoregressive (HAR) model with Exponential GARCH model. the HAR+GJR column has the results of the Heterogeneous Autoregressive (HAR) model with GJR-GARCH model. All the Significant coefficients at the 5% level are highlighted in bold. Also, the average values of the intercepts, slopes, and adjusted R squared across cryptocurrencies for each forecasting model are reported at the end of the table.

Table 6: Encompassing regressions for volatility forecasts: 30-day forecast horizon with Newey-West Standard Error (30-lag)

CC	LRE+GARCH	LRE+IGARCH	LRE+EGARCH	LRE+GJR	HAR+GARCH	HAR+IGARCH	HAR+EGARCH	HAR+GJR
BTC								
α	**0.103** (3.49)	**0.128** (4.52)	**0.083** (3.10)	**0.103** (3.65)	0.074 (1.16)	0.108 (1.54)	0.108 (1.62)	0.100 (1.25)
β_1	-0.024 (-0.19)	-0.017 (-0.14)	-0.044 (-0.36)	-0.010 (-0.09)	0.245 (0.49)	0.131 (0.27)	-0.229 (-0.44)	0.025 (0.04)
β_2	**0.478** (4.00)	**0.309** (4.02)	**0.600** (3.99)	**0.461** (5.10)	0.362 (1.65)	**0.268** (2.03)	**0.656** (2.56)	**0.444** (2.13)
$adj.R^2$	9.10%	9.56%	11.28%	10.01%	9.16%	9.56%	11.25%	10.00%
ETH								
α	**0.139** (4.19)	**0.180** (6.37)	**0.106** (2.44)	**0.146** (4.70)	0.025 (0.31)	0.017 (0.21)	0.058 (0.92)	0.015 (0.17)
β_1	-0.026 (-0.24)	-0.082 (-0.67)	-0.072 (-0.71)	0.008 (0.08)	0.788 (1.54)	**0.892** (2.01)	0.389 (0.75)	0.874 (1.56)
β_2	**0.438** (3.20)	**0.304** (2.71)	**0.611** (2.82)	**0.377** (3.41)	0.105 (0.48)	0.035 (0.25)	0.359 (0.99)	0.060 (0.28)
$adj.R^2$	7.80%	7.30%	9.77%	7.28%	8.94%	8.87%	9.78%	8.87%
XRP								
α	**0.163** (4.49)	**0.178** (5.47)	**0.158** (4.09)	**0.165** (4.41)	0.036 (0.36)	0.047 (0.49)	0.055 (0.63)	0.029 (0.31)
β_1	0.090 (0.96)	0.079 (0.83)	0.083 (0.89)	0.092 (0.98)	0.756 (1.68)	0.728 (1.69)	0.611 (1.53)	**0.803** (1.98)
β_2	0.228 (1.95)	0.164 (1.81)	0.262 (1.76)	0.220 (1.82)	0.096 (0.74)	0.073 (0.72)	0.167 (0.97)	0.080 (0.64)
$adj.R^2$	5.41%	5.38%	5.93%	5.16%	5.80%	5.82%	6.19%	5.75%
LTC								
α	**0.145** (2.98)	**0.181** (4.34)	**0.110** (2.13)	**0.147** (3.23)	0.010 (0.10)	0.027 (0.34)	0.071 (0.82)	0.018 (0.16)
β_1	0.048 (0.34)	-0.232 (-1.05)	0.002 (0.02)	0.055 (0.41)	0.913 (1.74)	**0.793** (1.99)	0.285 (0.55)	0.856 (1.54)
β_2	**0.391** (2.47)	**0.496** (2.22)	**0.559** (2.94)	**0.377** (2.89)	0.047 (0.22)	0.094 (0.56)	0.429 (1.41)	0.075 (0.37)
$adj.R^2$	7.67%	8.21%	10.65%	7.96%	9.40%	9.71%	10.83%	9.44%
BCH								
α	**0.153** (2.62)	**0.184** (3.46)	**0.130** (2.10)	**0.152** (2.59)	-0.011 (-0.11)	-0.015 (-0.14)	0.019 (0.18)	-0.010 (-0.10)
β_1	0.194 (1.13)	0.158 (0.83)	0.100 (0.53)	0.193 (1.13)	**1.139** (2.51)	**1.099** (2.47)	0.775 (1.47)	**1.128** (2.49)
β_2	0.280 (1.74)	0.196 (1.61)	**0.445** (1.97)	0.285 (1.77)	-0.098 (-0.59)	-0.043 (-0.36)	0.156 (0.58)	-0.091 (-0.54)
$adj.R^2$	10.29%	10.30%	12.33%	10.38%	13.98%	13.90%	14.11%	13.96%

Table 6 (Continued)

CC	LRE+GARCH	LRE+IGARCH	LRE+EGARCH	LRE+GJR	HAR+GARCH	HAR+IGARCH	HAR+EGARCH	HAR+GJR
EOS								
α	0.117 (1.61)	**0.208** (4.22)	0.023 (0.27)	0.112 (1.61)	0.009 (0.10)	0.006 (0.07)	0.002 (0.02)	0.019 (0.21)
β_1	-0.114 (-0.74)	-0.132 (-0.73)	-0.321 (-1.85)	-0.105 (-0.73)	0.741 (1.92)	**0.913** (2.50)	0.440 (1.08)	0.624 (1.61)
β_2	**0.661** (2.03)	0.342 (1.45)	**1.198** (2.90)	**0.671** (2.18)	0.217 (0.81)	0.057 (0.38)	0.533 (1.55)	0.293 (1.11)
$adj. R^2$	6.45%	3.54%	13.89%	7.54%	7.86%	7.49%	10.47%	8.25%
XMR								
α	**0.160** (5.15)	**0.183** (6.12)	**0.145** (4.96)	**0.159** (5.17)	0.041 (0.61)	0.052 (0.73)	0.074 (1.05)	0.056 (0.77)
β_1	-0.092 (-0.71)	-0.093 (-0.72)	-0.177 (-1.30)	-0.087 (-0.72)	0.681 (1.81)	0.657 (1.72)	0.369 (0.84)	0.573 (1.41)
β_2	**0.409** (3.68)	**0.292** (3.55)	**0.559** (3.48)	**0.407** (4.16)	0.145 (0.94)	0.110 (0.98)	0.314 (1.45)	0.186 (1.21)
$adj. R^2$	10.26%	10.49%	14.76%	11.22%	11.57%	11.67%	13.72%	12.00%
XLM								
α	**0.230** (5.55)	17.731 (1.43)	**0.223** (5.13)	**0.228** (5.43)	0.045 (0.47)	17.227 (1.49)	0.035 (0.35)	0.046 (0.48)
β_1	-0.082 (-0.88)	-0.038 (-0.38)	-0.077 (-0.82)	-0.082 (-0.88)	0.741 (1.89)	**0.996** (2.75)	0.777 (1.90)	0.736 (1.85)
β_2	**0.240** (2.60)	-65.276 (-1.41)	**0.264** (2.46)	**0.248** (2.59)	0.093 (0.93)	-64.439 (-1.49)	0.096 (0.80)	0.097 (0.91)
$adj. R^2$	3.42%	5.42%	3.11%	3.45%	4.08%	9.28%	4.03%	4.08%
DASH								
α	**0.165** (4.62)	**0.179** (5.15)	**0.148** (4.41)	**0.165** (4.58)	0.152 (1.28)	0.188 (1.53)	0.180 (1.67)	0.147 (1.28)
β_1	0.012 (0.09)	-0.034 (-0.25)	-0.109 (-0.75)	-0.008 (-0.06)	0.079 (0.13)	-0.069 (-0.12)	-0.237 (-0.40)	0.089 (0.15)
β_2	**0.363** (3.92)	**0.336** (3.83)	**0.558** (3.85)	**0.387** (3.71)	0.346 (1.91)	**0.337** (2.09)	**0.562** (2.30)	0.355 (1.90)
$adj. R^2$	15.48%	16.45%	19.08%	15.53%	15.49%	16.40%	18.65%	15.55%
ETC								
α	**0.176** (4.08)	**0.205** (5.01)	**0.148** (3.29)	**0.176** (4.09)	0.076 (0.75)	0.109 (0.97)	0.100 (1.14)	0.072 (0.74)
β_1	0.023 (0.15)	0.020 (0.13)	-0.009 (-0.06)	0.022 (0.14)	0.519 (1.08)	0.446 (0.91)	0.251 (0.55)	0.538 (1.15)
β_2	**0.354** (3.18)	**0.228** (3.28)	**0.492** (3.42)	**0.356** (2.98)	0.213 (1.18)	0.153 (1.32)	0.398 (1.75)	0.209 (1.16)
$adj. R^2$	8.53%	9.04%	10.62%	8.41%	9.26%	9.58%	10.80%	9.23%

Table 6 (Continued)

Aggregate Results								
Average α	0.155	1.936	0.127	0.155	0.046	1.777	0.070	0.049
Average β_1	0.003	-0.037	-0.062	0.008	0.660	0.659	0.343	0.625
Average β_2	0.384	-6.261	0.555	0.379	0.153	-6.335	0.367	0.171
Average $adj.R^2$	8.44%	8.57%	11.14%	8.69%	9.55%	10.23%	10.98%	9.71%

Table 6 shows the results of the encompassing regressions for 30 trading days horizon with Newey-West Standard Error (1986). Each column represent the results generated from the encompassing regressions for each due of models. The LRE+GARCH column has the results of the lagged realized volatility model with GARCH model . LRE+IGARCH column has the results of the lagged realized volatility model with Integrated GARCH model . LRE+EGARCH column has the results of the lagged realized volatility model with Exponential GARCH model. LRE+GJR column has the results of the lagged realized volatility model with GJR-GARCH model . Also, the HAR+GARCH column has the results of the Heterogeneous Autoregressive (HAR) model with GARCH model. the HAR+IGARCH column has the results of the Heterogeneous Autoregressive (HAR) model with Integrated GARCH model. the HAR+EGARCH column has the results of the Heterogeneous Autoregressive (HAR) model with Exponential GARCH model. the HAR+GJR column has the results of the Heterogeneous Autoregressive (HAR) model with GJR-GARCH model. All the Significant coefficients at the 5% level are highlighted in bold. Also, the average values of the intercepts, slopes, and adjusted R squared across cryptocurrencies for each forecasting model are reported at the end of the table.

Chapter Three: Examining The Relationships and Effects of Diverse Economic Policy Uncertainty Indices on Cryptocurrency Market Returns

1. Abstract

The purpose of this research is to investigate the relationship between cryptocurrency market returns and uncertainty indices by assessing the impact of the Covid-19 pandemic period on both indices and cryptocurrency returns, determining which index has the most impact on cryptocurrency market results, and determining which indices pair has the most influence on cryptocurrency market findings. Ten cryptocurrency returns and Eight uncertainty indices have been examined. The Quantile Regression, the Multivariate-Quantile Regression, and the Granger Causality test have been applied. The Quantile Regression findings revealed that the Cryptocurrency Policy Uncertainty index and the Cryptocurrency Price Uncertainty index significantly affect cryptocurrency returns. However, the rest of the indices show no effect on cryptocurrency returns. The Multivariate-Quantile Regression findings revealed that when the bull wave hits the cryptocurrency market, the UCRY Policy Index + Central Bank Digital Currency Attention Index pair significantly affects cryptocurrency returns. Nevertheless, when the bull wave hits the cryptocurrency market, the UCRY Policy Index + the Cryptocurrency Environmental Attention (ICEA) index pair significantly affects cryptocurrency returns. The results during the crisis period confirmed most of the total sample results. These findings will significantly help investors, portfolio managers, and policymakers.

2. INTRODUCTION

The development of the cryptocurrency markets has been one of the primary factors for investors to consider when making investment decisions. Cryptocurrency markets have been sharing the financial industry by relying on innovative technologies that prize them over traditional investment tools. Therefore, many investors, individuals, and firms have changed their investment pools to include cryptocurrencies to diversify their investments and avoid risks. Not only that, but also individuals and firms' investors have been cautious and pay attention to every factor that might affect them when they make their investment decisions. Therefore, nowadays, economic uncertainty factors have contributed directly and indirectly to investors' behaviors and shaped their investment decisions. These economic uncertainty factors vary between economy, policy, price, attention, and environmental attention uncertainty indices. Some of them were Twitter-based Economic Uncertainty. Other ones have been generated from 726.9 million data text mining. Others captured the relative extent of media discussion around the environmental impact of cryptocurrencies based on 778.2 million data. Also, some indices were generated Based on 663.9 million news stories from LexisNexis News & Business. These indices will influence the investment decision, mainly when focusing on the calm and turmoil period. As a result, this research will investigate and focus on measuring and examining the relationships of the various economic uncertainty indices and their effect on the cryptocurrency market returns considering ten cryptocurrencies. These cryptocurrencies vary from the most dominant cryptocurrency to less dominant cryptocurrencies.

3. LITERATURE REVIEW:

Uncertainty indices play an important role in financial markets by highlighting current economic and geopolitical issues influencing investor behaviors. These indices are frequently produced from various sources, including economic statistics, news sentiment analysis, and events related to geopolitics. In the context of traditional financial assets like stocks and bonds, uncertainty indices act as vital indicators of market risk and volatility. High degrees of uncertainty can result in higher market volatility, altering investor behavior and trading methods. During uncertain times, investors prefer to seek safe-haven assets, which causes adjustments in asset allocations and has an influence on market dynamics.

Because cryptocurrency markets are relatively new and active, uncertainty indices are significant. Cryptocurrencies have demonstrated vulnerability to macroeconomic insecurities and global financial surroundings. Cryptocurrencies have been perceived as a speculative safe haven while also experiencing higher volatility during moments of extreme uncertainty. Cryptocurrencies' decentralized and global character means they are impacted not just by traditional economic uncertainty but also by legislative changes, technology improvements, and market emotion. The interaction between uncertainty indices and cryptocurrency markets emphasizes the dynamic and linked nature of these digital assets in a more significant financial environment.

The impact of uncertainty indices on traditional financial assets and cryptocurrencies demonstrates the mutual dependence on global markets. Investors regularly follow uncertainty indices to identify risks and make intelligent choices regarding their investments when geopolitical and economic uncertainties indices change. Understanding how uncertainty affects different asset classes is critical for portfolio diversification, risk management, and establishing successful investing strategies in today's rapidly shifting financial world. The energetic nature of uncertainty indices underlines market players' need to be observant, adapt to changing conditions, and use creative tools to negotiate the complex dynamics of today's financial markets.

Consequently, it is critical to thoroughly assess the influence and impact of various uncertainty indices on the returns of cryptocurrency markets. The interconnection of these indices and cryptocurrency market dynamics underlines the need to understand how economic, geopolitical, and sentiment concerns influence cryptocurrency prices and investor behaviors. This evaluation is vital for market players such as investors, financial analysts, and legislators since it gives substantial insights into the risk indicators and market sentiment influencing the cryptocurrency environment. As the global financial ecosystem evolves, monitoring and analyzing the influence of uncertainty indices on cryptocurrencies becomes an increasingly important part of risk management and strategic decision-making in the fast-evolving and interrelated world of finance.

3.1. Uncertainty Indices for Cryptocurrency and Other Financial Assets.

Many studies have focused on the effects of economic policy uncertainty between cryptocurrency and traditional asset markets. It helps identify the hedging and forecasting capabilities between those assets. For example, Hasan et al. (2022) investigated the hedging and safe-haven properties of UCRY using the Quantile-on-Quantile technique. Their findings show that the UCRY index hedges against gold and the DJ Islamic Index. However, the UCRY index does not hedge Bitcoin returns in various quantiles. Also, Shang et al. (2022) research analyzed and compared the predictive potential of the UCRY Policy with numerous standard predictors for the gold market using a newly created cryptocurrency policy uncertainty index (UCRY Policy) and an efficient forecasting approach called Dynamic Occam's Window (DOW). Their empirical findings revealed that UCRY Policy has a strong predictive ability in projecting weekly gold returns, outperforming numerous frequently used predictors throughout a data set spanning 2014 to 2022. The UCRY Policy index that they used was developed by Lucy et al. (2022). Furthermore, the DOW technique with varied thresholds in forecasting weekly gold returns outperforms dynamic model averaging/selection (DMA/DMS) and several other traditional econometric models.

Likewise, Fang et al. (2019) investigated whether economic policy uncertainty affects Bitcoin's and other global assets' volatility and hedging effectiveness. The findings suggest that EPU has a considerable impact on Bitcoin's long-term volatility, and Bitcoin has poor hedging efficacy against EPU. These empirical investigations demonstrated that the relationship between Bitcoin and uncertainty change in upper quantiles means that Bitcoin functions as a hedge only during periods of greater uncertainty and risk.

Also, Mokni et al. (2020) investigate the effect of EPU on the Bitcoin-US stock connection and demonstrate the value of mixing Bitcoin and U.S. equities in the same portfolio. They investigate the impact of economic policy uncertainty (EPU) on the dynamic conditional correlations between Bitcoin and the U.S. stock markets, taking into consideration the accounting for price structural changes in Bitcoin. The findings demonstrate that EPU has a detrimental influence on the dynamic conditional correlations between Bitcoin and the U.S. stock markets only following the December 2017 Bitcoin meltdown. Additional investigation reveals that an increase in the EPU level is related to an increase in the ideal weight of Bitcoin in the portfolio prior to the Bitcoin crash. Nevertheless, EPU has had a negative (positive) influence on the hedging ratio during low (high) uncertainty levels after the Bitcoin crash.

However, Mokni et al. (2021) examined Bitcoin, contradicting the aggregate and categorical EPU in the United States. They used data from September 2011 to December 2019. The empirical results show that Bitcoin is not a good strategy to hedge against the overall US EPU. Furthermore, when the Bitcoin market is negative, it acts as a significant safe haven for this overall measure of uncertainty. Nonetheless, analyses incorporating categorical EPU data show Bitcoin's ability to function as a powerful hedge and safe haven against specific risks related to fiscal policy, taxation, national security, and trade policy when exploring deeper into the disaggregated level of US EPU data.

Nevertheless, Hernandez et al. (2021) examined the short- and long-term implications of U.S. economic policy uncertainty (EPU) on Bitcoin, gold, and the implied volatility of the U.S. stock market (VIX). They used an autoregressive distributed lag model (ARDL) on monthly data. Their findings indicated that the EPU has a considerable negative (positive) influence on Bitcoin across short (long) time periods. Contrary to previous research, they show that the intensity of the influence of EPU on Bitcoin returns diminishes over longer time horizons.

Furthermore, Fang et al. (2019) examine whether global economic policy uncertainty affects the long-run volatility of Bitcoin, global stocks, commodities, and bonds. Other than the case of bonds, empirical findings confirm this hypothesis. The findings suggest that Bitcoin investors will be able to utilize information about the level of global economic uncertainty to improve their predictions of Bitcoin volatility. They also investigate whether global economic policy uncertainty affects the correlation between Bitcoin and global stocks, commodities, and bonds. Empirical findings show that global economic policy uncertainty does have a significant negative impact on the Bitcoin-bonds correlation but a positive impact on the Bitcoin-equities and Bitcoin-commodities correlations, implying that Bitcoin can act as a hedge under certain economic uncertainty conditions. Also, surprisingly, when the extent of global economic policy uncertainty is taken into account, the hedging efficacy of Bitcoin for both global stocks and global bonds improves marginally. With such a minimal influence of global economic uncertainty on Bitcoin's hedging capacity, investors cannot significantly improve Bitcoin's hedging performance under diverse economic uncertainty situations.

Also, Wu et al. (2019) investigate the safe-haven features of gold and Bitcoin in the face of economic policy uncertainty. Gold and Bitcoin's hedging and safe-haven qualities are calculated using the GARCH model and quantile regression with dummy variables. Gold and Bitcoin, on average, cannot serve as an effective hedge or safe haven for economic policy uncertainty (EPU). In addition, the researchers observed that Bitcoin is more vulnerable to EPU shocks, whereas gold maintains stability despite having lower hedge and safe-haven coefficients. In most cases, gold and Bitcoin can act as a weak hedge and safe haven against EPU during extreme bearish and bullish markets, and they can also be considered for portfolio diversification under stable market conditions. However, the study of Bilgin et al. (2018) does not support the gold results of the previous study. They explored the gold pricing determinants in depth by considering the unique scenario of global economic instability and political disagreements using a nonlinear ARDL model. Empirical research indicated that rising economic policy uncertainty would eventually lead to an increase the gold prices.

Moreover, Papadamou et al. (2021) investigate the nonlinear causal link between economic policy uncertainty and gold in bull and bear market scenarios with cryptocurrency markets. They found that the EPU index influences the averages of over

50% of the digital currencies studied in bull and bear markets and volatility in all quantiles. Similar conclusions are discovered in the case of gold, which is more prominent during bear markets because of its hedging capabilities. In both bull and bear markets, there is evidence that causality in variance is significant in all except the upper quantile for both EPU and gold estimations.

Additionally, Raheem (2021) investigates Bitcoin's safe-haven characteristics against uncertainty measures (VIX, EPU, and oil shock) from 2019 to 2020. According to the literature, cryptocurrencies, notably Bitcoin, provide investors with safe haven benefits. The emergence of the COVID-19 pandemic provides an ideal chance to test this concept. Their study attempts to confirm this assumption by comparing Bitcoin's safe haven ability to uncertainty measurements (VIX, EPU, and Oil Shock). In addition, they compare pre- and post-COVID-19 analyses. The findings show that Bitcoin remained able to keep its generally recognized properties prior to COVID-19. Nevertheless, the post-COVID-19 release reversed the previously documented trends. Also, Choi and Shin (2022) explore the link between inflation, uncertainty, Bitcoin, and gold prices using two uncertainty measures (VIX and US EPU) and determined that financial uncertainty shocks cause Bitcoin prices to fall dramatically, whereas policy uncertainty shocks have little effect.

A limited number of research investigate whether economic policy uncertainty (EPU) affects cryptocurrency returns. A review of the literature reveals that the study undertaken by Bouri et al. (2017) investigated whether Bitcoin may be used to hedge global uncertainty, as assessed by the first primary component of the VIXs of 14 established and emerging equities markets. After decomposing Bitcoin returns into multiple frequencies, they used quantile regression and provided evidence of heavy tails. They show that Bitcoin functions as a hedge against uncertainty, responding favorably to uncertainty at both higher quantiles and shorter frequency fluctuations of Bitcoin returns. Moreover, they employ quantile-on-quantile regression to show that hedging occurs at both the lower and upper ends of Bitcoin returns and global uncertainty.

Matkovskyy and Jalan (2019) also considered that risk-averse investors avoided investing in Bitcoin markets, particularly during times of crisis. They investigated the

EPU's influence on the Bitcoin connection as well as traditional financial markets. Their research found that volatility spillovers between Bitcoin and traditional markets are typically more significant than volatility spillovers between conventional markets. In addition to these findings, these volatility dynamics suggest a complicated trend that spans time and culminates in December 2017, with a frenzied price phase after the announcement of Bitcoin's future. The findings revealed that the EPU had uneven impacts on the conventional assets chosen.

3.2. Uncertainty Indices within Cryptocurrency Markets

The Economic Policy Uncertainty Index is the uncertainty surrounding government and regulatory choices, and changes influence it in political and economic decisions. That means that EPU controls macroeconomic factors such as employment, consumption, and future investment (Demir et al., 2018; Yen and Cheng., 2021). However, the relationship between cryptocurrency and various uncertainty indices, such as geopolitical risk (Aysan et al., 2019), the volatility index (Akyildirim et al., 2020), news implied volatility (Manela and Moreria., 2017), and sentiment index (Corbet et al., 2020), has already been investigated in the current finance literature. Lucey et al. (2022) recently developed the UCRY index as a new uncertainty index for cryptocurrencies. Their UCRY Index tracks cryptocurrency price uncertainty (UCRY Price) and cryptocurrency policy uncertainty (UCRY Policy). They demonstrate that the created index displays different fluctuations in response to crucial occurrences in the Bitcoin field.

Nguyen and Nguyen (2023) investigated the short-term and long-term influence of crypto-specific policy uncertainty and overall economic policy uncertainty (EPU) on Bitcoin exchange inflows. Their findings revealed that the crypto-specific policy uncertainty has both short-term and long-term effects on BTC exchange inflows, but the general EPU solely explains these inflows in the near run. Furthermore, the authors discover that BTC "Granger" exchange inflows increase price volatility. Additionally, the authors show that BTC volatility has an intense and rather persistent reaction to shocks to its exchange inflows.

Also, Xia et al. (2023) investigated the anticipation of the Economic Policy Uncertainty (EPU) and Cryptocurrency Uncertainty (UCRY) indices with BTC volatility. Their research results show that in-sample calculations show that the global EPU index has considerable adverse effects on long-term Bitcoin volatility. However, the UCRY indices positively affect long-term Bitcoin volatility. Furthermore, out-of-sample validation shows that the One-Side Asymmetric GARCH-MIDAS with UCRY price index is the best-performing model, and forecasting models, including the UCRY indices, beat models with global and national EPUs in out-of-sample forecasting. Given their limited scope, UCRY indexes have emerged as a viable data source for directing Bitcoin trading behaviors.

Karaömer (2022) investigated the time-varying connection between cryptocurrency policy uncertainty (UCRY Policy) and cryptocurrency returns. He analyses whether these relationships differ depending on the uncertainty generated by essential events such as cryptocurrency exchange incidents, the Coronavirus (COVID-19) pandemic situation, China's ICO prohibition, and the Security and Exchange Commission's (SEC) statement concerning Ripple. Using weekly data and the DCC-GARCH model, the study found negative connections between the UCRY Policy and the returns of BTC, ETH, LTC, XRP, XLM, DASH, and XMR. As a consequence, an increase in the volatility of the UCRY Policy may reduce the volatility of the returns of BTC, ETH, LTC, XRP, XLM, DASH, and XMR. Additionally, the research's results demonstrate that the projected DCC varies over time and is strongly sensitive to key events like as China's ICO ban, the Covid-19 outbreak, cryptocurrency exchange breaches, and the SEC's Ripple statement. Furthermore, empirical findings show that the UCRY Policy has had a negative impact on cryptocurrency returns during key events like as China's ICO ban, the Covid-19 crisis, and the cryptocurrency exchange hack, signaling that they are useless as a hedge or safe-haven asset.

Wang et al. (2023) investigated time- and frequency-domain spillover effects across cryptocurrency markets and a newly constructed central bank digital currencies attention index (CBDCAI). They applied two TVP-VAR-based spillover models. The research's findings show that CBDC's attention substantially influences cryptocurrency prices. Furthermore, they found that most Bitcoin investors want to trade in the short term.

Furthermore, Ayadi et al. (2023) explore the relationship and directional predictability of central bank digital currencies (CBDCs) with leading cryptocurrencies and stablecoins returns. They applied the "Cross-Quantilogram" model to investigate how and whether traditional digital currencies react to CBDC uncertainty and attention shocks. According to the research, the CBDC uncertainty index negatively connects cryptocurrency and stablecoin returns. In addition, the CBDC attention index negatively correlates with Bitcoin, Ethereum, XPR, and Terra USD. Nevertheless, it positively correlates with Tether, USD Coin, Binance, and Dai.

Another area of study pursued by Bouri et al. (2017) is the forecasting capability of the uncertainty index over cryptocurrency using a wavelet-based technique. Their findings demonstrate that Bitcoin can hedge against uncertainty over shorter periods. Furthermore, Bitcoin's hedging behavior is reflected at the bottom and upper ends of the Bitcoin return. Likewise, Balcilar et al. (2017) evaluated the predictability of cryptocurrency (Bitcoin) using a quantile-based model. Except for bear and bull market environments, their data show that trading volume has predictive potential over cryptocurrency. Demir et al. (2018) demonstrate that the EPU index has a favorable influence on bitcoin returns and may anticipate bitcoin price returns. According to Demir et al. (2018), ambiguity about government actions might cause investors to lose faith in their fiat currencies or be concerned about the broader economy, particularly following the 2008 financial crisis. As a result, a change in the EPU may prompt investors to reassess their portfolio in order to minimize future wealth loss.

Shaikh (2020) continued the investigation by expanding on the previous study and investigating the Bitcoin market and EPU. His research examined the EPU, EMPU, and EPU and worldwide MPU indices of other vital economies. The model also includes control variables such as VIX and SPX returns. The quantile regression and Markov regime-switching models' robust assessments show that EPU affects Bitcoin returns. One of the study's main results is that Bitcoin returns are more sensitive to EPU in the United States, China, and Japan. Uncertainty harms the Bitcoin market in the

United States and Japan but benefits China. Understanding Bitcoin exchange rates also requires an understanding of global MPU uncertainty. Furthermore, the Bitcoin market suffers from uncertainty in the Federal Open Market Committee (FOMC), the gross domestic product, and other macroeconomic indicators. Uncertainty in the stock market and Bitcoin returns are inversely related.

These results are supported by the findings of the study of Cheng and Yen (2020). They used the predictive regression model to examine the influence of China's EPU index on forecasting the returns of critical cryptocurrencies (such as Bitcoin, Ethereum, Litecoin, and Ripple). According to the data, the China EPU index has strong prediction potential for Bitcoin returns, but the EPU indices of the United States, Korea, and Japan have limited predictive power. Also, these results are supported by the study of Cheng and Yen (2020). They emphasized that the U.S. EPU index results demonstrate no substantial capacity to anticipate Bitcoin returns and stated that their findings contradict Demir et al. (2018). Also, according to Cheng and Yen (2020), concentrating on the long-term effect of utilizing monthly data, the U.S. EPU index has no predictive potential for monthly Bitcoin returns for the U.S. or other Asian countries, whereas China's EPU index can predict the monthly returns. These studies show the possible mixed influence of economic policy uncertainty on cryptocurrency markets.

Panagiotidis et al. (2020) investigate the importance of forty-one possible determinants of bitcoin returns from 2010 to 2018. (2872 daily observations). The freshly developed principle component-guided sparse regression method is used. They discover that economic policy uncertainty and stock market volatility are two of Bitcoin's most critical variables.

Gozgor et al. (2019) evaluated the relationship between the trade policy uncertainty index and Bitcoin returns in the United States using several models and indices. The study findings reveal that Bitcoin is positively connected with the trade policy uncertainty index using Wavelet Power Spectrum, Wavelet Coherency, and Cross-Wavelet Techniques. Nonetheless, at times of extreme uncertainty, Bitcoin fails to act as a hedging mechanism against other financial assets.

Through another lens, it has been discovered that investment sentiments could be used to forecast cryptocurrency volatility and returns. Corbet et al. (2020b) created a sentiment index using news reports on four macroeconomic indicators: GDP, unemployment, Consumer Price Index (CPI), and durable goods. The findings revealed that Bitcoin returns reacted differently to news than stock market returns. Additionally, it was shown that the reaction of cryptocurrency prices to news and announcements varies based on the kind of digital assets. Consequently, according to Corbet et al. (2020), currency-based digital assets are likely more vulnerable to U.S. monetary policy pronouncements, whereas application- or protocol-based digital assets are resistant to similar shocks. Corresponding variances are identified for mineable and non-mineable currencies, implying that certain digital assets' responses to various sources of uncertainty would differ from Bitcoin's.

Also, Wu et al. (2021) use the dynamic Granger causality test to examine the impact of economic policy uncertainty (EPU), Twitter-based economic uncertainty (TEU), and Twitter-based market uncertainty (TMU) on the returns of Bitcoin, Ethereum, Litecoin, and Ripple from August 9, 2015, to July 7, 2020, and their results indicate that there is causality from the EPU indices to significant cryptocurrencies for some periods, excluding the COVID19 period. On the other hand, changes in the Twitter-based EPU indices for these periods are positively related to Bitcoin returns.

Similarly, French (2021) examines the effect of the Twitter-based market uncertainty index on Bitcoin returns using data from 2013 to 2020 covering the period before and after COVID-19 and reveals that TMU is a leading indicator of Bitcoin returns only during the pandemic, and people's uncertain tweets have a major impact on Bitcoin price and conditional volatility. The study results imply that information provided in virtual communities like Twitter significantly influences bitcoin prices due to COVID-19.

Aharon et al. (2022) investigate the connection between Twitter-based economic and market uncertainty with the movement of Bitcoin, Ethereum, Bitcoin Cash, and Ripple. They discover a substantial link between the uncertainty metrics utilized and cryptocurrency returns, and the impact is most noticeable for Bitcoin and towards the tails of return distributions.

Furthermore, Lehrer et al. (2021) conducted an out-of-sample experiment. They found that using social media sentiment may enhance the prediction accuracy of a popular volatility index, particularly in the near run. High-frequency data has been proven to be beneficial for predicting. Furthermore, Tumasjan et al. (2021) contend that a positive relationship exists between signaling and venture capital valuation. Still, Twitter sentiment is not shown to be connected to long-term investment performance.

Philippas et al. (2019) analyze if Bitcoin price surges are connected to Twitter and Google Trends informative signals in a series of relevant publications focusing on the implications of Twitter-based investor sentiment on cryptocurrencies. The dual diffusion model results show that the momentum of media attention in social networks drives Bitcoin market prices, and investors seek information to make investment decisions. Likewise, Li et al. (2021) discovered bi-directional causalities and spillovers between the majority of the twenty-seven cryptocurrencies studied and investor interest. These interlinkages are highlighted when investor sentiment is based on a mix of Twitter and Google search data. Huynh (2021) examined the influence of President Trump's tweets on Bitcoin price and trading activity, claiming that negative sentiment tweets are far more potent than good sentiment tweets in terms of predicting returns, trading volume, realized volatility, and surges in Bitcoin markets. Kraaijeveld and De Smedt (2020) investigate the predicting abilities of Twitter sentiment using lexicon-based sentiment analysis and bilateral Granger causality on the nine significant cryptocurrencies. It has been discovered that Twitter considerably impacts the returns of Bitcoin, Bitcoin Cash, and Litecoin, as well as EOS and TRON if a bullishness ratio is used.

In some conditions, a study initiated by Bermpei et al., (2022) indicated that the link between economic uncertainty and Bitcoin market crashes is negative. Hence, investors may prefer to keep their Bitcoin holdings in order to prevent this uncertainty. Walther et al. (2019) forecast cryptocurrency volatility using 17 distinct economic and financial indices. They emphasize that it is fueled by global commerce and a network of interconnected driving variables. The Financial Stress Index and the Chinese Policy Uncertainty Index are valuable and influential indicators of cryptocurrency volatility, although the Global Real Economic Activity Index dominates them. The unpredictability size in the bitcoin price is measured by cryptocurrency price uncertainty.

Bouri and Gupta (2021) examine the prediction efficacy of newspaper- and internet-based uncertainty measures for Bitcoin returns using different indices and measures. They show that Bitcoin is a hedge against both indicators using monthly data. Nevertheless, the predictive ability of the internet-based economic uncertainty-related queries index in predicting Bitcoin returns is statically significantly more extraordinary than the measure of uncertainty derived from newspapers. This is possible because individual investors acquire the former measure of uncertainty based on searching the internet for words related to uncertainty.

Umar et al. (2021) use the wavelet-based quantile-on-quantile approach and the quantile-based Granger causality method to evaluate the influence of political and economic uncertainty in the United States on the Bitcoin price from 2010/06 to 2020/10. The results suggest that political and economic concerns impact Bitcoin values both adversely and favorably during times of increasing uncertainty in the U.S. Therefore, the safe-haven characteristics tend to fluctuate in the short and long run.

Aysan et al. (2019) investigated how geopolitical risk affects Bitcoin returns and volatility. The authors employed Caldara and Iacoviello's (2018) Geopolitical Uncertainty Index (GPR) to quantify worldwide terrorism, conflicts, and state tensions. Aysan et al. (2019) discovered that GPR has predictive power on price volatility and Bitcoin returns using the Bayesian graphical structural vector autoregressive model, indicating Bitcoin's capacity to operate as a beneficial hedging tool during periods of heightened global geopolitical risks. Further, Conlon et al. (2020) evaluated the effects of the Global Economic Policy Uncertainty Index (GEPU) and GPR index on cryptocurrency returns. However, they found insignificant safe-haven or hedging capabilities of cryptocurrencies against either uncertainty indices, with the exception of a limited capacity to hedge against GEPU during a bull market. Their findings are compatible with previous studies in this field, such as (Wu et al., 2019; Al Mamun et al., 2020).

Su et al. (2020) demonstrate how investors may use the Bitcoin market to optimize their portfolio investments during times of elevated geopolitical risk. Gozgor et al. (2019) discover a substantial association between U.S. Trade Policy Uncertainty (TPI) and Bitcoin returns and additional evidence of regime changes between 2010-11 and 2017-18. During regime changes, this relationship is revealed to be powerful. Baker et al. (2021) extend their Economic Policy Uncertainty index by relying on tweets to determine market sentiment. They develop four unique economic mood indices and four market sentiment indices based on tweets, proposing that Twitter users' risk and uncertainty views are pretty comparable to journalist opinions.

Fang et al. (2020) investigated the effect of the News-based Implied Volatility index (NVIX) on cryptocurrency returns, showing that the NVIX, developed by Manela and Moreira (2017), is a better predictor of long-term volatility in selected cryptocurrencies than the Davis (2016) proposed Global Economic Policy Uncertainty index.

Finally, a thorough evaluation of the current literature reveals significant gaps in the analysis of various uncertainty indices on cryptocurrency market returns. This key discovery serves as a catalyst for this chapter, which is intentionally aimed to close these gaps and provide new insights to investors knowledge of the relationship between uncertainty indices and cryptocurrency market behaviors. The chapter seeks to examine the complex effect of multiple uncertainty indices on cryptocurrency market returns, recognizing the importance of such indices in affecting investor attitude and market behaviors. This study aims to extend the scholarly discussion on the complex link between uncertainty and the cryptocurrency environment by measuring and analyzing the impact of these variables on cryptocurrency market returns.

4. RESEARCH GAP AND CONTRIBUTION:

Because cryptocurrencies are still relatively new compared to traditional financial instruments, there remains limited empirical research concerning the linkage between their returns and uncertainty indices. Although some studies emphasize the additional risk such investments might pose to investors in developing economies, numerous researchers recognize the various benefits of cryptocurrencies. Thus, understanding and predicting the connectedness of cryptocurrency returns and uncertainty indices using high-frequency data will reveal the usefulness and benefits of improving the decision-making for potential investors, portfolio managers, and policymakers. Each index accounts for different risks and uncertainties. For example, the Economic Policy Uncertainty Index for Europe, the Cryptocurrency Policy Uncertainty Index (UCRY Policy), and the Cryptocurrency Price Uncertainty Index (UCRY Price) focus on the uncertainty associated with the new policies globally and in Europe specifically that have been imposed on cryptocurrency markets globally and the factors that might affect the price fluctuations of cryptocurrency markets.

Conversely, the Cryptocurrency Environmental Attention (ICEA) Index aims to capture the environmental attention devoted to cryptocurrency market investors and non-investors that might affect investment intentions and market prices. On the contrary, the CBDC Uncertainty Index (CBDCUI) and the CBDC Attention Index (CBDCAI) capture the uncertainty, risks, and attention that central banks' digital currencies impose on cryptocurrency markets as major competitors backed by central banks. Also, the Twitter Economic Uncertainty (TEU) index provides insights into how tweets from investors and non-investors might affect economic uncertainty in general. Therefore, this research's contribution sets out to measure the relationship between the cryptocurrency market returns and different uncertainty indices and determine which index (pairs) affects the most of the returns of cryptocurrencies. Furthermore, this research will compare the indices and their effect on cryptocurrency returns. Not only that, but this research will also focus on the COVID-19 pandemic period and will account for and test for its effects as a crisis period on the chosen indices and cryptocurrency returns. These contributions have differentiated the current study from previous studies by examining the effect of multiple uncertainty indices on more than ten cryptocurrency returns.

Additionally, the research field currently has a gap in the scientific literature because more attention needs to be devoted to cryptocurrencies other than Bitcoin, Ethereum, Litecoin, and Ripple. As such, there is inadequate knowledge about the retunes of the less dominant cryptocurrencies. Therefore, the current research will strive to contribute to the literature by testing the less dominant cryptocurrencies. Thus, this research will help scholars with future investigations and assist investors, financial corporations, portfolio managers, and policymakers shape their investment decisions.

Wang et al. (2022) introduced two of these indices. The first index is the Central Bank Digital Currency Attention Index. The second index is the Central Bank Digital Currency Uncertainty Index. Also, there is another Cryptocurrency Uncertainty Index (UCRY) introduced by Lucey et al. (2022) that covers two forms of uncertainty: cryptocurrency policy uncertainty (UCRY Policy) and cryptocurrency price uncertainty (UCRY Price).

Furthermore, the Cryptocurrency Environmental Attention Index will be applied to cryptocurrency returns to measure its effect and connectedness. To the best of the researcher's knowledge, that index has not been applied to cryptocurrency returns. Also, few studies have used the Central Bank Digital Currency Uncertainty Index effect on cryptocurrency returns, and it is an immense contribution to this paper since the index was proposed in 2022 by Wang et al. Moreover, the daily and weekly Twitter Economic Uncertainty (TEU) indices and the Economic Policy Uncertainty Index for Europe index will be investigated. Therefore, this research will contribute to the empirical literature measuring the dataset's relationship to eight indices in two frequencies.

4.1.Research Questions:

1- Which uncertainty index can strongly affect the returns of the cryptocurrency market?
2- Which uncertainty indices pair can strongly affect the returns of the cryptocurrency market during bear market periods?
3- Which uncertainty indices pair can strongly affect the returns of the cryptocurrency market during bull market periods?

4.2. Research objectives:

1- Identify the relationship between the cryptocurrency market returns and uncertainty indices.
2- Measuring the effect of the Covid-19 pandemic period on both the indices and cryptocurrency returns.
3- Determine the positive and negative relationship between the cryptocurrency market returns and uncertainty indices.
4- Determine which index has the most substantial effect on cryptocurrency market returns.
5- Determine which indices pair has the most significant impact on cryptocurrency market returns.
6- Measuring the effect of the uncertainty indices on ten different cryptocurrency returns.

5. METHODOLOGY

5.1. Research Design:

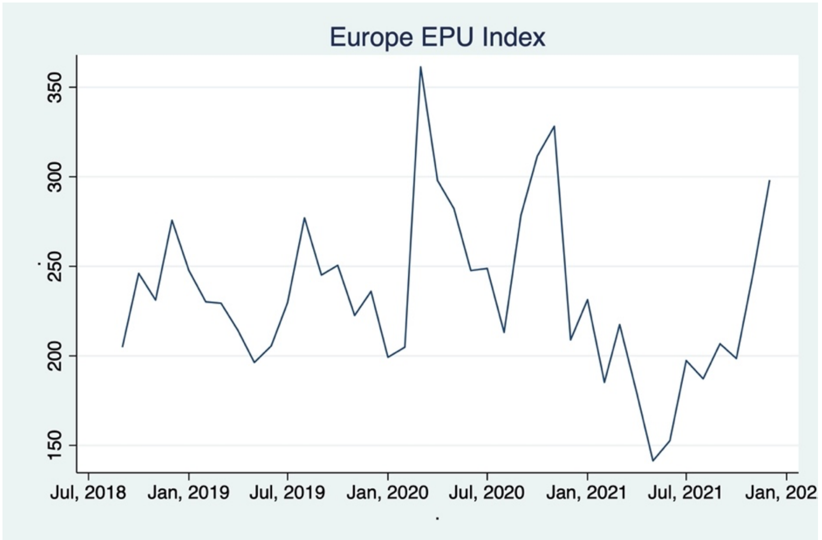
This research measures the relationships between cryptocurrency's returns with multiple indices. Each index has its own measurement and concentrates on a different aspect of possible linkages that might affect the returns. The first and second indices are the Cryptocurrency Policy Uncertainty Index (UCRY Policy) and the Cryptocurrency Price Uncertainty Index (UCRY Price). The two indices have been generated from 726.9 million data text mining. The third index is "the Cryptocurrency Environmental Attention (ICEA) Index aims to capture the relative extent of media discussion around the environmental impact of cryptocurrencies based on 778.2 million data". The fourth and fifth indices are "Based on 663.9 million news stories from LexisNexis News & Business, we provide two new indices for central bank digital currency (CBDC) analysis: the CBDC Uncertainty Index (CBDCUI) and CBDC Attention Index (CBDCAI)". The sixth index is Economic Policy Uncertainty Index for Europe which is an indicator created using newspaper stories about policy uncertainty from major newspapers. It calculates the number of newspaper stories containing uncertain or uncertain, economic or economy, and one or more policy-relevant words. The seventh index is the Twitter Economic Uncertainty (TEU) index, derived from tweets from June 2011 to the present. Thomas Renault (University Paris 1 Panthéon-Sorbonne) created it with the help of Scott R. Baker (Northwestern), Nicholas Bloom (Stanford), and Steve Davis (University of Chicago). The models that will be applied in this research will be the Quantile Regression and the Granger Causality model.

5.2. Data Collection:

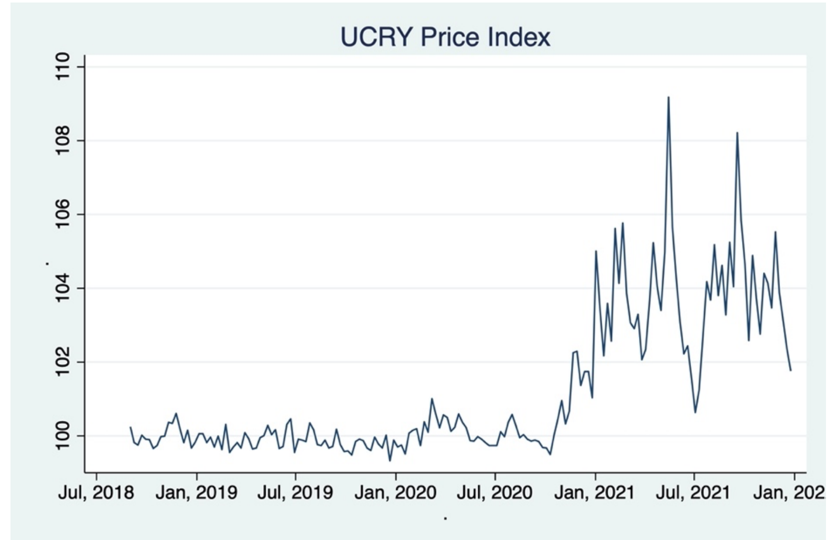
This research uses daily, weekly, and monthly historical data computed from 5-minute log returns for the following ten cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), Bitcoin Cash (BTH), Eos (EOS), Monero (XMR), Stellar (XLM), Dash (DASH), and Ethereum Classic (ETC) between 1st September 2018 to 31st December 2021 (Table A). These cryptocracies have different market capitalizations varying from dominant to less dominant cryptos. The data were obtained from https://www.kraken.com. Weekly data on the Cryptocurrency Policy Uncertainty index, Cryptocurrency Price Uncertainty index are obtained from https://sites.google.com/view/cryptocurrency-indices/the-indices/crypto-uncertainty?authuser=0. Weekly Cryptocurrency Environmental Attention (ICEA) index data is obtained from https://sites.google.com/view/cryptocurrency-indices/the-indices/crypto-environemntal. Weekly data of the Central Bank Digital Currency Uncertainty Index (CBDCUI) and Central Bank Digital Currency Attention Index are obtained from https://sites.google.com/view/cryptocurrency-indices/the-indices/cbdc-indices. Monthly data of the Economic Policy Uncertainty Index for Europe index is obtained from https://fred.stlouisfed.org/series/EUEPUINDXM. Daily Twitter-based Economic Uncertainty (TEU) index data is obtained from Economic Policy

Uncertainty https://www.policyuncertainty.com/twitter_uncert.html. Here are the indices and cryptocurrency returns figures of the research dataset.

Monthly Data



Weekly Data



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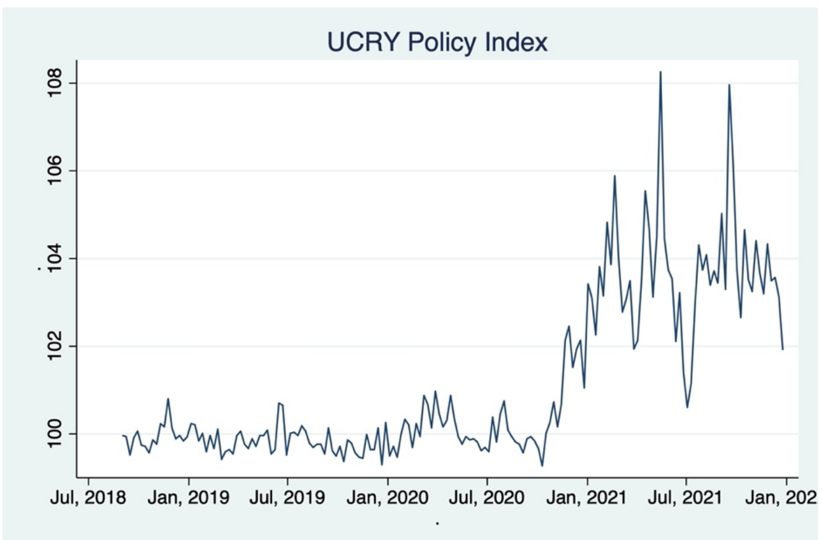

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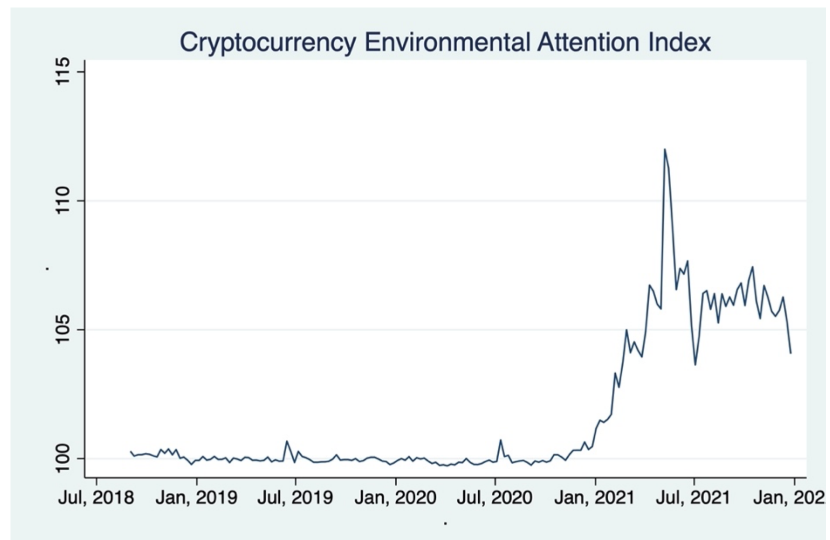

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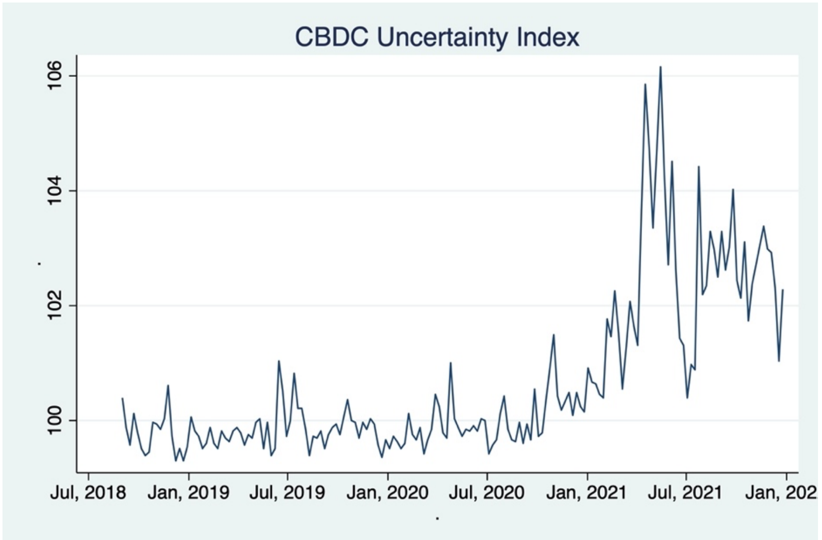

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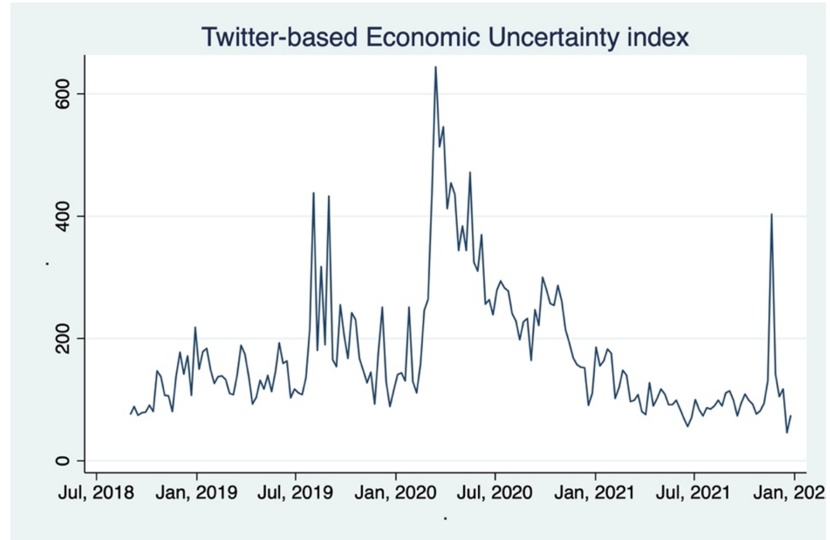
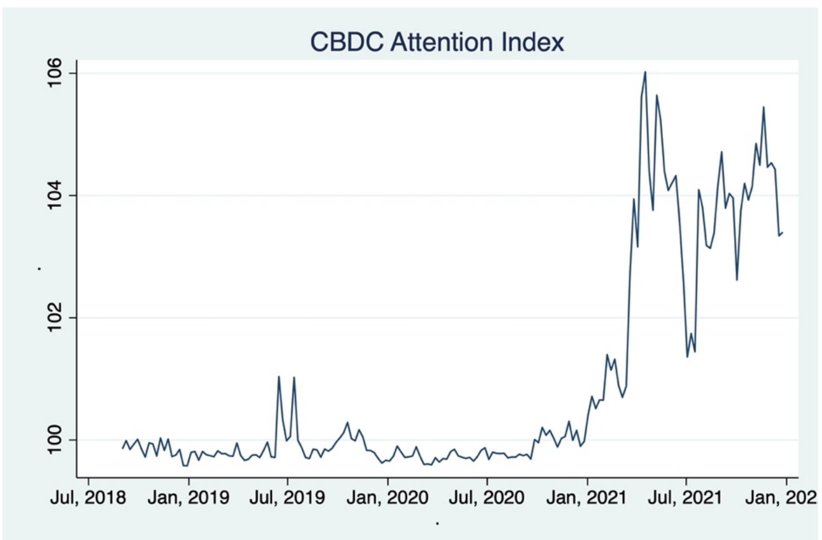
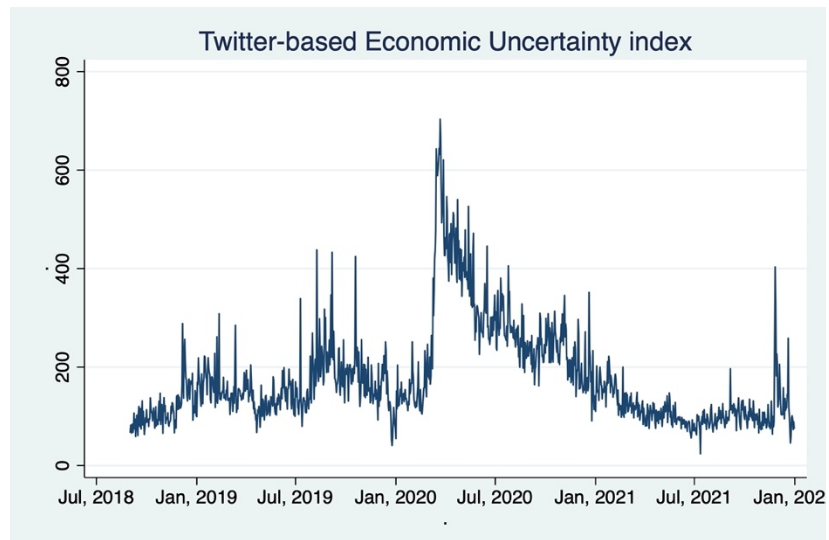


Weekly Data



Daily Data



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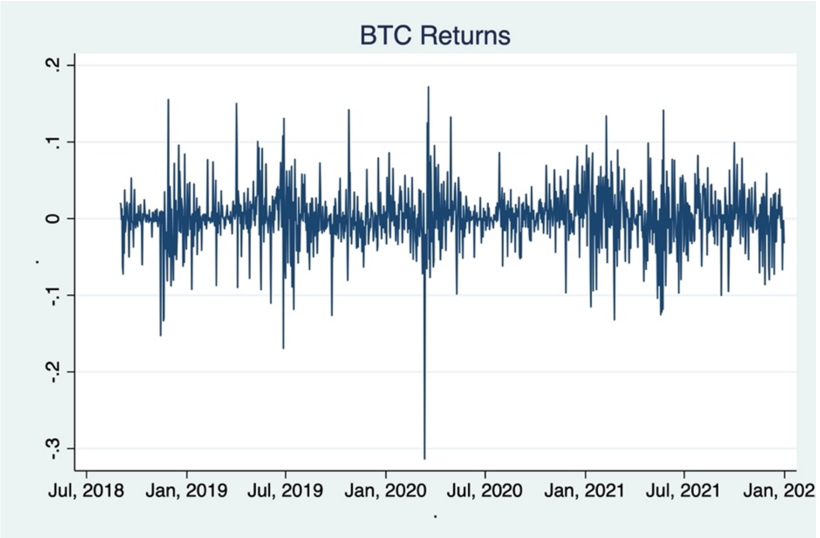
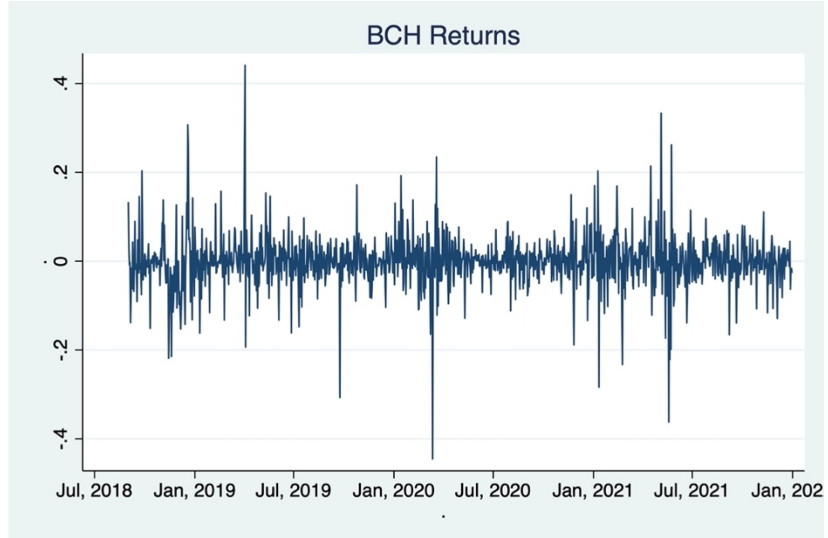


Daily Data



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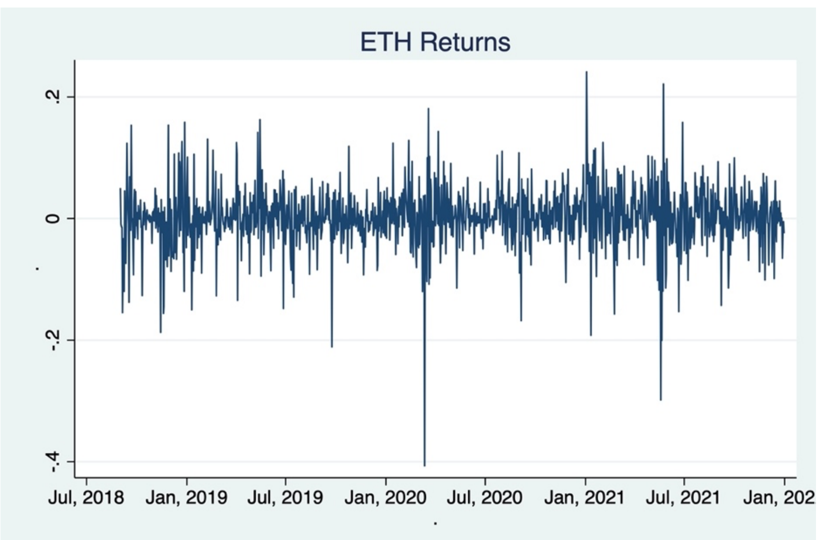

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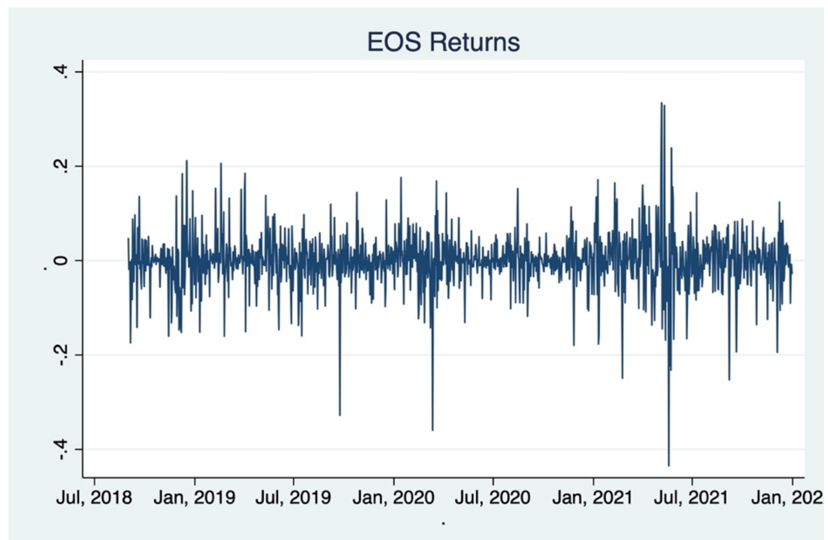

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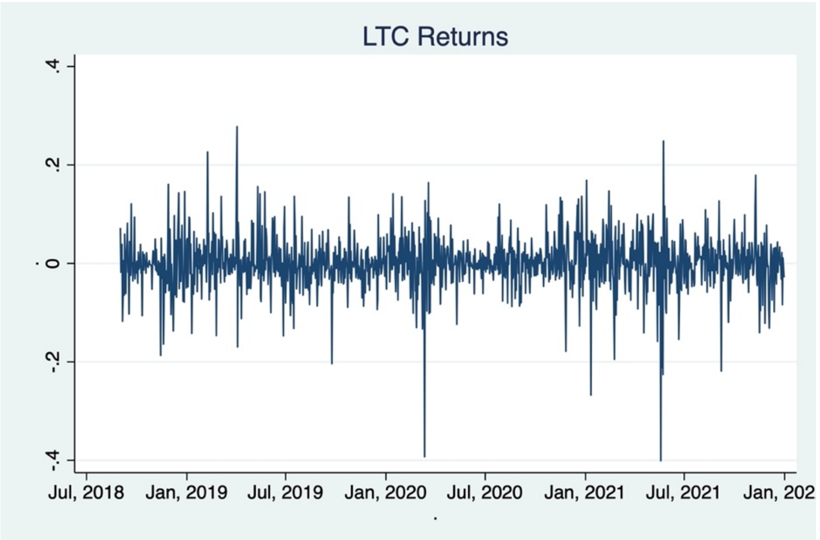

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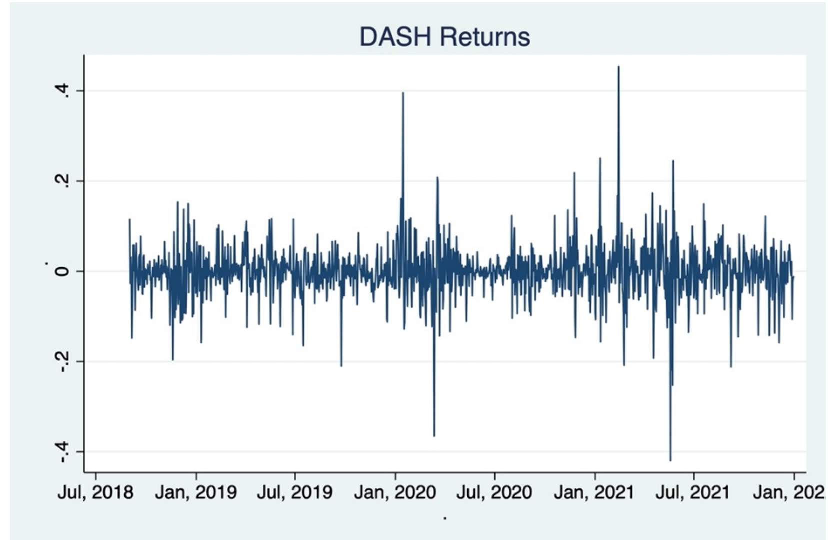

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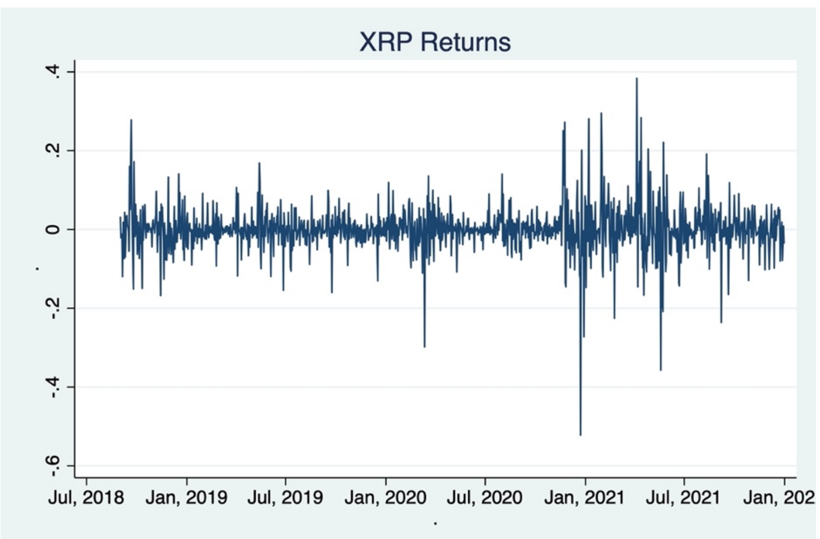
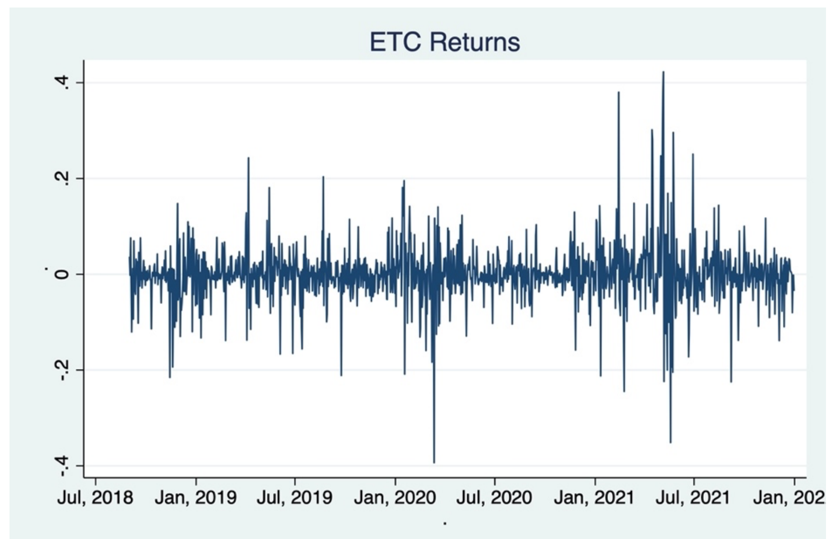
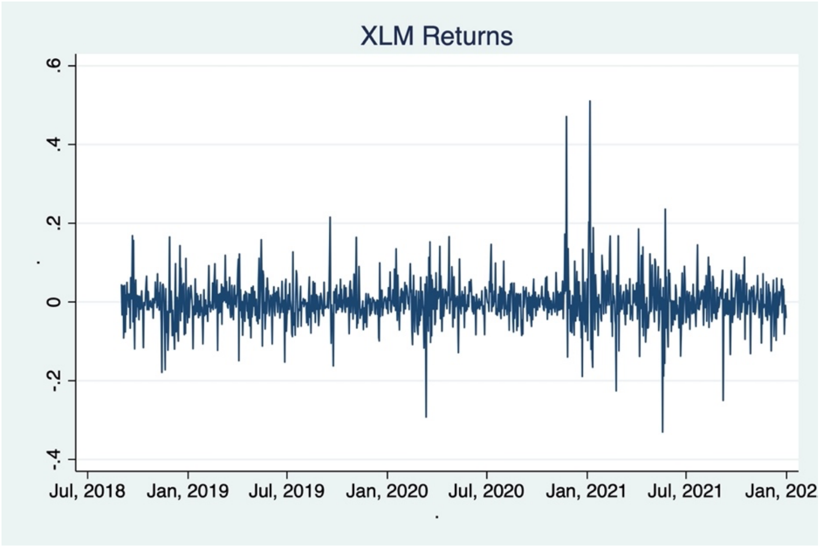


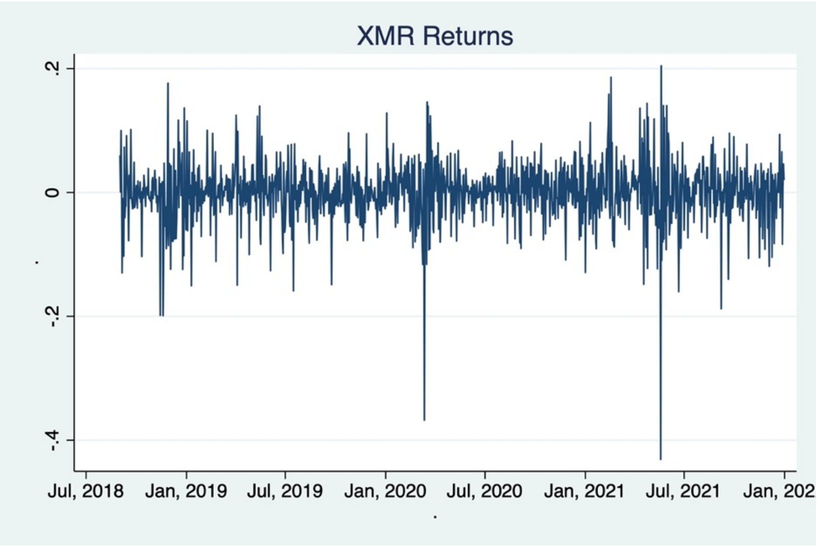
Daily Data



Daily Data



Daily Data



5.3.Research Models:

5.3.1. Quantile Regression Model

The quantile regression (QR) approach, proposed by Koenker and Bassett (1978), predicts the effect of an independent variable on the varied quantiles of the conditional mean of the dependent variable. The τ = quantile range of this study will be from $\tau = 0.10$ to $\tau = 0.9$.

$$Q\,(\tau \mid X) = X\beta\,(\tau)$$

The $Q\,(\tau \mid X)$ denotes the τ-th quantile of the response variable providing the predictor X, and the $\beta\,(\tau)$ represents the vector of the coefficients. The τ = quantile range of this study that will be from $\tau = 0.10$ to $\tau = 0.9$. This model will test the hypothesis of whether there is a relationship between each index and cryptocurrency returns or not for each chosen quantile.

5.3.2. Multivariate Quantile Regression Model

In this model, additionally referred to as joint quantile regression, is an extension of the classic quantile regression model in which several quantiles of the response variable are estimated concurrently given the predictor variables. The main objective for utilizing multi-quantile regression is to increase estimating efficiency, provide smoother coefficient estimates, and more completely represent all of the distributions of the response variable.

The multivariate quantile regressions have been applied by using six independent variables. The seven weekly indices are the Cryptocurrency Policy Uncertainty index, Cryptocurrency Price Uncertainty index, the Cryptocurrency Environmental Attention (ICEA) Index, the Central Bank Digital Currency Uncertainty Index (CBDCUI), the Central Bank Digital Currency Attention Index, the Cryptocurrency policy uncertainty index (UCRY Policy), and the cryptocurrency price uncertainty index (UCRY Price). Also, the daily data of the Twitter-based Economic Uncertainty (TEU) index were added after converting the dataset to weekly data by accounting for the last value of the week (Fridays' values) to be consistent with the other three indices. This model will test the hypothesis of whether there is a relationship between the indices and cryptocurrency returns or not for each chosen quantile.

5.3.3. Granger Causality Model

The Granger causality model was produced by Granger (1969)'s. Before the Granger causality model is applied, the Vector autoregressive model should be applied to set the specifications of the GC test. Furthermore, to determine the best-lagged order to include in the VAR model to find the best accurate results for each variable, the AIC criteria have been chosen to determine the best-lagged order in each variable to apply the VAR model. Then, the lagged order was applied to all the research variables to be consistent. The lagged order that has been taken into consideration based on the AIC criteria is lag = 6. Therefore, the results of the Granger Causality test consist of two results for the majority of cryptocurrencies, and the rest have three lag orders. The first result considers only the first lagged (lag = 1), and the second result consists of only the sixth lagged (lag = 6). Also, the results show the two-sided effects that showed whether the null hypothesis is rejected or accepted.

The null hypothesis is that the chosen index lagged 1 (6) does not cause the chosen CC, and the alternative hypothesis is that the chosen index lagged 1 (6) does cause the chosen CC. Also, vis-versa, the null hypothesis is that the chosen CC does not cause the chosen index lagged 1 (6), and the alternative hypothesis is that the chosen CC does cause the chosen index lagged 1 (6). For the Cryptocurrency Environmental Attention (ICEA) index and Monthly data of the Economic Policy Uncertainty Index for Europe index, the AIC criteria showed different lag order than the other indices. For the Cryptocurrency Environmental Attention (ICEA) index, the AIC criteria showed a lag order = 7, and for the Monthly data of the Economic Policy Uncertainty Index for Europe index, the AIC criteria showed a lag order = 10. All indices results include the lag 1 and 6 in addition to the two added lags of 7 and 10 for the last two indices, respectively.

6. THE EMPERICAL RESULTS:

6.1.Full Sample Results:

The results contain three phases. Each phase shows the results of a one approach that has been applied.

6.1.1. Quantile Regression Results:

The daily and weekly data of the Twitter-based Economic Uncertainty (TEU) index exhibited insignificant effects on cryptocurrency returns across all quantiles chosen for most cryptocurrencies, as Table 1 and Table 4 indicated. These results are consistent with Aharon et al. (2022) study. They found no evidence of a significant coexistent or lagged relationship between the four cryptocurrencies, namely BTC, ETH, XRP, and BCH, and the Twitter-Based Economic Uncertainty (TEU) or Twitter-Based Market Uncertainty (TMU). The results show the positive and negative relationships across all cryptocurrency returns for all quantile levels.

However, the Cryptocurrency Policy Uncertainty index has significant effects on bear periods for cryptocurrency returns across some quantiles, as shown in Table 2. ETH is the most affected cryptocurrency by the Cryptocurrency Policy Uncertainty index, followed by XRP and LTC, with fewer effects than ETH. Also, the index influences the prices of BTC, XRP, LTC, EOS, and XLM on the bull period of the 10 and 20 quantiles. These results contradict the results of Karaömer (2022) research findings that reveal that the UCRY Policy negatively influences cryptocurrency returns throughout significant events. Nevertheless, the Cryptocurrency Price Uncertainty index exhibited fewer effects on cryptocurrency returns, as Table 3 revealed. For instance, there are no effects on ETH for the bear periods. However, the index has significant effects on the BTC, XRP, LTC, XMR, EOS, and DASH returns on the bear market. Although they study only BTC volatility, these results support the research findings of Xia et al. (2023) study that the UCRY indices have positive effects on long-term Bitcoin volatility. UCRY indices have emerged as a viable data source for directing Bitcoin trading behaviors.

Also, Tables 5 and 6 exhibited the quantile regression results of the Central Bank Digital Currency Uncertainty Index and the Central Bank Digital Currency Attention Index effect across all quantiles on cryptocurrency returns. The results reveal the insignificant relationship between the index and the returns for most cryptocurrencies. These results support the research findings of Ayadi et al. (2023). According to the research, the CBDC uncertainty index has a negative connection to cryptocurrency and stable-coin returns. Nevertheless, the XRP result shows a significant effect in early quantiles (10, 20, and 30 quantiles at 5%, 1%, and 1%, respectively), meaning there is a significant relationship between the index and the XRP in the bull period. Also, the ETH result indicates a significant effect in late quantiles (60, 70, and 80 quantiles at a 5% significant level). That means a significant positive relationship between the index and the ETH in the bear period. Also, according to the research's results, the CBDC attention index has a negative correlation with Bitcoin, Ethereum, XPR, and Terra USD, but it has a positive correlation with Tether, USD Coin, Binance, and Dai. Table 6 shows that the XRP result has a significant effect in early quantiles (20 and 30 quantiles at 1%), which means a significant relationship between the index and the XRP in the bull period. Also, the ETH result indicates a significant effect in late quantiles (70 and 80 quantiles at 10% and 5% significant levels). That means a significant relationship in the bear period between the index and the ETH. The results show the positive and negative relationships across all cryptocurrency returns for all quantile levels. The results show the positive and negative relationships across all cryptocurrency returns for all quantile levels.

The results of the Cryptocurrency Environmental Attention (ICEA) index effect across all quantiles on cryptocurrency returns disclose the insignificant relationship between the index and the returns for the majority of the cryptocurrencies, as shown in Table 7. Nevertheless, the XRP result confirms the significant effect in early quantiles (10, 20, and 30 quantiles at 5%, 1%, and 1%, respectively), which means a significant relationship exists between the index and the XRP in the bull period. The results show the positive and negative relationships across all cryptocurrency returns for all quantile levels.

Also, Table 8 shows the Economic Policy Uncertainty Index for Europe index effect across all quantiles on cryptocurrency returns. The results reveal the insignificant relationship between the index and the returns for most cryptocurrencies. This result oppose the findings of Shaikh's (2020) research findings. With a one-period lag in both bull and bear regimes, he concludes that policy uncertainty in Europe adds favorably to the

Bitcoin market. This index is the only index that shows almost no connections with cryptocurrency returns quantile regressions. However, the results show the positive and negative relationships across all cryptocurrency returns for all quantile levels.

These results highlight the intense volatility in the cryptocurrency market and identify the effect of the indices studied in the current research. Some results were unexpected and unanticipated. However, some effects cannot be deducted since they exhibit indirect relationships. These indirect relationships can be captured when measuring the multivariate quantile regressions and causality tests.

6.1.2. Multivariate Quantile Regression Results:

Before explaining the interpretations of the results of Table 9, it is worth mentioning that the Twitter-based Economic Uncertainty (TEU) index was converted from daily to weekly data to compare the index with the other weekly indices. Table 9 revealed the results of the multi-indices effect on cryptocurrency returns. The table showed that the early quantile (quantile = 5) exhibits insignificant impact across most cryptocurrency returns, which means that these indices have the miner effect when the market experiences a bull wave. These results supported the findings of (Aharon et al. 2022, Xia et al. 2023, Ayadi et al. 2023, and Shaikh, 2020),

For the rest of the quantiles, the results show no evidence of a significant impact of the indices on most of the returns of cryptocurrencies, except for the 95% quantiles for The UCRY Price Index and the Cryptocurrency Environmental Attention (ICEA) index. The Cryptocurrency Environmental Attention (ICEA) index significantly affects BTC, XRP, XLM, and DASH with a 5% significant level and LTC and XMR with a 1% significant level. The UCRY Price Index substantially affects XLM with a 1% significant level, LTC, EOS, DASH, and ETC with a 5% significant level, and XMR with a 10% significant level.

The research indices were divided into pairs for the following table to test and measure their effects on cryptocurrency returns. Four pairs were chosen due to their strong effects on cryptocurrency returns in the bull and bear market periods. The four pairs are:

- The UCRY Policy Index + Central Bank Digital Currency Attention Index
- The UCRY Policy Index + the Cryptocurrency Environmental Attention (ICEA) index
- The UCRY Price Index + Central Bank Digital Currency Attention Index
- The UCRY Price Index + the Cryptocurrency Environmental Attention (ICEA) index

Table 10 shows that the UCRY Policy Index + the Central Bank Digital Currency Attention Index pair strongly affects all the cryptocurrency retunes at the 5% significant level (bull market) except BTC returns. However, It strongly affects BTC returns in the 75% and 95% quantiles. These results contradict the results of Karaömer (2022) research findings that reveal that the UCRY Policy negatively influences cryptocurrency returns throughout significant events. Also, these results contradict the research findings of Ayadi et al. (2023) for the Central Bank Digital Currency Attention Index.

Conversely, the UCRY Policy Index and the Cryptocurrency Environmental Attention (ICEA) index pair considerably affect the bear period more than the bull period. For example, Table 11 reveals that the effect of the pair is powerful on BTC returns for the 50%, 75%, and 95% quantiles. It also has fewer effects on XRP, LTC, XMR, and XLM retunes.

Like Table 10, Table 12 shows that the UCRY Price Index + the Cryptocurrency Environmental Attention (ICEA) index pair strongly affects all the cryptocurrency retunes at the 5% significant level (bull market). It also strongly affects BTC in the 75% and 95% quantiles.

Nevertheless, the UCRY Price Index + the Cryptocurrency Environmental Attention (ICEA) index pair substantially affects the bear period more than the bull period. For example, Table 13 discovered that the impact of the pair is powerful on BTC returns for the 50%, 75%, and 95% quantiles. Also, the pair strongly affects ETH, XMR, and XLM returns at the 95% significant level.

To rank these pairs for the bull and n, the following ranks have been identified:

For the bull periods, the pairs ranking is as follows:

1. The UCRY Policy Index + Central Bank Digital Currency Attention Index.
2. The UCRY Price Index + Central Bank Digital Currency Attention Index.
3. The UCRY Price Index + the Cryptocurrency Environmental Attention (ICEA) index.
4. The UCRY Policy Index + the Cryptocurrency Environmental Attention (ICEA) index.

For the bear periods, the pairs ranking is as follows:

1. The UCRY Policy Index + the Cryptocurrency Environmental Attention (ICEA) index.
2. The UCRY Price Index + the Cryptocurrency Environmental Attention (ICEA) index.
3. The UCRY Price Index + Central Bank Digital Currency Attention Index.
4. The UCRY Policy Index + Central Bank Digital Currency Attention Index.

6.1.3. Granger Causality Test Results:

The results of the Granger Causality Test at lagged order (LO) = 1 show insignificant relationships between the daily data of the Twitter-based Economic Uncertainty (TEU) index and cryptocurrency returns as Table 14 reveals. This result is consistent with Aharon et al. (2022) study. However, the results exhibited a significant relationship between the daily data of the TEU index on cryptocurrency returns at LO = 6 as Table 15 indicated. This result contradict the results of Aharon et al. (2022) study. Also, the result indicates the long-term effect of all the cryptocurrency returns except EOS, XLM, ETC. The tables also show no evidence of significant effect of cryptocurrency returns on the TEU index. These results support the findings of Kraaijeveld and De Smedt's 2020 study. However, they used Twitter data manually for each cryptocurrency in their research. Also, the maximum lagged order that they applied was = 5. Moreover, the result supports the Gök et al. (2022) study. Correspondingly, these results supported the findings of Wu et al. (2021) study. They studied the influence of economic policy uncertainty (a Twitter-based uncertainty measure) on the top four cryptocurrencies and discovered a significant causality between cryptocurrencies and cryptocurrencies. Utilizing the Rolling Window technique and the Granger Causality test, they found a positive relationship between Twitter-based uncertainty, VIX, and Cryptocurrencies.

Table 16 shows the results of the Granger Causality Test at LO = 1 for the weekly data of the UCRY Policy Index and Cryptocurrencies returns for the two-sided effects. There is a significant effect between the UCRY Policy Index and ETH, XRP, LTC, BCH, EOS, XMR, XLM, DASH, and ETC returns. These results support the results of Karaömer (2022) research findings that reveal that the UCRY Policy negatively influences cryptocurrency returns throughout significant events. Yet, BTC showed an insignificant effect at the LO = 1. Also, there is no evidence of a significant impact of cryptocurrency returns on the UCRY Policy Index. Nevertheless, XRP, LTC, and ETC returns have significant effects on the UCRY Policy Index, while BTC and XMR returns showed no evidence of any impact from the UCRY Policy Index at LO = 6 that Table 17 displays.

The results of the Granger Causality Test at LO = 1 for the weekly data of the UCRY Price Index and Cryptocurrencies returns for the two-sided effects are similar to the results of the UCRY Policy Index in Table 15, Table 18 shows. There is a significant effect between the UCRY Price Index and ETH, XRP, LTC, BCH, EOS, XMR, XLM, DASH, and ETC returns. Still, BTC shows an insignificant effect at the LO = 1. Also, there is no evidence of a significant effect of cryptocurrency returns on the UCRY Price Index. Nevertheless, BCH and DASH returns have significant effects on the UCRY Policy Index, while all cryptocurrencies returns showed strong evidence of impact from the UCRY Price Index at LO = 6 that Table 19 exhibited. This result supports the research findings of Xia et al. (2023) study that the UCRY indices have positive effects on long-term Bitcoin volatility.

Table 20 shows the results of the Granger Causality Test at LO = 1 for the weekly data of the Twitter-based Economic Uncertainty (TEU) index and cryptocurrency returns for the two-sided effects. The results show significant and strong relationships between the index and all the cryptocurrency returns except for XLM returns. This result disagrees with

Aharon et al. (2022) study. However, there is no evidence of any effects from cryptocurrency returns on the index. Surprisingly, Table 21 reveals the same results for LO = 6. That results indicate the long-term effect of the weekly Twitter-based Economic Uncertainty (TEU) index on cryptocurrency returns.

The results of the Granger Causality Test at LO = 1 for the weekly data of the Central Bank Digital Currency Uncertainty Index (CBDCUI) and Cryptocurrencies returns for the two-sided effects show a significant effect between the CBDCU Index and ETH, XRP, BCH, EOS, XLM, DASH, ETC, and the rest of the cryptocurrencies reveal no evidence of significant effect in Table 22. Also, there is no evidence of a significant impact of cryptocurrency returns on the CBDCU Index. Yet, there are significant effects for the CBDCU Index on all the cryptocurrency returns at LO = 6 that Table 23 displays. Also, on the other side, there are significant effects from BTC, LTC, EOS, DASH, and ETC returns on the CBDCU Index, and the rest of the cryptos show no effect at all.

Table 24 reveals the results of the Granger Causality Test at LO = 1 for the weekly data of the Central Bank Digital Currency Attention Index and Cryptocurrencies returns for the two-sided effects. At LO = 1, there is a significant effect between the CBDCA Index and all the cryptocurrency returns except for BTC. This result supports the findings of Wang et al. (2023)'s study. They found that CBDC attention significantly influences cryptocurrency markets. Yet, there is no evidence of a significant effect of cryptocurrency returns on the ICEA index. Still, the is no evidence of a significant impact between cryptocurrency returns and the CBDCA Index at lagged order = 1. Table 25 discloses that at LO = 6, there is a significant effect for all cryptocurrency returns from the Central Bank Digital Currency Attention Index. Correspondingly, there is a significant effect from XRP, LTC, BCH, EOS, and ETC returns on the CBDCA Index.

Table 26 displayed the results of the Granger Causality Test at LO = 1 for the weekly data of the Cryptocurrency Environmental Attention (ICEA) index and Cryptocurrencies returns for the two-sided effects. Like the Central Bank Digital Currency Attention Index, the ICEA index significantly impacts all cryptocurrency returns except for BTC at LO = 1. This result supports the findings of Wang et al. (2022)'s study. The ICEA shows stronger correlations between environmental attention, Bitcoin, and UCRY indexes during big events that significantly affect the values of digital assets. However, table 27 revealed that the ICEA index significantly affects all cryptocurrency returns. Nevertheless, only XRP, LTC, and EOS significantly affect the ICEA index. The results exhibit a short and long-period effect of the ICEA index on cryptocurrency returns except for BTC in the short period.

Furthermore, Table 28 displays the results of the weekly data of the Cryptocurrency Environmental Attention (ICEA) index and Cryptocurrencies returns for the two-sided effects at LO = 7. The LO = 7 was chosen because the AIC criteria deducted lagged 7 to best fit the Granger Causality Test. The tables reveal the same results as the results of LO = 6 on the effect of the ICEA index on cryptocurrency returns. Nevertheless, all cryptocurrency returns show no evidence of a significant impact on the ICEA index.

Table 29 contains the results of the Granger Causality Test for both-sided at LO = 1 for the Monthly data of the Economic Policy Uncertainty Index for Europe index and Cryptocurrencies returns. It shows no evidence of a significant impact from the Economic Policy Uncertainty Index for Europe index on cryptocurrencies returns. This result contradict the findings of Shaikh's (2020) research findings. However, there is an apparent significant effect from the cryptocurrency returns on the Economic Policy Uncertainty Index for Europe index. The results indicate the ability of the cryptocurrency markets to influence the Economic Policy Uncertainty Index for Europe index in the short period. It is worth noticing that Table 30 revealed the results after considering the LO order = 6. The results show that there is still a limited effect on some cryptocurrency returns, such as the LTC, XLM, and DASH. The rest of the cryptocurrency returns show no effect from the Economic Policy Uncertainty Index for Europe index. Also, cryptocurrency returns significantly affect the Economic Policy Uncertainty Index for Europe index at a 1% significant level.

After applying the AIC criteria between the Economic Policy Uncertainty Index for Europe index on Cryptocurrencies returns, the LO = 10 was chosen. Table 31 revealed evidence of a significant effect of the Economic Policy Uncertainty Index for Europe index on all the cryptocurrency returns except for EOS. Correspondingly, there is a significant effect at a 1% significant level for all cryptocurrency returns on the Economic Policy Uncertainty Index for Europe index. This result supports the findings of the Cheema et al. (2020) study. They used different approaches (OLS, Multivariate Augmented regression, and Quantile regression) and determined that EPU has better predictive power over Bitcoin returns in the long run, six and twelve months, than in the short run, one month.

That means that the cryptocurrency markets significantly affect the Economic Policy Uncertainty Index for Europe index in the short and long periods. Yet, the Economic Policy Uncertainty Index for Europe index can affect cryptocurrency returns and markets in the long term.

6.2.During crisis period Results (Covid-19 Period):

The results contain three phases. Each phase shows the results of a one approach that has been applied.

6.2.1. Quantile Regression Results During Crisis Period:

Table 32 and Table 35 confirm the previous results of the full sample analysis. The daily and weekly Twitter-based Economic Uncertainty (TEU) indices have insignificant effects on cryptocurrency returns across all quantiles chosen for most cryptocurrencies. It shows no evidence of any influence factors that covid-19 pandemic might impose. These results are aligned with the full sample results. However, there is more evidence on the effect of the Cryptocurrency Policy Uncertainty index on cryptocurrency returns for the 10%, 80%, and 90% quantiles that Table 33 reveals. The index significantly affects all cryptocurrency returns' bull period (10% quantile). These results further challenge the results of Karaömer (2022) research findings as mentioned in the full sample analysis. However, ETH returns are not affected by the Cryptocurrency Policy Uncertainty index as in the full sample analysis. Also, Table 34 exhibits more evidence on the effect of the Cryptocurrency Price Uncertainty index on cryptocurrency returns. For instance, The index significantly affects all cryptocurrency returns' bull period (10% quantile). These results support the research findings of Xia et al. (2023) study and are aligned with the full sample results. However, the index has insignificant effects on BTC and XRP returns at the 80% and 90% quantiles.

Likewise, there is a slight negative difference in the effectiveness of the relationship between the Central Bank Digital Currency Uncertainty Index and the cryptocurrency returns for most cryptocurrencies that Table 36 shows. For example, the index affected all cryptocurrency returns except LTC, BCH, and ETC returns at the 10% quantile, with 5% and 1% significant levels. These results are aligned with the full sample results.

During crisis period results of the Central Bank Digital Currency Attention Index, the Cryptocurrency Environmental Attention (ICEA) index, and the Economic Policy Uncertainty Index for Europe index effect across all quantiles on cryptocurrency returns that Tables 37, 38, and 39 reveal. The results confirm the full sample results of an insignificant relationship between the index and the returns for almost all cryptocurrencies.

The Quantile Regression results during crisis period show the positive and negative relationships across all cryptocurrency returns for all quantile levels and support the results of the full sample analysis.

6.2.2. Multivariate Quantile Regression Results During Crisis Period:

The results of the multi-indices effect on cryptocurrency returns are shown in Table 40. The table shows and confirms that the early quantile (quantile = 5) exhibits insignificant impact across most cryptocurrency returns, which means that these indices have the miner effect when the market experiences a bull wave. For the rest of the quantiles, the results show and confirm no evidence of a significant impact of the indices on most of the returns of cryptocurrencies, even for the 95% quantile.

The UCRY Policy Index + the Central Bank Digital Currency Attention Index pair strongly affects all the cryptocurrency retunes at the 5% quantile at a 1% significant level (bull market), as Table 41 displays. Also, It strongly affects BTC returns at the 75% and 95% quantiles. On the contrary, the UCRY Policy Index and the Cryptocurrency Environmental Attention (ICEA) index pair considerably affect the bear period more than the bull period. For example, Table 42 confirms and shows that the effect of the pair is influential on BTC returns for the 75% and 95% quantiles. However, the pair generally has fewer effects on cryptocurrency returns during crisis period than in the full-sample analysis.

The UCRY Price Index + the Cryptocurrency Environmental Attention (ICEA) index pair has less effect on the cryptocurrency retunes at the 5% significant level (bull market) than the full sample results, even for the BTC returns at the 75% and 95% quantiles as Table 43 shows. Nevertheless, the UCRY Price Index + the Cryptocurrency Environmental Attention (ICEA) index pair substantially affects the bull period more than the bear period. For example, Table 44 reveals that the impact of the pair is powerful on cryptocurrency returns at the 5% quantile.

To rank these pairs for the bull and bear market, the following ranks have been identified:

For the bull periods, the pairs ranking of during crisis period results is as follows:

1. The UCRY Policy Index + Central Bank Digital Currency Attention Index
2. The UCRY Price Index + the Cryptocurrency Environmental Attention (ICEA) index
3. The UCRY Price Index + Central Bank Digital Currency Attention Index
4. The UCRY Policy Index + the Cryptocurrency Environmental Attention (ICEA) index

For the bear periods, the pairs ranking of during crisis period results is as follows:

1. The UCRY Policy Index + the Cryptocurrency Environmental Attention (ICEA) index
2. The UCRY Price Index + the Cryptocurrency Environmental Attention (ICEA) index
3. The UCRY Policy Index + Central Bank Digital Currency Attention Index
4. The UCRY Price Index + Central Bank Digital Currency Attention Index

6.2.3. Granger Causality Test Results During Crisis Period:

Confirming the result of the full sample, table 45 shows the insignificant relationships of the Granger Causality Test at lagged order = 1 between the daily data of the Twitter-based Economic Uncertainty (TEU) index and cryptocurrency returns. However, the results of Table 46 show a significant relationship between the daily data of the TEU index on cryptocurrency returns at lagged order = 6 for BTC, ETH, BCH, and

XMR returns. This result indicates the long-term effect of all the cryptocurrency returns except XRP, LTC, EOS, XLM, DASH, and ETC returns. The tables also show no evidence of significant cryptocurrency returns on the TEU index.

Table 47 confirms the significant relationships of the Granger Causality Test at lagged order = 1 between the UCRY Policy Index and Cryptocurrencies returns for the one-sided effects. There is a significant effect from the UCRY Policy Index on all cryptocurrency returns except BTC returns. Also, there is no evidence of a significant impact of cryptocurrency returns on the UCRY Policy Index. Also, Table 48 shows the exact outcomes of the results of lagged order = 1. Nevertheless, XRP, LTC, DASH, and ETC returns significantly affect the UCRY Policy Index, while BTC and XMR returns showed no evidence of any impact from the UCRY Policy Index at lagged order = 6.

The results confirm the full sample results and exhibit a significant effect between the weekly data of the UCRY Price Index and ETH, LTC, BCH, EOS, DASH, and ETC returns at lagged order = 1 in Table 49. Still, BTC, XRP, XMR, and XLM returns show an insignificant effect. Also, there is no evidence of a significant effect of cryptocurrency returns on the UCRY Price Index. Nevertheless, BCH XMR, DASH, and ETC returns have significant effects on the UCRY Policy Index, while all cryptocurrencies returns showed strong evidence of impact from the UCRY Price Index at lagged order = 6 except XMR returns that Table 50 exhibits.

The results of the Granger Causality Test at LO = 1 for the weekly data of the Twitter-based Economic Uncertainty (TEU) index and Cryptocurrencies returns show a significant relationship between the index and cryptocurrency returns for all the cryptocurrency returns except for XPR, XLM, and ETC returns in Table 51. This result is not consistent with Aharon et al. (2022) study. However, the results of Table 52 show a strong insignificant relationship between the weekly data of the TEU index on cryptocurrency returns at LO = 6 for all the cryptocurrency returns. This result supports the results of Aharon et al. (2022) study. This result indicates the lack of long-term effect of all the cryptocurrency returns. Also, there is an insignificant relationship between cryptocurrency returns on the TEU index weekly data at LO = 1 and 6.

Table 53 confirms most of the full sample results of the Granger Causality Test at LO = 1 for the weekly data of the Central Bank Digital Currency Uncertainty Index

(CBDCUI), and Cryptocurrencies returns for the two-sided effects. There is a significant effect between the CBDCU Index and ETH, XRP, LTC, BCH, EOS, XLM, DASH, ETC returns, and the rest of the cryptocurrencies reveal no evidence of significant effects at the LO = 1. These results deny the research findings of Ayadi et al. (2023). According to the research, the CBDC uncertainty index has a negative connection to cryptocurrency and stable-coin returns. Also, there is no evidence of a significant impact of cryptocurrency returns on the CBDCU Index. Yet, there are significant effects for the CBDCU Index on all the cryptocurrency returns at LO = 6 that Table 54 displays, except for ETH and XMR returns. Also, on the other side, there are significant effects from all cryptocurrency returns on the CBDCU Index except XRP returns.

The results of the Granger Causality Test at LO = 1 for the weekly data of the Central Bank Digital Currency Attention Index and Cryptocurrencies returns for the two-sided effects are shown in Table 55. At LO = 1, there is a significant effect between the CBDCA Index and all the cryptocurrency returns except for BTC and ETH returns. This result supports the findings of Wang et al. (2023)'s study. They found that CBDC attention significantly influences cryptocurrency markets. Still, the is no evidence of a significant impact between cryptocurrency returns on the CBDCA Index at LO = 1 except for BTC and XLM returns. Table 56 reveals that at lagged order = 6, there is a significant effect for all cryptocurrency returns from the Central Bank Digital Currency Attention Index except for XLM returns. Correspondingly, there is a significant effect from all cryptocurrency returns except ETH returns on the CBDCA Index.

Table 57 confirms most of the full sample results of the Granger Causality Test at LO = 1 for the weekly data of the Cryptocurrency Environmental Attention (ICEA) index, and Cryptocurrencies returns for the two-sided effects. The ICEA index significantly impacts all cryptocurrency returns except BTC, XRP, and XLM returns at LO = 1. This result supports the findings of Wang et al. (2022)'s study. The ICEA shows stronger correlations between environmental attention, Bitcoin, and UCRY indexes during big events that significantly affect the values of digital assets. Nevertheless, there is no evidence of a significant effect of cryptocurrency returns on the ICEA index except for BTC, LTC, and XLM. However, table 58 reveals that the ICEA index significantly affects all cryptocurrency returns except for XLM returns at LO = 6. Nevertheless, only XMR returns significantly affect the ICEA index. Also, Table 59 shows almost the same results as Table 58. The ICEA index significantly impacts all cryptocurrency returns at LO = 7. However, only XRP and XMR returns significantly affect the ICEA index.

During crisis period results of the Granger Causality Test at LO = 1 for the Monthly data of the Economic Policy Uncertainty Index for Europe index and Cryptocurrencies returns confirm that there is no evidence of a significant impact from the index on cryptocurrencies returns in Table 60. Nonetheless, there are significant effects from all cryptocurrency returns except for BTC and XLM returns on the Economic Policy Uncertainty Index for Europe index. The results indicate the ability of the cryptocurrency markets to influence the Economic Policy Uncertainty Index for Europe index in the short period. Surprisingly, Table 61 reveals the results after considering the LO = 6. The results show significant effects from the index on all cryptocurrency returns except DASH and ETC returns. Also, most cryptocurrency returns significantly affect the Economic Policy Uncertainty Index for Europe index at a 1% significant level. That means that the cryptocurrency markets significantly affect the Economic Policy Uncertainty Index for Europe index in the short and long periods. Yet, the Economic Policy Uncertainty Index for Europe index can affect cryptocurrency returns and markets in the long term.

7. EXECTIVE RESULTS SUMMARY:

In this research, an enormous number of results have been generated. Therefore, this summary will aim to highlight the most important outcomes of this research. The quantile regression model has been applied to all the research variables. The daily and weekly data of the Twitter-based Economic Uncertainty (TEU) index has insignificant effects on cryptocurrency returns across all quantiles. These results have been supported by Covid-19 pandemic period results. The results show insignificant effects from the indices on cryptocurrency returns across all quantiles. These results are consistent with Aharon et al. (2022) study. They found no evidence of a significant contemporaneous or lagged relationship between BTC, ETH, XRP, and BCH and the Twitter-Based Economic Uncertainty (TEU) or Twitter-Based Market Uncertainty (TMU).

However, the weekly data of the Cryptocurrency Policy Uncertainty index significantly affects bear periods for cryptocurrency returns across some quantiles. Those findings contradict the results of Karaömer (2022) research findings that reveal that the UCRY Policy negatively influences cryptocurrency returns throughout significant events. On the other hand, the Cryptocurrency Price Uncertainty index exhibited fewer effects on cryptocurrency returns. During crisis period results supported these results by revealing more evidence of the effect of the Cryptocurrency Policy Uncertainty index on cryptocurrency returns for the 10%, 80%, and 90% quantiles. The index has a significant impact on the bull period (10% quantile) for all cryptocurrency returns as well. Also, there is more evidence of the effect of the Cryptocurrency Price Uncertainty index on cryptocurrency returns. For example, the index significantly affects all cryptocurrency returns' bull period (10% quantile). However, the index has insignificant effects on BTC and XRP returns at the 80% and 90% quantiles. Though they study only BTC volatility, these results support the research findings of Xia et al. (2023) study. They found that the UCRY indices positively affect long-term Bitcoin volatility, and UCRY indices have emerged as viable data sources for directing Bitcoin trading behaviors.

Also, the Central Bank Digital Currency Uncertainty Index, the Central Bank Digital Currency Attention Index, the Cryptocurrency Environmental Attention (ICEA) index, and monthly data of the Economic Policy Uncertainty Index for Europe index have an insignificant relationship on most cryptocurrency returns across most of the quantiles. The results during crisis period confirm the full sample results of an insignificant relationship between the Central Bank Digital Currency Uncertainty Index, the Central Bank Digital Currency Uncertainty Index, the Cryptocurrency Environmental Attention (ICEA) index, and monthly data of the Economic Policy Uncertainty Index for Europe index and the returns for almost all of the cryptocurrency returns. These results support the research findings of Ayadi et al. (2023) study for the Central Bank Digital Currency Uncertainty Index, Ayadi et al. (2023) study for the Central Bank Digital Currency Attention Index, and Shaikh's (2020) study for the Economic Policy Uncertainty Index for Europe index.

Regarding the Multivariate Quantile Regression model, unexpected results have been obtained. The results of the multi-indices effect on cryptocurrency returns showed that the early quantile (quantile = 5) exhibits insignificant impact across most cryptocurrency returns, which means that these indices have less effect when the market experiences a bull wave. For the rest of the quantiles, the results show no evidence of a significant impact of the indices on most of the returns of cryptocurrencies, except for the 95% quantiles for The UCRY Price Index and the Cryptocurrency Environmental Attention (ICEA) index.

Also, the pairs effects approach has been applied, and it found that the UCRY Policy Index + Central Bank Digital Currency Attention Index pair was the most influential pair when the bear period wave hit the market. At the same time, the UCRY Policy Index + the Cryptocurrency Environmental Attention (ICEA) index is the least influential pair on cryptocurrency returns when the bear period wave hit the market. Nevertheless, when accounting for only the bull period wave, the UCRY Policy Index + the Cryptocurrency Environmental Attention (ICEA) index pair is the most influential on cryptocurrency returns under study. At the same time, the UCRY Policy Index + Central Bank Digital Currency Attention Index is the least influential pair on cryptocurrency returns under study when the bull wave period hit the market. These results contradict the results of Karaömer (2022) research findings that reveal that the UCRY Policy negatively influences cryptocurrency returns throughout significant events. Too, these results contradict the research findings of Ayadi et al. (2023) for the Central Bank Digital Currency Attention Index.

Regarding the Granger Causality Test results, during crisis period results show different results on some indices. The results of the daily data of the Twitter-based Economic Uncertainty (TEU) index and cryptocurrency returns at lagged = 1 reveal an insignificant relationship. In contrast, the weekly data show significant and strong relationships between the index and all the cryptocurrency returns except for XLM returns. Also, for the lagged = 6, there is a significant relationship for all cryptocurrency returns except for EOS, XLM, and ETC returns in the full sample results and except for XRP, LTC, EOS, XLM, DASH, and ETC returns during crisis period results while the weekly data show there is a significant relationship for all cryptocurrency returns. These results indicate the long-term effect of the daily and weekly data of the Twitter-based Economic Uncertainty (TEU) index on cryptocurrency returns. Also, these results support the findings of Kraaijeveld and De Smedt's 2020 study, Gök et al. (2022) study, and Wu et al. (2021) study.

The UCRY Policy Index and the UCRY Price Index Granger Causality Test results significantly affect all cryptocurrency returns except for BTC returns at lagged order =1. Also, there is no evidence of a significant impact of cryptocurrency returns on the UCRY Policy Index and UCRY Policy Index. Still, XRP, LTC, and ETC returns significantly affect the UCRY Policy Index, and BCH and DASH returns significantly affect the UCRY Policy Index. During crisis period results confirmed these results.

The results of the Granger Causality Test for the weekly data of the Central Bank Digital Currency Uncertainty Index (CBDCUI) show a significant effect between the CBDCU Index and ETH, XRP, BCH, EOS, XLM, DASH, ETC, and the rest of the cryptocurrencies reveal no evidence of significant effect at the lagged order = 1. Also, there is no evidence of a significant impact of cryptocurrency returns on the CBDCU Index. Yet, there are significant effects for the CBDCU Index on all the cryptocurrency returns at lagged order = 6, and there are significant effects from BTC, LTC, EOS, DASH, and ETC returns on the CBDCU Index, and the rest of the cryptos show no effect at all. The results during crisis period confirmed most of the results of the full sample results.

The Central Bank Digital Currency Attention Index and the Cryptocurrency Environmental Attention (ICEA) index Granger Causality Test results reveal significant effects between the indices index and all the cryptocurrency returns except for BTC. Also, the is no evidence of a significant impact between cryptocurrency returns and the two indices at lagged order = 1. Likewise, there is a significant effect on all cryptocurrency returns from the Central Bank Digital Currency Attention Index. Correspondingly, there is a significant effect from XRP, LTC, BCH, EOS, and ETC returns on the CBDCA Index. Similarly, the ICEA index significantly affects all cryptocurrency returns. Only XRP, LTC, and EOS significantly affect the ICEA index. The results during crisis period confirmed most of the results of the full sample results.

The results of the Granger Causality Test for both-sided at lagged order = 1 for the Monthly data of the Economic Policy Uncertainty Index for Europe index and Cryptocurrencies returns show no evidence of a significant impact from the index on cryptocurrencies returns. However, there is an apparent significant effect from the cryptocurrency returns on the Economic Policy Uncertainty Index for Europe index. After considering the lagged order = 6, the results show that there is still a limited effect on some cryptocurrency returns, such as the LTC, XLM, and DASH. The rest of the cryptocurrency returns show no effect from the Economic Policy Uncertainty Index for Europe index. Also, cryptocurrency returns significantly affect the Economic Policy Uncertainty Index for Europe index at a 1% significant level. The results during crisis period confirmed the results of the full sample results. Also, the results support the findings of the Cheema et al. (2020) study.

8. LIMITATIONS

In Chapter Three, the research encounters specific limitations. the dataset lacks information for the years 2022 and 2023 due to data unavailability during the study's conclusion. Furthermore, due to time limits in this chapter, as well as the additional effort necessary for data cleaning and filtering, it was difficult to expand the dataset to include 2022. As a result, future researchers should investigate increasing the dataset in order to obtain more thorough results. Also, future examination should extend on this work by investigating the impact of the COVID-19 period on these indices and their impact on cryptocurrency returns. Researchers might investigate how these uncertainty indices impact cryptocurrency returns before, during, and after COVID-19. Furthermore, the research did not include other economic uncertainty indices, especially those used by important nations such as China. Therefore, investigating other economic uncertainty indices, such as China, might provide useful information. Furthermore, the research only used three regressions. Therefore, future research might look at the link between uncertainty indices and cryptocurrency returns using a wide range of models that take into account a variety of elements and viewpoints. Exploring new uncertainty indices may also help us better understand bitcoin markets and the external forces that influence their performance.

9. CONCLUSION:

This chapter investigated the relationships and effects of eight different indices, namely the daily and weekly Twitter-based Economic Uncertainty (TEU) index, the UCRY Policy Index, the UCRY Price Index, the Central Bank Digital Currency Uncertainty Index (CBDCUI), the Central Bank Digital Currency Attention Index (CBDCAI), the Cryptocurrency Environmental Attention (ICEA) index, and the Economic Policy Uncertainty Index for Europe index on cryptocurrency returns. The quantile regressions, multivariate quantile regressions, and Granger causality tests were applied.

The quantiles 10% to 90% were chosen and tested for the quantile regressions. Quantiles 5%, 25%, 50%, 75%, and 95% were selected and tested for the multivariate quantile regressions. The quantile regressions revealed insignificant effects for the TEU, CBDCU, CBDCA, ICEA, and EPUIE indices on cryptocurrency return for most of the quantiles. However, there is evidence of effects for some cryptocurrencies' returns on bear periods for the UCRY Policy Index and the UCRY Price Index.

However, the research results show that the effectiveness of the indices can be more vital when accounting for two indices together to get accurate results better, Piratically, when considering two different indices. Each index focuses on different aspects, such as the UCRY Policy Index + Central Bank Digital Currency Attention Index pair. The first index focuses on the policy aspect, and the second focuses on the attention to investor behavior. With that focus, the results could be much more accurate and effective because they account for a broader and bigger image of external factors that might affect and chape the investor's decisions. These findings were further and deeper tested. Most of the Covid-19 pandemic period results supported the results of the entire sample analysis.

Nonetheless, the multivariate quantile regression results revealed different results when considering testing all the indices together. The results showed that the early quantile (quantile = 5) exhibits insignificant impact across most cryptocurrency returns, which means that these indices have the miner effect when the market experiences a bull wave. For the rest of the quantiles, the results show no evidence of a significant impact of the indices on most of the returns of cryptocurrencies, except for the 95% quantiles for The UCRY Price Index and the Cryptocurrency Environmental Attention (ICEA) index. The Cryptocurrency Environmental Attention (ICEA) index significantly affects BTC, XRP, XLM, and DASH with a 5% significant level and LTC and XMR with a 1% significant level. The UCRY Price Index substantially affects XLM with a 1% significant level, LTC, EOS, DASH, and ETC with a 5% significant level, and XMR with a 10% significant level.

The Granger causality test results show insignificant relationships between the TEU index and cryptocurrency returns in the short term (lagged order =1) for both side effects. However, there are significant relationships in the long term (lagged order = 6) for the TEU index on cryptocurrency returns only. Furthermore, the Granger causality test results show significant relationships between the UCRY Policy Index and Cryptocurrencies returns in the short term (lagged order =1) for all cryptocurrency returns except BTC returns. Still, there are insignificant relationships between the Cryptocurrencies returns and the UCRY Policy Index for all cryptocurrency returns. However, BTC and XMR returns showed no evidence of any impact from the UCRY Policy Index at lagged order = 6. Also, there is no evidence of a significant effect of cryptocurrency returns on the UCRY Policy Index lagged order = 1. Nevertheless, XRP, LTC, and ETC returns significantly affect the UCRY Policy Index.

Also, the results are similar to the results of the UCRY Policy Index. There is a significant effect between the UCRY Price Index and ETH, XRP, LTC, BCH, EOS, XMR, XLM, DASH, and ETC returns. Still, BTC showed an insignificant effect at the lagged order = 1. Also, there is no evidence of a significant effect of cryptocurrency returns on the UCRY Price Index. Nevertheless, BCH and DASH returns significantly affect the UCRY Price Index, while all cryptocurrencies returns showed strong evidence of impact from the UCRY Price Index at lagged order = 6.

Also, there is a significant effect between the CBDCU Index and ETH, XRP, BCH, EOS, XLM, DASH, ETC. The rest of the cryptocurrencies reveal no evidence of significant effect at the lagged order = 1. Also, there is no evidence of a significant impact of cryptocurrency returns on the CBDCU Index. Yet, there are significant effects for the CBDCU Index on all the cryptocurrency returns at lagged order = 6. Also, on the other side, there are significant effects from BTC, LTC, EOS, DASH, and ETC on the CBDCU Index, and the rest of the cryptos show no effect at all.

Furthermore, At lagged order = 1, there is a significant effect between the CBDCA Index and all the cryptocurrency returns except for BTC. Still, the is no evidence of a significant effect between cryptocurrency returns and the CBDCA Index at lagged order = 1. In fact, at lagged order = 6, there is a significant effect for all cryptocurrency returns from the Central Bank Digital Currency Attention Index. Correspondingly, there is a significant effect from XRP, LTC, BCH, EOS, and ETC on the CBDCA Index. Corresponding to the Central Bank Digital Currency Attention Index, the ICEA index significantly impacts all cryptocurrency returns except for BTC at lagged order = 1. Still, there is no evidence of a significant effect of cryptocurrency returns on the ICEA index. However, tables 21 and 22 revealed that the ICEA index significantly affects all cryptocurrency returns.

Nevertheless, only XRP, LTC, and EOS significantly affect the ICEA index. The results exhibit a short and long-period effect of the ICEA index on cryptocurrency returns except for BTC in the short period. Investigating in-depth, the lagged order = 7 was chosen because the AIC criteria deducted lagged 7 to fit the Granger Causality Test best. The tables reveal the same results as the results of lagged order = 6 on the effect of the ICEA index on cryptocurrency returns. Nevertheless, all cryptocurrency returns show no evidence of a significant impact on the ICEA index. Also, the Monthly data of the Economic Policy Uncertainty Index for Europe index and Cryptocurrencies returns for the two-sided effects were tested. It shows no evidence of a significant impact from the EPUIE index on cryptocurrency returns. However, there is an apparent significant effect from the cryptocurrency returns on the EPUIE index. The results indicate the ability of the cryptocurrency markets to influence the Economic Policy Uncertainty Index for Europe index in the short period. The results of the lagged order = 6 show that there is still a limited effect on some cryptocurrency returns, such as the LTC, XLM, and DASH. The rest of the cryptocurrency returns show no effect from the Economic Policy Uncertainty Index for Europe index. However, cryptocurrency returns significantly affect the Economic Policy Uncertainty Index for Europe index at a 1% significant level. To examine the effectiveness of the Economic Policy Uncertainty Index for Europe index on Cryptocurrencies returns over a more extended period, the lagged order = 10 was chosen after applying the AIC criteria. The results reveal evidence of significant effects of the Economic Policy Uncertainty Index for Europe index on all the cryptocurrency returns except for EOS.

Similarly, there is a significant effect at a 1% significant level for all cryptocurrency returns on the Economic Policy Uncertainty Index for Europe index.

The findings of this study can assist investors and financial institutions in avoiding investment risks, mitigating losses, and forecasting the return of specific cryptocurrencies. Also, they will help policymakers better understand the impact of market structures and policies and serve as a reference for them when formulating policies.

References:

Aharon, D.Y., Demir, E., Lau, C.K.M. and Zaremba, A., 2022. Twitter-Based uncertainty and cryptocurrency returns. *Research in International Business and Finance*, *59*, p.101546.

Akyildirim, E., Corbet, S., Lucey, B., Sensoy, A. and Yarovaya, L., 2020. The relationship between implied volatility and cryptocurrency returns. *Finance Research Letters*, *33*, p.101212.

Al Mamun, M., Uddin, G.S., Suleman, M.T. and Kang, S.H., 2020. Geopolitical risk, uncertainty and Bitcoin investment. *Physica A: Statistical Mechanics and its Applications*, *540*, p.123107.

Ayadi, A., Ghabri, Y. and Guesmi, K., 2023. Directional predictability from central bank digital currency to cryptocurrencies and stablecoins. *Research in International Business and Finance*, *65*, p.101909.

Aysan, A.F., Demir, E., Gozgor, G. and Lau, C.K.M., 2019. Effects of the geopolitical risks on Bitcoin returns and volatility. *Research in International Business and Finance*, *47*, pp.511-518.

Azzimonti, M. and Talbert, M., 2014. Polarized business cycles. *Journal of Monetary Economics*, *67*, pp.47-61.

Azzimonti, M., 2018. Partisan conflict and private investment. *Journal of Monetary Economics*, *93*, pp.114-131.

Baker, S.R., Bloom, N., Davis, S.J. and Renault, T., 2021. Twitter-derived measures of economic uncertainty. *Available online: PolicyUncertainty.Com (accessed on 15 June 2022)*.

Balcilar, M., Bouri, E., Gupta, R. and Roubaud, D., 2017. Can volume predict Bitcoin returns and volatility? A quantiles-based approach. *Economic Modelling*, *64*, pp.74-81.

Benedetti, H. and Nikbakht, E., 2021. Returns and network growth of digital tokens after cross-listings. *Journal of Corporate Finance*, *66*, p.101853.

Bermpei, T., Kalyvas, A.N., Neri, L. and Russo, A., 2022. Does economic policy uncertainty matter for financial reporting quality? Evidence from the United States. *Review of Quantitative Finance and Accounting*, *58*(2), pp.795-845.

Bilgin, M.H., Gozgor, G., Lau, C.K.M. and Sheng, X., 2018. The effects of uncertainty measures on the price of gold. *International Review of Financial Analysis*, *58*, pp.1-7.

Borri, N., 2019. Conditional tail-risk in cryptocurrency markets. *Journal of Empirical Finance*, *50*, pp.1-19.

Bouri, E. and Gupta, R., 2021. Predicting Bitcoin returns: Comparing the roles of newspaper- and internet search-based measures of uncertainty. *Finance Research Letters*, *38*, p.101398.

Bouri, E., Gupta, R., Tiwari, A.K. and Roubaud, D., 2017. Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters*, *23*, pp.87-95.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D. and Hagfors, L.I., 2017. On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier?. *Finance Research Letters*, *20*, pp.192-198.

Caldara, D. and Iacoviello, M., 2018. Measuring geopolitical risk. Board of Governors of the Federal Reserve Board Working Paper.

Cheema, M.A., Szulczuk, K. and Bouri, E., 2020. Predicting cryptocurrency returns based on economic policy uncertainty: A multicountry analysis using linear and quantile-based models. *SSRN Electronic Journal,* pp.1-34.

Cheng, H.P. and Yen, K.C., 2020. The relationship between the economic policy uncertainty and the cryptocurrency market. *Finance Research Letters*, *35*, p.101308.

Choi, S. and Shin, J., 2022. Bitcoin: An inflation hedge but not a safe haven. *Finance Research Letters*, *46*, p.102379.

Colon, F., Kim, C., Kim, H. and Kim, W., 2021. The effect of political andeconomic uncertainty on the cryptocurrency market. *Finance Research Letters*, *39*, p.101621.

Corbet, S., Larkin, C., Lucey, B., Meegan, A. and Yarovaya, L., 2020b. Cryptocurrency reaction to fomc announcements: Evidence of heterogeneity based on blockchain stack position. *Journal of FinancialStability*, *46*, p.100706.

Corbet, S., Larkin, C., Lucey, B.M., Meegan, A. and Yarovaya, L., 2020. The impact of macroeconomic news on Bitcoin returns. *The European Journal of Finance*, *26*(14), pp.1396-1416.

Davis, S.J., 2016. An index of global economic policy uncertainty (No. w22740). *National Bureau of Economic Research.*

Demir, E., Gozgor, G., Lau, C.K.M. and Vigne, S.A., 2018. Does economic policy uncertainty predict the Bitcoin returns? An empirical investigation. *Finance Research Letters, 26, pp.145-149.*

Fang, L., Bouri, E., Gupta, R. and Roubaud, D., 2019. Does global economic uncertainty matter for the volatility and hedging effectiveness of Bitcoin?. *International Review of Financial Analysis*, *61*, pp.29-36.

Fang, T., Su, Z. and Yin, L., 2020. Economic fundamentals or investor perceptions? The role of uncertainty in predicting long-term cryptocurrency volatility. *International Review of Financial Analysis*, *71*, p.101566.

French, J.J., 2021. # Bitcoin,# COVID-19: Twitter-Based Uncertainty and Bitcoin Before and during the Pandemic. *International Journal of Financial Studies*, *9*(2), p.28.

Gerritsen, D.F., Bouri, E., Ramezanifar, E. and Roubaud, D., 2020. The profitability of technical trading rules in the Bitcoin market. *Finance Research Letters*, *34*, p.101263.

Gök, R., Bouri, E. and Gemici, E., 2022. Can Twitter-based economic uncertainty predict safe haven assets under all market conditions and investment horizons?. *Technological Forecasting and Social Change*, *185*, p.122091.

Gozgor, G., Tiwari, A.K., Demir, E. and Akron, S., 2019. The relationship between Bitcoin returns and trade policy uncertainty. *Finance Research Letters*, *29*, pp.75-82.

Granger, C.W., 1969. Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: journal of the Econometric Society*, pp.424-438.

Gupta, R., Pierdzioch, C., Selmi, R. and Wohar, M.E., 2018. Does partisan conflict predict areduction in US stock market (realized) volatility? Evidence from a quantile-on-quantile regression model☆. *The North American Journal of Economics and Finance*, *43*, pp.87-96.

Hasan, M.B., Hassan, M.K., Karim, Z.A. and Rashid, M.M., 2022. Exploring the hedge and safe haven properties of cryptocurrency in policy uncertainty. *Finance Research Letters*, *46*, p.102272.

Hernandez, J.A., Hasan, M.Z. and McIver, R.P., 2022. Bitcoin, gold, and the VIX:short-and long-term effects of economic policy uncertainty. *Applied Economics Letters*, pp.1-5.

Hu, Y., Valera, H.G.A. and Oxley, L., 2019. Market efficiency of the top market cap cryptocurrencies: Further evidence from a panel framework. *Finance Research Letters*, *31*, pp.138-145.

Huynh, T.L.D., 2021. Does bitcoin react to Trump's tweets?. *Journal of Behavioral and Experimental Finance*, *31*, p.100546.

Karaömer, Y., 2022. The time-varying correlation between cryptocurrency policy uncertainty and cryptocurrency returns. *Studies in Economics and Finance*.

Kraaijeveld, O. and De Smedt, J., 2020. The predictive power of public Twitter sentiment for forecasting cryptocurrency prices. *Journal of International Financial Markets, Institutions and Money*, *65*, p.101188.

Lehrer, S., Xie, T. and Zhang, X., 2021. Social media sentiment, model uncertainty, and volatility forecasting. *Economic Modelling*, *102*, p.105556.

Li, Y., Goodell, J.W. and Shen, D., 2021. Comparing search-engine and social media attentions in finance research: Evidence from cryptocurrencies. *International Review of Economics & Finance*, *75*, pp.723-746.

Lucey, B.M., Vigne, S.A., Yarovaya, L. and Wang, Y., 2022. The cryptocurrency uncertainty index. *Finance Research Letters*, *45*, p.102147.

Manela, A. and Moreira, A., 2017. News implied volatility and disaster concerns. *Journal of Financial Economics*, *123*(1), pp.137-162.

Matkovskyy, R. and Jalan, A., 2019. From financial markets to Bitcoin markets: A fresh look at the contagion effect. *Finance Research Letters*, *31*, pp.93-97.

Mokni, K., Ajmi, A.N., Bouri, E. and Vo, X.V., 2020. Economic policy uncertainty and the Bitcoin-US stock nexus. *Journal of Multinational Financial Management*, *57*, p.100656.

Mokni, K., Bouri, E., Ajmi, A.N. and Vo, X.V., 2021. Does Bitcoin hedge categorical economic uncertainty? A quantile analysis. *Sage Open*, *11*(2), p.21582440211016377.

Nguyen, L.T.M. and Nguyen, P.T., 2023. Do crypto investors wait and see during policy uncertainty? An examination of the dynamic relationships between policy uncertainty and exchange inflows of Bitcoin. *Review of Behavioral Finance*.

Panagiotidis, T., Stengos, T. and Vravosinos, O., 2020. A principal component guided sparse regression approach for the determination of bitcoin returns. *Journal of Risk and Financial Management*, *13*(2), p.33.

Papadamou, S., Kyriazis, N.A. and Tzeremes, P.G., 2021. Non-linear causal linkages of EPU and gold with major cryptocurrencies during bull and bear markets. *The North American Journal of Economics and Finance*, *56*, p.101343.

Philippas, D., Rjiba, H., Guesmi, K. and Goutte, S., 2019. Media attention and Bitcoin prices. *Finance Research Letters*, *30*, pp.37-43.

Philippas, D., Rjiba, H., Guesmi, K. and Goutte, S., 2019. Media attention and Bitcoin prices. *Finance Research Letters*, *30*, pp.37-43.

Raheem, I.D., 2021. COVID-19 pandemic and the safe haven property of Bitcoin. *The Quarterly Review of Economics and Finance*, *81*, pp.370-375.

Shaikh, I., 2020. Policy uncertainty and Bitcoin returns. *Borsa Istanbul Review*, *20*(3), pp.257-268.

Shang, Y., Wei, Y. and Chen, Y., 2022. Cryptocurrency policy uncertainty and gold return forecasting: A dynamic Occam's window approach. *Finance Research Letters, 50, p.103251.*

Su, C.W., Qin, M., Tao, R. and Umar, M., 2020. Financial implications of fourth industrial revolution: Can bitcoin improve prospects of energy investment?. *Technological Forecasting and Social Change*, *158*,p.120178.

Su, C.W., Qin, M., Tao, R., Shao, X.F., Albu, L.L. and Umar, M., 2020. Can Bitcoin hedge the risks of geopolitical events?. *Technological Forecasting and Social Change*, *159*, p.120182.

Tumasjan, A., Braun, R. and Stolz, B., 2021. Twitter sentiment as a weak signal in venture capital financing. *Journal of Business Venturing*, *36*(2), p.106062.

Turatti, D.E., Mendes, F.H.P. and Caldeira, J.F., 2020. Testing for mean reversion in Bitcoin returns with Gibbs-sampling-augmented randomization. *Finance Research Letters*, *34*, p.101252.

Umar, M., Su, C.W., Rizvi, S.K.A. and Shao, X.F., 2021. Bitcoin: A safe haven asset and a winner amid political and economic uncertainties in the US?. *Technological Forecasting and Social Change*, *167*, p.120680.

Urquhart, A., 2016. The inefficiency of Bitcoin. *Economics Letters*, *148*, pp.80-82.

Walther, T., Klein, T. and Bouri, E., 2019. Exogenous drivers of Bitcoin and Cryptocurrency volatility–A mixed data sampling approach to forecasting. *Journal of International Financial Markets, Institutions and Money*, *63*, p.101133.

Wang, Y., Lucey, B.M., Vigne, S.A. and Yarovaya, L., 2022. The effects of central bank digital currencies news on financial markets. *Technological Forecasting and Social Change, 180, p.121715.*

Wang, Y., Wei, Y., Lucey, B.M. and Su, Y., 2023. Return spillover analysis across central bank digital currency attention and cryptocurrency markets. *Research in International Business and Finance, 64, p.101896.*

Wang, Y., Lucey, B., Vigne, S.A. and Yarovaya, L., 2022. An index of cryptocurrency environmental attention (ICEA). China Finance Review International, 12(3), pp.378-414.

Wu, S., Tong, M., Yang, Z. and Derbali, A., 2019. Does gold or Bitcoin hedge economic policy uncertainty?. *Finance Research Letters*, *31*, pp.171-178.

Wu, W., Tiwari, A.K., Gozgor, G. and Leping, H., 2021. Does economic policy uncertainty affect cryptocurrency markets? Evidence from Twitter-based uncertainty measures. *Research in International Business and Finance*, *58*, p.101478.

Xia, Y., Sang, C., He, L. and Wang, Z., 2023. The role of uncertainty index in forecasting volatility of Bitcoin: fresh evidence from GARCH-MIDAS approach. *FinanceResearch Letters*, *52*, p.103391.

Yarovaya, L. and Zięba, D., 2022. Intraday volume-return nexus in cryptocurrency markets: Novel evidence from cryptocurrency classification. *Research in International Business and Finance*, *60*, p.101592.

Yen, K.C. and Cheng, H.P., 2021. Economic policy uncertainty and cryptocurrency volatility. *Finance Research Letters, 38, p.1.*

Chapter Three Research Tables

Table A: Descriptive Analysis for the Daily Data and Index

	Mean	Median	SD	Kurtosis	Skewness	Range	Observation
TEPU	176.19	144.94	100.50	4.16	1.85	679.29	1218
BTC	0.002	0.001	0.04	6.19	-0.52	0.49	1218
ETH	0.002	0.001	0.05	6.86	-0.72	0.65	1218
XRP	0.001	-0.001	0.06	11.73	-0.22	0.91	1218
LTC	0.001	-0.001	0.05	6.85	-0.63	0.68	1218
BCH	0.000	0.001	0.06	9.84	-0.04	0.89	1218
EOS	-0.001	0.000	0.06	7.28	-0.49	0.77	1218
XMR	0.001	0.001	0.05	8.77	-1.00	0.64	1218
XLM	0.000	-0.001	0.06	11.38	0.88	0.84	1218
DASH	0.000	0.000	0.06	9.38	0.10	0.87	1218
ETC	0.001	0.000	0.06	9.41	0.46	0.82	1218

Table B: Descriptive Analysis for the Weekly Data and Indices

	Mean	Median	SD	Kurtosis	Skewness	Range	Observation
UCRY Policy Index	101.124	100.135	1.896	1.086	1.320	8.987	174
UCRY Price Index	101.194	100.174	1.977	1.492	1.441	9.853	174
TEPU	175.557	141.392	105.118	3.294	1.736	598.238	174
CBDC Uncertainty Index	100.662	100.001	1.428	2.122	1.631	6.857	174
CBDC Attention Index	100.873	99.916	1.788	0.408	1.404	6.444	174
CC Environmental Attention Index	101.666	100.057	2.803	0.865	1.409	12.277	174
BTC	0.011	0.012	0.100	3.893	-0.828	0.789	174
ETH	0.015	0.022	0.133	4.530	-0.953	1.055	174
XRP	0.005	-0.009	0.152	4.277	0.666	1.186	174
LTC	0.005	0.013	0.140	3.362	-0.672	1.026	174
BCH	-0.001	0.000	0.175	6.112	-0.205	1.536	174
EOS	-0.004	0.008	0.155	4.485	-0.978	1.184	174
XMR	0.004	0.015	0.124	5.057	-1.230	0.935	174
XLM	0.001	-0.005	0.151	7.444	1.249	1.268	174
DASH	-0.002	0.001	0.165	5.778	0.033	1.441	174
ETC	0.006	0.003	0.174	13.797	1.999	1.699	174

Table C: Descriptive Analysis for the Monthly Data and Index

	Mean	Median	SD	Kurtosis	Skewness	Range	Count
EURO-EPU-Index	234.2	229.9	45.8	0.7	0.6	220.0	40
BTC	0.045	0.019	0.228	1.445	-0.829	1.121	40
ETH	0.058	0.098	0.284	1.037	-0.564	1.375	40
XRP	0.026	-0.058	0.344	0.650	0.129	1.678	40
LTC	0.022	0.033	0.294	0.929	-0.872	1.262	40
BCH	-0.002	-0.024	0.359	1.666	-0.549	1.797	40
EOS	-0.011	-0.030	0.311	1.402	-0.554	1.560	40
XMR	0.018	0.031	0.284	3.072	-1.215	1.520	40
XLM	0.006	0.003	0.318	0.064	-0.020	1.511	40
DASH	-0.004	0.018	0.343	1.981	-0.371	1.952	40
ETC	0.033	-0.011	0.432	7.019	1.648	2.734	40

First: the results of the Quantile Regressions.

Table 1: Effects of the Daily data of the Twitter-based Economic Uncertainty (TEU) index on Cryptocurrencies returns.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
10	**Estimate**	-0.0000183	-0.0000198	0.0000276	0.0000073	0.0000039	0.0000294	-0.0000138	-0.0000019	0.0000152	0.0000108
	P-value	0.444	0.534	0.311	0.867	0.913	0.305	0.718	0.949	0.654	0.753
20	**Estimate**	-0.0000067	-0.0000024	0.0000186	-0.0000047	-0.0000046	0.0000150	-0.0000048	0.0000112	0.0000068	0.0000245
	P-value	0.751	0.903	0.088*	0.809	0.839	0.444	0.822	0.568	0.773	0.084*
30	**Estimate**	-0.0000082	0.0000003	0.0000112	0.0000057	0.0000114	0.0000154	0.0000044	0.0000190	0.0000133	0.0000029
	P-value	0.489	0.964	0.230	0.677	0.495	0.208	0.819	0.300	0.398	0.854
40	**Estimate**	-0.0000010	-0.0000045	0.0000009	-0.0000004	0.0000035	0.0000026	0.0000227	0.0000058	0.0000019	-0.0000097
	P-value	0.921	0.602	0.904	0.971	0.750	0.732	0.143	0.664	0.893	0.525
50	**Estimate**	-0.0000052	-0.0000111	-0.0000021	-0.0000045	-0.0000016	-0.0000113	0.0000160	0.0000057	0.0000012	-0.0000068
	P-value	0.538	0.398	0.856	0.792	0.909	0.180	0.182	0.744	0.936	0.584
60	**Estimate**	-0.0000023	-0.0000066	-0.0000085	-0.0000066	-0.0000111	-0.0000331	0.0000036	-0.0000032	-0.0000117	-0.0000129
	P-value	0.816	0.740	0.523	0.747	0.380	0.002***	0.795	0.847	0.390	0.421
70	**Estimate**	0.0000005	0.0000008	-0.0000227	-0.0000175	-0.0000152	-0.0000349	0.0000035	-0.0000087	-0.0000352	-0.0000282
	P-value	0.960	0.976	0.197	0.424	0.228	0.033**	0.839	0.640	0.011**	0.143
80	**Estimate**	-0.0000042	0.0000070	-0.0000341	-0.0000314	-0.0000189	-0.0000219	0.0000178	-0.0000176	-0.0000167	-0.0000194
	P-value	0.852	0.812	0.064*	0.311	0.408	0.285	0.513	0.354	0.503	0.338
90	**Estimate**	0.0000149	0.0000148	-0.0000524	-0.0000149	-0.0000101	-0.0000286	0.0000213	0.0000033	-0.0000257	0.0000027
	P-value	0.540	0.625	0.072*	0.767	0.795	0.395	0.425	0.930	0.598	0.960

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 2: Effects of the Weekly data of the Cryptocurrency policy uncertainty index on Cryptocurrencies returns.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
10	Estimate	-0.015	-0.013	-0.029	-0.028	-0.016	-0.038	-0.016	-0.025	-0.028	-0.013
	P-value	0.062*	0.571	0.032**	0.078*	0.429	0.064*	0.181	0.009***	0.060	0.476
20	Estimate	-0.011	-0.006	-0.020	-0.018	-0.013	-0.026	-0.005	-0.015	-0.012	-0.016
	P-value	0.037**	0.544	0.025**	0.179	0.460	0.077*	0.733	0.263	0.377	0.270
30	Estimate	-0.009	-0.002	-0.011	-0.016	-0.002	-0.014	-0.007	-0.003	-0.015	-0.011
	P-value	0.150	0.779	0.211	0.142	0.876	0.209	0.480	0.788	0.260	0.373
40	Estimate	-0.003	0.008	-0.003	-0.009	-0.007	0.001	-0.004	0.000	0.002	-0.003
	P-value	0.711	0.376	0.685	0.409	0.580	0.925	0.540	0.974	0.861	0.731
50	Estimate	0.004	0.009	0.001	0.001	0.004	0.003	0.003	0.001	0.008	0.002
	P-value	0.551	0.038**	0.871	0.931	0.675	0.645	0.612	0.816	0.228	0.876
60	Estimate	0.006	0.012	0.006	0.005	0.003	0.003	0.007	0.006	0.008	0.009
	P-value	0.352	0.031**	0.466	0.448	0.776	0.658	0.243	0.383	0.204	0.276
70	Estimate	0.012	0.012	0.012	0.012	0.002	0.010	0.010	0.007	0.012	0.014
	P-value	0.076*	0.055**	0.317	0.245	0.812	0.084*	0.109	0.260	0.247	0.054*
80	Estimate	0.009	0.016	0.035	0.031	0.012	0.012	0.015	0.014	0.019	0.011
	P-value	0.214	0.007***	0.012**	0.002***	0.375	0.060*	0.078*	0.164	0.128	0.209
90	Estimate	0.012	0.006	0.050	0.018	0.012	0.007	0.016	0.007	0.033	0.018
	P-value	0.295	0.552	0.009***	0.082*	0.378	0.631	0.134	0.590	0.014	0.251

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 3: Effects of the Weekly data of the Cryptocurrency Price Uncertainty Index on Cryptocurrencies returns.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
10	Estimate	-0.017	-0.012	-0.026	-0.031	-0.022	-0.039	-0.015	-0.022	-0.035	-0.012
	P-value	0.107	0.425	0.024**	0.016**	0.247	0.159	0.416	0.096*	0.072*	0.468
20	Estimate	-0.010	-0.006	-0.020	-0.016	-0.013	-0.023	-0.005	-0.014	-0.011	-0.019
	P-value	0.727	0.444	0.517	0.428	0.515	0.962	0.765	0.866	0.669	0.088*
30	Estimate	-0.009	-0.002	-0.009	-0.016	-0.002	-0.013	-0.007	-0.003	-0.015	-0.009
	P-value	0.236	0.765	0.219	0.073*	0.835	0.349	0.144	0.631	0.130	0.313
40	Estimate	-0.002	0.005	-0.005	-0.007	-0.006	0.001	-0.002	0.001	0.005	-0.003
	P-value	0.727	0.444	0.517	0.428	0.515	0.962	0.765	0.866	0.669	0.765
50	Estimate	0.002	0.009	0.001	0.001	0.005	0.003	0.003	0.001	0.008	0.001
	P-value	0.673	0.039**	0.895	0.892	0.549	0.732	0.598	0.802	0.283	0.875
60	Estimate	0.006	0.009	0.004	0.005	0.003	0.006	0.003	0.007	0.006	0.009
	P-value	0.111	0.050**	0.662	0.447	0.725	0.502	0.526	0.295	0.399	0.157
70	Estimate	0.005	0.010	0.012	0.011	0.003	0.010	0.008	0.008	0.011	0.015
	P-value	0.382	0.059*	0.240	0.165	0.656	0.179	0.190	0.146	0.295	0.062*
80	Estimate	0.010	0.013	0.031	0.025	0.011	0.013	0.014	0.015	0.020	0.011
	P-value	0.031**	0.112	0.045**	0.010***	0.301	0.015**	0.066*	0.330	0.109	0.118
90	Estimate	0.021	0.007	0.043	0.015	0.017	0.007	0.017	0.015	0.035	0.023
	P-value	0.022**	0.683	0.030**	0.085*	0.178	0.587	0.138	0.342	0.001***	0.157

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 4: The Effects of the Weekly data of the Twitter-based Economic Uncertainty (TEU) index on Cryptocurrencies returns.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
10	Estimate	0.00014	0.00021	0.00021	0.00018	0.00039	0.00040	0.00030	0.00006	0.00033	0.00032
	P-value	0.341	0.520	0.162	0.650	0.521	0.000***	0.365	0.726	0.081*	0.237
20	Estimate	0.00014	0.00013	0.00019	0.00013	0.00031	0.00033	0.00027	0.00007	0.00025	0.00017
	P-value	0.117	0.896	0.235	0.639	0.190	0.867	0.387	0.669	0.605	0.088*
30	Estimate	0.00004	0.00007	0.00012	0.00015	0.00020	0.00011	0.00020	0.00005	0.00015	0.00010
	P-value	0.534	0.252	0.035**	0.163	0.001***	0.490	0.026**	0.643	0.038**	0.330
40	Estimate	0.00010	-0.00002	0.00008	0.00005	0.00010	0.00002	0.00010	0.00004	0.00003	0.00002
	P-value	0.117	0.896	0.235	0.639	0.190	0.867	0.387	0.669	0.605	0.783
50	Estimate	0.00006	0.00006	0.00004	-0.00004	0.00002	0.00002	0.00004	0.00002	-0.00006	0.00001
	P-value	0.353	0.513	0.443	0.704	0.830	0.837	0.674	0.814	0.547	0.876
60	Estimate	0.00005	0.00001	0.00000	0.00001	-0.00008	0.00000	0.00008	-0.00001	-0.00012	-0.00003
	P-value	0.476	0.871	0.994	0.858	0.303	0.972	0.309	0.861	0.202	0.641
70	Estimate	0.00005	-0.00002	-0.00008	-0.00005	-0.00004	-0.00005	0.00005	-0.00004	-0.00006	-0.00007
	P-value	0.461	0.781	0.184	0.460	0.424	0.593	0.471	0.604	0.651	0.409
80	Estimate	0.00003	-0.00010	-0.00015	-0.00014	-0.00006	-0.00017	-0.00001	0.00001	-0.00016	-0.00007
	P-value	0.826	0.159	0.025**	0.052**	0.534	0.038**	0.955	0.954	0.496	0.270
90	Estimate	0.00000	-0.00023	-0.00033	-0.00029	0.00005	-0.00016	-0.00008	-0.00013	-0.00024	-0.00027
	P-value	0.960	0.008***	0.091*	0.007***	0.733	0.080*	0.616	0.462	0.398	0.007***

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 5: Effects of the Weekly data of the Central Bank Digital Currency Uncertainty Index on Cryptocurrencies returns.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
10	**Estimate**	-0.022	-0.013	-0.038	-0.026	-0.023	-0.051	-0.007	-0.023	-0.043	-0.013
	P-value	0.111	0.605	0.012**	0.374	0.494	0.099*	0.689	0.354	0.062*	0.628
20	**Estimate**	-0.020	-0.006	-0.019	-0.023	-0.012	-0.038	-0.013	-0.011	-0.022	-0.023
	P-value	0.031**	0.493	0.008***	0.235	0.482	0.139	0.258	0.417	0.203	0.195
30	**Estimate**	-0.012	-0.003	-0.018	-0.013	-0.003	-0.021	-0.009	-0.003	-0.019	-0.018
	P-value	0.229	0.776	0.001***	0.240	0.839	0.275	0.403	0.766	0.295	0.117
40	**Estimate**	-0.005	0.003	-0.014	-0.014	-0.007	-0.002	-0.006	0.000	-0.005	-0.017
	P-value	0.455	0.824	0.198	0.182	0.530	0.883	0.631	0.967	0.744	0.205
50	**Estimate**	0.000	0.010	-0.006	-0.002	-0.006	-0.002	0.003	0.000	0.009	-0.007
	P-value	0.956	0.303	0.687	0.845	0.495	0.830	0.734	0.972	0.523	0.603
60	**Estimate**	0.004	0.016	0.008	0.004	0.003	0.006	0.005	0.001	0.003	0.008
	P-value	0.626	0.025**	0.504	0.696	0.757	0.498	0.574	0.931	0.765	0.443
70	**Estimate**	0.000	0.013	0.015	0.015	0.000	0.013	0.012	0.006	0.010	0.014
	P-value	0.981	0.047**	0.144	0.125	0.994	0.150	0.137	0.546	0.462	0.136
80	**Estimate**	0.010	0.018	0.023	0.018	0.011	0.016	0.016	0.005	0.016	0.012
	P-value	0.288	0.017**	0.078*	0.300	0.448	0.007***	0.116	0.705	0.252	0.203
90	**Estimate**	0.006	0.003	0.045	0.027	0.011	0.007	0.019	0.002	0.027	0.033
	P-value	0.638	0.758	0.030**	0.091*	0.589	0.697	0.017**	0.889	0.052*	0.398

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 6: The Effects of the Weekly data of the Central Bank Digital Currency Attention Index on Cryptocurrencies returns.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
10	Estimate	-0.013	-0.006	-0.015	-0.017	-0.009	-0.015	-0.006	-0.011	-0.024	-0.010
	P-value	0.112	0.397	0.333	0.073*	0.727	0.464	0.728	0.601	0.324	0.400
20	Estimate	-0.013	-0.004	-0.017	-0.014	-0.012	-0.026	-0.010	-0.002	-0.014	-0.017
	P-value	0.079*	0.479	0.001***	0.241	0.196	0.05**	0.369	0.841	0.050**	0.010***
30	Estimate	-0.007	-0.002	-0.014	-0.011	-0.001	-0.010	-0.006	-0.001	-0.016	-0.010
	P-value	0.219	0.661	0.001***	0.245	0.855	0.498	0.311	0.813	0.235	0.317
40	Estimate	-0.004	0.003	-0.008	-0.011	-0.006	-0.001	-0.005	0.000	-0.002	-0.010
	P-value	0.457	0.597	0.248	0.133	0.261	0.950	0.374	0.962	0.850	0.371
50	Estimate	-0.004	0.002	-0.001	-0.002	-0.004	-0.001	0.002	0.000	0.009	-0.004
	P-value	0.466	0.744	0.909	0.777	0.437	0.882	0.779	0.978	0.251	0.728
60	Estimate	0.001	0.008	0.006	0.003	-0.001	0.005	0.002	0.001	0.006	0.007
	P-value	0.918	0.205	0.500	0.667	0.905	0.578	0.775	0.908	0.375	0.549
70	Estimate	-0.001	0.010	0.010	0.008	0.001	0.012	0.008	0.004	0.006	0.010
	P-value	0.775	0.066**	0.402	0.229	0.919	0.037**	0.147	0.455	0.557	0.378
80	Estimate	-0.001	0.012	0.012	0.010	0.006	0.008	0.007	0.003	0.015	0.012
	P-value	0.915	0.022**	0.439	0.339	0.483	0.240	0.298	0.739	0.286	0.417
90	Estimate	-0.002	0.004	0.047	0.019	0.009	0.007	0.016	0.001	0.019	0.027
	P-value	0.828	0.501	0.022**	0.072*	0.655	0.678	0.027**	0.893	0.162	0.485

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 7: The Effects of the Weekly data of the Cryptocurrency Environmental Attention (ICEA) index on Cryptocurrencies returns.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
10	**Estimate**	-0.006	-0.008	-0.016	-0.013	-0.006	-0.014	-0.012	-0.007	-0.012	-0.011
	P-value	0.431	0.519	0.033	0.324	0.682	0.524	0.321	0.505	0.464	0.240
20	**Estimate**	-0.008	-0.003	-0.009	-0.011	-0.008	-0.015	-0.006	-0.001	-0.011	-0.008
	P-value	0.056*	0.699	0.002***	0.178	0.168	0.068*	0.145	0.875	0.202	0.275
30	**Estimate**	-0.006	-0.001	-0.007	-0.008	-0.001	-0.005	-0.005	-0.001	-0.008	-0.007
	P-value	0.236	0.783	0.006***	0.136	0.892	0.466	0.342	0.891	0.157	0.299
40	**Estimate**	-0.002	0.004	-0.005	-0.005	-0.002	0.000	-0.004	0.001	0.001	-0.007
	P-value	0.583	0.461	0.219	0.239	0.405	0.945	0.442	0.852	0.793	0.241
50	**Estimate**	-0.002	0.006	0.000	-0.001	-0.003	0.000	0.002	0.002	0.005	-0.002
	P-value	0.611	0.083	0.962	0.792	0.518	0.980	0.700	0.580	0.229	0.765
60	**Estimate**	0.000	0.005	-0.002	0.002	0.001	0.003	0.001	0.003	0.002	0.005
	P-value	0.900	0.116	0.726	0.630	0.822	0.628	0.738	0.383	0.623	0.525
70	**Estimate**	-0.001	0.006	0.006	0.004	0.000	0.007	0.003	0.004	0.003	0.006
	P-value	0.891	0.160	0.324	0.465	0.956	0.165	0.382	0.301	0.370	0.271
80	**Estimate**	0.000	0.004	0.008	0.006	0.003	0.006	0.003	0.004	0.011	0.005
	P-value	0.938	0.360	0.448	0.549	0.533	0.102	0.592	0.416	0.144	0.252
90	**Estimate**	-0.001	0.003	0.031	0.005	0.007	0.002	0.007	0.001	0.015	0.014
	P-value	0.909	0.633	0.043**	0.564	0.521	0.883	0.333	0.915	0.091	0.218

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 8: Effects of the Monthly data of the Economic Policy Uncertainty Index for Europe index on Cryptocurrencies returns.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
10	**Estimate**	-0.002	0.000	0.002	-0.002	-0.001	0.002	0.000	-0.001	0.000	-0.003
	P-value	0.511	0.862	0.478	0.634	0.653	0.709	0.923	0.758	0.950	0.439
20	**Estimate**	-0.001	0.001	0.001	-0.001	-0.001	0.000	-0.002	0.000	-0.002	-0.002
	P-value	0.467	0.647	0.477	0.541	0.344	0.979	0.456	0.681	0.297	0.353
30	**Estimate**	-0.001	0.000	0.001	-0.001	-0.001	-0.001	-0.002	0.000	-0.003	-0.002
	P-value	0.149	0.841	0.616	0.246	0.271	0.581	0.160	0.956	0.059*	0.381
40	**Estimate**	-0.001	-0.001	0.000	-0.002	-0.002	-0.001	-0.001	-0.002	-0.003	-0.001
	P-value	0.418	0.466	0.835	0.123	0.011	0.679	0.368	0.473	0.018**	0.518
50	**Estimate**	-0.001	-0.001	-0.001	-0.001	-0.002	-0.001	-0.001	-0.003	-0.002	-0.001
	P-value	0.336	0.507	0.749	0.403	0.090	0.472	0.694	0.292	0.139	0.463
60	**Estimate**	-0.001	-0.001	-0.002	-0.002	-0.002	0.000	-0.001	-0.002	-0.002	-0.001
	P-value	0.208	0.709	0.199	0.291	0.172	0.836	0.676	0.407	0.238	0.444
70	**Estimate**	0.000	0.000	-0.002	-0.001	-0.001	-0.002	-0.001	0.000	-0.002	-0.003
	P-value	0.618	0.887	0.438	0.579	0.709	0.489	0.448	0.934	0.230	0.169
80	**Estimate**	0.000	0.001	-0.002	0.000	0.001	-0.003	0.000	0.000	-0.001	-0.002
	P-value	0.550	0.456	0.213	0.892	0.814	0.203	0.903	0.839	0.624	0.199
90	**Estimate**	-0.001	0.001	-0.002	-0.001	-0.001	-0.001	0.000	-0.001	-0.001	-0.001
	P-value	0.257	0.632	0.368	0.574	0.632	0.309	0.718	0.777	0.435	0.711

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Second: The Results of The Multivariate Quantile Regressions Model.

Table 9: The effects of the UCRY Policy Index, the UCRY Price Index, the Central Bank Digital Currency Uncertainty Index (CBDCUI), the Cryptocurrency Environmental Attention (ICEA) index, the Cryptocurrency Environmental Attention (ICEA) index, and the Twitter-based Economic Uncertainty (TEU) index on Cryptocurrencies returns of the 5, 25, 50, 75, and 95 quantiles.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
5	UCRY Policy Index	0.003	0.045	-0.267	0.039	0.001	-0.036	0.078	-0.037	-0.011	0.013
		0.981	0.674	0.067*	0.790	0.997	0.763	0.605	0.710	0.940	0.931
	UCRY Price Index	0.011	-0.059	0.191	-0.037	-0.048	0.044	-0.091	0.001	0.006	-0.007
		0.916	0.626	0.137	0.796	0.728	0.704	0.524	0.991	0.966	0.958
	CBDC Uncertainty Index	-0.073	-0.060	-0.037	-0.079	-0.074	-0.140	0.011	-0.046	-0.116	-0.050
		0.152	0.504	0.587	0.117	0.494	0.040**	0.839	0.508	0.132	0.507
	CBDC Attention Index	0.067	0.115	0.079	0.097	0.136	0.137	0.081	0.048	0.126	0.091
		0.196	0.127	0.181	0.077*	0.089*	0.066*	0.198	0.474	0.054*	0.021**
	CC Environmental Attention Index	-0.021	-0.039	-0.001	-0.048	-0.022	-0.045	-0.056	0.003	-0.041	-0.050
		0.424	0.336	0.989	0.215	0.574	0.287	0.151	0.924	0.292	0.048**
	TEU Index	-0.0003	0.0000	-0.0002	-0.0008	0.0002	-0.0008	0.0001	-0.0003	-0.0005	-0.0006
		0.700	0.932	0.497	0.173	0.830	0.270	0.947	0.520	0.522	0.356
25	UCRY Policy Index	0.024	-0.057	-0.011	-0.001	-0.045	-0.094	0.001	-0.046	-0.014	-0.018
		0.675	0.282	0.822	0.989	0.424	0.222	0.981	0.343	0.875	0.760
	UCRY Price Index	-0.027	0.052	0.006	-0.017	0.027	0.075	-0.001	0.042	0.006	0.018
		0.639	0.268	0.898	0.808	0.637	0.346	0.992	0.410	0.941	0.805
	CBDC Uncertainty Index	-0.041	0.018	-0.029	-0.030	-0.029	-0.029	-0.025	-0.049	-0.017	-0.030
		0.207	0.605	0.420	0.416	0.485	0.617	0.336	0.277	0.683	0.324
	CBDC Attention Index	-0.002	-0.017	0.003	-0.003	0.013	-0.015	0.020	0.029	-0.012	-0.003
		0.945	0.615	0.917	0.950	0.649	0.831	0.647	0.435	0.806	0.954
	CC Environmental Attention Index	0.019	0.003	0.011	0.020	0.014	0.022	-0.006	0.002	0.011	0.010
		0.301	0.876	0.502	0.377	0.428	0.586	0.786	0.915	0.631	0.703
	TEU Index	0.0002	0.0001	0.0002	0.0002	0.0002	0.0002	0.0002	0.0001	0.0002	0.0001
		0.229	0.442	0.051*	0.120	0.006***	0.187	0.027**	0.576	0.093*	0.486

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
50	UCRY Policy Index	0.024	0.005	0.020	-0.022	-0.016	0.007	0.008	0.001	-0.004	-0.038
		0.372	0.851	0.634	0.704	0.796	0.892	0.849	0.981	0.910	0.304
	UCRY Price Index	-0.007	0.011	-0.005	0.051	0.034	0.003	-0.011	0.001	0.037	0.057
		0.837	0.719	0.927	0.364	0.552	0.964	0.819	0.987	0.299	0.189
	CBDC Uncertainty Index	0.007	-0.029	-0.037	-0.017	-0.015	-0.018	0.003	-0.008	-0.042	-0.036
		0.796	0.492	0.479	0.535	0.650	0.697	0.920	0.876	0.121	0.139
	CBDC Attention Index	-0.017	-0.003	0.011	0.002	-0.008	-0.015	-0.015	-0.011	0.016	-0.016
		0.386	0.862	0.721	0.951	0.644	0.737	0.576	0.733	0.454	0.697
	CC Environmental Attention Index	-0.003	0.008	-0.004	-0.015	0.000	0.014	0.010	0.010	-0.008	0.011
		0.841	0.251	0.828	0.602	0.995	0.624	0.520	0.594	0.700	0.625
	TEU Index	0.0000	0.0001	0.0000	0.0000	0.0000	0.0001	0.0001	0.0000	0.0000	0.0001
		0.767	0.186	0.613	0.411	0.419	0.668	0.528	0.837	0.792	0.386
75	UCRY Policy Index	-0.003	0.023	0.033	-0.006	-0.029	-0.042	0.038	-0.043	0.024	-0.040
		0.930	0.639	0.641	0.892	0.322	0.341	0.356	0.542	0.553	0.396
	UCRY Price Index	0.038	-0.003	0.023	0.057	0.059	0.042	-0.015	0.099	0.024	0.052
		0.226	0.964	0.736	0.096*	0.027**	0.357	0.665	0.282	0.681	0.209
	CBDC Uncertainty Index	0.013	0.014	0.000	-0.025	-0.015	-0.001	0.004	-0.029	-0.022	-0.007
		0.482	0.615	0.990	0.461	0.668	0.968	0.922	0.580	0.494	0.877
	CBDC Attention Index	-0.015	0.003	0.026	0.034	0.030	0.023	0.026	-0.007	0.037	0.024
		0.509	0.937	0.472	0.413	0.231	0.561	0.400	0.758	0.160	0.604
	CC Environmental Attention Index	-0.018	-0.011	-0.044	-0.040	-0.032	-0.008	-0.021	-0.012	-0.035	-0.015
		0.223	0.571	0.045**	0.121	0.047	0.721	0.313	0.437	0.169	0.602
	TEU Index	0.0000	0.0000	-0.0002	-0.0001	-0.0002	0.0000	0.0000	0.0000	-0.0001	0.0000
		0.781	0.787	0.224	0.158	0.102	0.728	0.710	0.991	0.739	0.882

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
95	UCRY Policy Index	0.046	-0.052	0.095	-0.121	-0.152	-0.101	-0.014	-0.093	-0.056	-0.165
		0.265	0.543	0.419	0.278	0.243	0.101	0.746	0.222	0.391	0.074*
	UCRY Price Index	0.004	0.093	0.045	0.176	0.166	0.134	0.059	0.188	0.260	0.156
		0.901	0.313	0.710	0.086*	0.130	0.083*	0.074*	0.004***	0.044**	0.024**
	CBDC Uncertainty Index	0.037	-0.002	-0.091	-0.019	-0.016	-0.054	0.002	-0.026	-0.125	0.009
		0.125	0.934	0.225	0.657	0.846	0.481	0.963	0.640	0.024**	0.923
	CBDC Attention Index	-0.014	-0.005	0.152	0.086	0.095	0.092	0.037	0.029	0.083	0.137
		0.696	0.813	0.114	0.045**	0.222	0.091*	0.182	0.486	0.003***	0.171
	CC Environmental Attention Index	-0.037	-0.025	-0.115	-0.084	-0.053	-0.044	-0.050	-0.060	-0.082	-0.044
		0.039**	0.126	0.041**	0.009***	0.141	0.282	0.000***	0.011**	0.027**	0.501
	TEU Index	-0.0001	-0.0005	-0.0001	-0.0005	0.0000	-0.0003	0.0001	0.0000	0.0001	0.0000
		0.499	0.015**	0.735	0.154	0.982	0.022**	0.628	0.913	0.669	0.869

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 10: The effects of the UCRY Policy Index and CBDC Attention Index on Cryptocurrencies returns.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
5	UCRY Policy Index	-0.040	-0.094	-0.107	-0.105	-0.123	-0.093	-0.066	-0.062	-0.105	-0.083
		0.060*	0.012**	0.033**	0.000***	0.014**	0.050**	0.025**	0.001***	0.020**	0.041**
	CBDC Attention Index	0.023	0.074	0.068	0.079	0.112	0.050	0.045	0.045	0.064	0.073
		0.279	0.004***	0.123	0.001***	0.001***	0.236	0.130	0.040**	0.165	0.060*
25	UCRY Policy Index	-0.003	0.001	-0.003	-0.017	-0.018	-0.026	-0.008	-0.016	-0.012	-0.005
		0.901	0.948	0.845	0.435	0.548	0.214	0.770	0.434	0.669	0.824
	CBDC Attention Index	-0.011	-0.005	-0.011	0.003	0.008	0.002	0.000	0.013	-0.004	-0.012
		0.566	0.763	0.482	0.878	0.725	0.898	0.988	0.343	0.858	0.499
50	UCRY Policy Index	0.018	0.013	0.013	0.016	0.011	0.010	0.009	0.010	0.013	0.013
		0.122	0.181	0.315	0.403	0.164	0.547	0.510	0.561	0.367	0.277
	CBDC Attention Index	-0.019	-0.011	-0.012	-0.019	-0.013	-0.008	-0.010	-0.008	-0.006	-0.018
		0.076*	0.373	0.446	0.361	0.216	0.574	0.430	0.579	0.680	0.086
75	UCRY Policy Index	0.037	0.022	0.020	0.044	0.010	0.016	0.013	0.020	0.034	0.013
		0.022**	0.231	0.447	0.002***	0.517	0.165	0.315	0.413	0.070*	0.391
	CBDC Attention Index	-0.034	-0.011	0.000	-0.026	-0.001	-0.005	-0.004	-0.013	-0.014	-0.004
		0.030**	0.578	0.988	0.145	0.929	0.646	0.683	0.589	0.477	0.839
95	UCRY Policy Index	0.056	0.019	0.095	0.016	0.006	-0.022	0.031	0.052	0.027	-0.016
		0.000***	0.632	0.088*	0.542	0.692	0.491	0.171	0.471	0.581	0.652
	CBDC Attention Index	-0.035	-0.017	-0.014	-0.005	0.020	0.058	-0.016	-0.044	0.000	0.099
		0.001***	0.571	0.811	0.835	0.382	0.165	0.465	0.442	0.992	0.237

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 11: The effects of the UCRY Policy Index and the Cryptocurrency Environmental Attention (ICEA) index on Cryptocurrencies returns**.**

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
5	UCRY Policy Index	-0.045	-0.061	-0.076	-0.129	-0.078	-0.076	-0.029	-0.081	-0.065	-0.072
		0.069*	0.250	0.121	0.016**	0.185	0.139	0.362	0.019**	0.213	0.096*
	Cryptocurrency Environmental Index	0.015	0.028	0.028	0.053	0.045	0.033	-0.001	0.040	0.027	0.027
		0.333	0.426	0.196	0.047**	0.092*	0.339	0.963	0.024**	0.539	0.287
25	UCRY Policy Index	-0.008	0.000	-0.002	-0.022	-0.022	-0.034	-0.003	-0.023	-0.013	-0.004
		0.634	0.995	0.891	0.272	0.344	0.221	0.884	0.095*	0.621	0.868
	Cryptocurrency Environmental Index	-0.001	-0.004	-0.008	0.006	0.010	0.010	-0.005	0.014	-0.001	-0.007
		0.892	0.775	0.269	0.525	0.500	0.569	0.694	0.075*	0.927	0.580
50	UCRY Policy Index	0.031	0.011	0.014	0.017	0.012	0.009	0.000	0.000	0.014	0.013
		0.011**	0.538	0.389	0.215	0.474	0.560	0.994	0.972	0.547	0.491
	Cryptocurrency Environmental Index	-0.016	-0.002	-0.007	-0.012	-0.008	-0.005	0.001	0.002	-0.004	-0.010
		0.009***	0.898	0.398	0.140	0.393	0.604	0.866	0.802	0.758	0.427
75	UCRY Policy Index	0.040	0.021	0.050	0.048	0.018	0.018	0.023	0.024	0.037	0.015
		0.001***	0.167	0.021**	0.000***	0.348	0.225	0.010***	0.235	0.211	0.429
	Cryptocurrency Environmental Index	-0.025	-0.007	-0.019	-0.019	-0.010	-0.005	-0.011	-0.009	-0.012	-0.004
		0.000***	0.439	0.074*	0.003***	0.356	0.577	0.019**	0.362	0.474	0.751
95	UCRY Policy Index	0.058	0.024	0.121	0.017	0.009	0.042	0.044	0.110	0.101	-0.010
		0.000***	0.565	0.017**	0.651	0.737	0.348	0.030**	0.091*	0.161	0.823
	Cryptocurrency Environmental Index	-0.024	-0.015	-0.049	-0.006	0.005	-0.011	-0.026	-0.057	-0.039	0.065
		0.054*	0.504	0.131	0.803	0.849	0.758	0.087*	0.051*	0.286	0.356

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 12: The effects of the UCRY Price Index and the CBDC Attention Index on Cryptocurrencies returns.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
5	UCRY Price Index	-0.029	-0.077	-0.125	-0.082	-0.098	-0.071	-0.072	-0.053	-0.078	-0.069
		0.027**	0.026**	0.004***	0.025**	0.018**	0.034**	0.005***	0.131	0.044**	0.078*
	CBDC Attention Index	0.012	0.061	0.069	0.056	0.089	0.027	0.064	0.040	0.034	0.062
		0.421	0.027**	0.159	0.096*	0.055*	0.314	0.042**	0.246	0.400	0.115
25	UCRY Price Index	-0.003	0.005	-0.002	-0.017	-0.004	-0.018	-0.007	-0.009	-0.012	-0.006
		0.865	0.768	0.880	0.396	0.835	0.424	0.720	0.656	0.613	0.784
	CBDC Attention Index	-0.009	-0.008	-0.012	0.003	-0.003	-0.002	-0.001	0.007	-0.003	-0.012
		0.618	0.581	0.423	0.870	0.860	0.943	0.944	0.688	0.885	0.502
50	UCRY Price Index	0.019	0.014	0.014	0.019	0.012	0.010	0.008	0.008	0.015	0.017
		0.264	0.111	0.415	0.348	0.157	0.405	0.469	0.599	0.258	0.091*
	CBDC Attention Index	-0.018	-0.010	-0.012	-0.022	-0.013	-0.009	-0.009	-0.008	-0.011	-0.023
		0.226	0.456	0.489	0.300	0.174	0.542	0.499	0.652	0.544	0.044**
75	UCRY Price Index	0.032	0.021	0.016	0.040	0.016	0.015	0.009	0.026	0.034	0.013
		0.008***	0.334	0.415	0.005***	0.224	0.234	0.565	0.252	0.096*	0.528
	CBDC Attention Index	-0.034	-0.011	0.001	-0.022	-0.012	-0.003	-0.003	-0.021	-0.016	-0.003
		0.011**	0.591	0.937	0.306	0.516	0.812	0.894	0.433	0.439	0.882
95	UCRY Price Index	0.035	0.052	0.128	0.011	0.009	0.019	0.025	0.118	0.026	0.007
		0.001***	0.136	0.078*	0.769	0.743	0.547	0.137	0.113	0.685	0.784
	CBDC Attention Index	-0.023	-0.039	-0.034	-0.002	0.021	0.040	-0.010	-0.074	0.003	0.087
		0.001***	0.191	0.567	0.961	0.572	0.367	0.597	0.116	0.958	0.097*

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 13: The effects of the UCRY Price Index and the Cryptocurrency Environmental Attention (ICEA) index on Cryptocurrencies returns.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
5	UCRY Price Index	-0.041	-0.074	-0.088	-0.081	-0.100	-0.089	-0.033	-0.059	-0.091	-0.045
		0.078*	0.045**	0.096*	0.030**	0.046**	0.011**	0.215	0.025**	0.023**	0.106
	CC Environmental Attention Index	0.015	0.025	0.038	0.023	0.044	0.026	-0.003	0.024	0.026	0.010
		0.356	0.149	0.190	0.343	0.052*	0.171	0.888	0.133	0.262	0.543
25	UCRY Price Index	-0.010	0.000	-0.002	-0.018	-0.022	-0.028	-0.003	-0.018	-0.012	-0.005
		0.487	0.994	0.911	0.362	0.368	0.202	0.855	0.268	0.551	0.789
	CC Environmental Attention Index	-0.001	-0.004	-0.008	0.005	0.011	0.002	-0.004	0.010	-0.001	-0.007
		0.910	0.742	0.392	0.694	0.484	0.898	0.666	0.278	0.911	0.596
50	UCRY Price Index	0.023	0.009	0.014	0.024	0.015	0.010	0.000	0.000	0.012	0.018
		0.175	0.375	0.357	0.384	0.404	0.578	0.990	0.986	0.581	0.314
	CC Environmental Attention Index	-0.013	-0.001	-0.008	-0.015	-0.009	-0.006	0.001	0.002	-0.003	-0.013
		0.206	0.945	0.398	0.344	0.297	0.691	0.850	0.861	0.783	0.278
75	UCRY Price Index	0.036	0.022	0.044	0.046	0.019	0.015	0.022	0.029	0.035	0.020
		0.000***	0.176	0.016**	0.000***	0.141	0.265	0.000***	0.357	0.152	0.264
	CC Environmental Attention Index	-0.022	-0.007	-0.016	-0.020	-0.010	-0.002	-0.011	-0.014	-0.011	-0.009
		0.002***	0.407	0.131	0.026**	0.329	0.764	0.017**	0.352	0.441	0.560
95	UCRY Price Index	0.049	0.062	0.164	0.011	0.007	0.035	0.055	0.123	0.113	0.024
		0.005***	0.000***	0.058*	0.825	0.739	0.323	0.001***	0.084*	0.165	0.407
	CC Environmental Attention Index	-0.018	-0.030	-0.074	-0.002	0.011	-0.007	-0.030	-0.064	-0.049	0.012
		0.149	0.000***	0.188	0.941	0.570	0.841	0.017**	0.034**	0.268	0.840

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Third: The results of the Granger Causality Test.

Table 14: The effects of the Daily data of the Twitter-based Economic Uncertainty (TEU) index on Cryptocurrencies returns with lag = 1, and the effects of Cryptocurrencies returns on the Daily data of the Twitter-based Economic Uncertainty (TEU) index with lag = 1.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
TEPU	BTC	P-value	0.481	BTC	TEPU	P-value	0.334
		lag	1			lag	1
TEPU	ETH	P-value	0.675	ETH	TEPU	P-value	0.484
		lag	1			lag	1
TEPU	XRP	P-value	0.201	XRP	TEPU	P-value	0.864
		lag	1			lag	1
TEPU	LTC	P-value	0.167	LTC	TEPU	P-value	0.685
		lag	1			lag	1
TEPU	BCH	P-value	0.284	BCH	TEPU	P-value	0.616
		lag	1			lag	1
TEPU	EOS	P-value	0.322	EOS	TEPU	P-value	0.752
		lag	1			lag	1
TEPU	XMR	P-value	0.412	XMR	TEPU	P-value	0.227
		lag	1			lag	1
TEPU	XLM	P-value	0.836	XLM	TEPU	P-value	0.466
		lag	1			lag	1
TEPU	DASH	P-value	0.288	DASH	TEPU	P-value	0.676
		lag	1			lag	1
TEPU	ETC	P-value	0.682	ETC	TEPU	P-value	0.642
		lag	1			lag	1

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 15: The Effects of the Daily data of the Twitter-based Economic Uncertainty (TEU) index on Cryptocurrencies returns with lag = 6, and the Effects of Cryptocurrencies returns on the Daily data of the Twitter-based Economic Uncertainty (TEU) index with lag = 6.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
TEPU	BTC	P-value	0.014**	BTC	TEPU	P-value	0.745
		lag	6			lag	6
TEPU	ETH	P-value	0.030**	ETH	TEPU	P-value	0.766
		lag	6			lag	6
TEPU	XRP	P-value	0.075*	XRP	TEPU	P-value	0.462
		lag	6			lag	6
TEPU	LTC	P-value	0.041**	LTC	TEPU	P-value	0.919
		lag	6			lag	6
TEPU	BCH	P-value	0.012**	BCH	TEPU	P-value	0.953
		lag	6			lag	6
TEPU	EOS	P-value	0.137	EOS	TEPU	P-value	0.952
		lag	6			lag	6
TEPU	XMR	P-value	0.007***	XMR	TEPU	P-value	0.798
		lag	6			lag	6
TEPU	XLM	P-value	0.365	XLM	TEPU	P-value	0.42
		lag	6			lag	6
TEPU	DASH	P-value	0.031**	DASH	TEPU	P-value	0.792
		lag	6			lag	6
TEPU	ETC	P-value	0.427	ETC	TEPU	P-value	0.846
		lag	6			lag	6

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 16: The effects of the Weekly data of the UCRY Policy Index on Cryptocurrencies returns with lag = 1, and the effects of Cryptocurrencies returns on the Weekly data of the UCRY Policy Index with lag = 1.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
UCRY Policy Index	BTC	P-value	0.211	BTC	UCRY Policy Index	P-value	0.650
		lag	1			lag	1
UCRY Policy Index	ETH	P-value	0.000***	ETH	UCRY Policy Index	P-value	0.248
		lag	1			lag	1
UCRY Policy Index	XRP	P-value	0.023**	XRP	UCRY Policy Index	P-value	0.793
		lag	1			lag	1
UCRY Policy Index	LTC	P-value	0.001***	LTC	UCRY Policy Index	P-value	0.962
		lag	1			lag	1
UCRY Policy Index	BCH	P-value	0.008***	BCH	UCRY Policy Index	P-value	0.889
		lag	1			lag	1
UCRY Policy Index	EOS	P-value	0.000***	EOS	UCRY Policy Index	P-value	0.704
		lag	1			lag	1
UCRY Policy Index	XMR	P-value	0.056*	XMR	UCRY Policy Index	P-value	0.406
		lag	1			lag	1
UCRY Policy Index	XLM	P-value	0.028**	XLM	UCRY Policy Index	P-value	0.884
		lag	1			lag	1
UCRY Policy Index	DASH	P-value	0.002****	DASH	UCRY Policy Index	P-value	0.580
		lag	1			lag	1
UCRY Policy Index	ETC	P-value	0.001***	ETC	UCRY Policy Index	P-value	0.171
		lag	1			lag	1

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 17: The effects of the Weekly data of the UCRY Policy Index on Cryptocurrencies returns with lag = 6, and the effects of Cryptocurrencies returns on the Weekly data of the UCRY Policy Index with lag = 6.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
UCRY Policy Index	BTC	P-value	0.164	BTC	UCRY Policy Index	P-value	0.163
		lag	6			lag	6
UCRY Policy Index	ETH	P-value	0.004***	ETH	UCRY Policy Index	P-value	0.132
		lag	6			lag	6
UCRY Policy Index	XRP	P-value	0.000***	XRP	UCRY Policy Index	P-value	0.064*
		lag	6			lag	6
UCRY Policy Index	LTC	P-value	0.009***	LTC	UCRY Policy Index	P-value	0.096*
		lag	6			lag	6
UCRY Policy Index	BCH	P-value	0.025**	BCH	UCRY Policy Index	P-value	0.451
		lag	6			lag	6
UCRY Policy Index	EOS	P-value	0.014**	EOS	UCRY Policy Index	P-value	0.276
		lag	6			lag	6
UCRY Policy Index	XMR	P-value	0.329	XMR	UCRY Policy Index	P-value	0.127
		lag	6			lag	6
UCRY Policy Index	XLM	P-value	0.002***	XLM	UCRY Policy Index	P-value	0.490
		lag	6			lag	6
UCRY Policy Index	DASH	P-value	0.024**	DASH	UCRY Policy Index	P-value	0.133
		lag	6			lag	6
UCRY Policy Index	ETC	P-value	0.002***	ETC	UCRY Policy Index	P-value	0.095*
		lag	6			lag	6

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 18: The effects of the Weekly data of the UCRY Price Index on Cryptocurrencies returns with lag = 1, and the effects of Cryptocurrencies returns on the Weekly data of the UCRY Price Index with lag = 1.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
UCRY Price Index	BTC	P-value	0.164	BTC	UCRY Price Index	P-value	0.916
		lag	1			lag	1
UCRY Price Index	ETH	P-value	0.000	ETH	UCRY Price Index	P-value	0.375
		lag	1			lag	1
UCRY Price Index	XRP	P-value	0.052	XRP	UCRY Price Index	P-value	0.940
		lag	1			lag	1
UCRY Price Index	LTC	P-value	0.002	LTC	UCRY Price Index	P-value	0.774
		lag	1			lag	1
UCRY Price Index	BCH	P-value	0.016	BCH	UCRY Price Index	P-value	0.958
		lag	1			lag	1
UCRY Price Index	EOS	P-value	0.000	EOS	UCRY Price Index	P-value	0.971
		lag	1			lag	1
UCRY Price Index	XMR	P-value	0.183	XMR	UCRY Price Index	P-value	0.565
		lag	1			lag	1
UCRY Price Index	XLM	P-value	0.116	XLM	UCRY Price Index	P-value	0.680
		lag	1			lag	1
UCRY Price Index	DASH	P-value	0.006	DASH	UCRY Price Index	P-value	0.606
		lag	1			lag	1
UCRY Price Index	ETC	P-value	0.003	ETC	UCRY Price Index	P-value	0.310
		lag	1			lag	1

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 19: The effects of the Weekly data of the UCRY Price Index on Cryptocurrencies returns with lag = 6, and the effects of Cryptocurrencies returns on the Weekly data of the UCRY Price Index with lag = 6.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
UCRY Price Index	BTC	P-value	0.027**	BTC	UCRY Price Index	P-value	0.171
		lag	6			lag	6
UCRY Price Index	ETH	P-value	0.001***	ETH	UCRY Price Index	P-value	0.267
		lag	6			lag	6
UCRY Price Index	XRP	P-value	0.000***	XRP	UCRY Price Index	P-value	0.173
		lag	6			lag	6
UCRY Price Index	LTC	P-value	0.000***	LTC	UCRY Price Index	P-value	0.117
		lag	6			lag	6
UCRY Price Index	BCH	P-value	0.006***	BCH	UCRY Price Index	P-value	0.510
		lag	6			lag	6
UCRY Price Index	EOS	P-value	0.001***	EOS	UCRY Price Index	P-value	0.267
		lag	6			lag	6
UCRY Price Index	XMR	P-value	0.138	XMR	UCRY Price Index	P-value	0.285
		lag	6			lag	6
UCRY Price Index	XLM	P-value	0.000***	XLM	UCRY Price Index	P-value	0.379
		lag	6			lag	6
UCRY Price Index	DASH	P-value	0.013**	DASH	UCRY Price Index	P-value	0.083*
		lag	6			lag	6
UCRY Price Index	ETC	P-value	0.001***	ETC	UCRY Price Index	P-value	0.224
		lag	6			lag	6

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 20: The effects of the weekly data of the Twitter-based Economic Uncertainty (TEU) index on Cryptocurrencies returns with lag = 1, and the effects of Cryptocurrencies returns on the Daily data of the Twitter-based Economic Uncertainty (TEU) index with lag = 1.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
TEPU	BTC	P-value	0.004	BTC	TEPU	P-value	0.505
		lag	1			lag	1
TEPU	ETH	P-value	0.018	ETH	TEPU	P-value	0.667
		lag	1			lag	1
TEPU	XRP	P-value	0.098	XRP	TEPU	P-value	0.930
		lag	1			lag	1
TEPU	LTC	P-value	0.024	LTC	TEPU	P-value	0.995
		lag	1			lag	1
TEPU	BCH	P-value	0.023	BCH	TEPU	P-value	0.717
		lag	1			lag	1
TEPU	EOS	P-value	0.034	EOS	TEPU	P-value	0.647
		lag	1			lag	1
TEPU	XMR	P-value	0.003	XMR	TEPU	P-value	0.456
		lag	1			lag	1
TEPU	XLM	P-value	0.353	XLM	TEPU	P-value	0.385
		lag	1			lag	1
TEPU	DASH	P-value	0.03	DASH	TEPU	P-value	0.777
		lag	1			lag	1
TEPU	ETC	P-value	0.056	ETC	TEPU	P-value	0.707
		lag	1			lag	1

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 21: The effects of the weekly data of the Twitter-based Economic Uncertainty (TEU) index on Cryptocurrencies returns with lag = 6, and the effects of Cryptocurrencies returns on the Daily data of the Twitter-based Economic Uncertainty (TEU) index with lag = 6.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
TEPU	BTC	P-value	0.009***	BTC	TEPU	P-value	0.785
		lag	6			lag	6
TEPU	ETH	P-value	0.021**	ETH	TEPU	P-value	0.800
		lag	6			lag	6
TEPU	XRP	P-value	0.497	XRP	TEPU	P-value	0.808
		lag	6			lag	6
TEPU	LTC	P-value	0.064*	LTC	TEPU	P-value	0.979
		lag	6			lag	6
TEPU	BCH	P-value	0.063*	BCH	TEPU	P-value	0.908
		lag	6			lag	6
TEPU	EOS	P-value	0.022**	EOS	TEPU	P-value	0.937
		lag	6			lag	6
TEPU	XMR	P-value	0.009***	XMR	TEPU	P-value	0.613
		lag	6			lag	6
TEPU	XLM	P-value	0.691	XLM	TEPU	P-value	0.789
		lag	6			lag	6
TEPU	DASH	P-value	0.024**	DASH	TEPU	P-value	0.984
		lag	6			lag	6
TEPU	ETC	P-value	0.076*	ETC	TEPU	P-value	0.758
		lag	6			lag	6

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 22: The effects of the Weekly data of the Central Bank Digital Currency Uncertainty Index (CBDCUI) on Cryptocurrencies returns with lag = 1, and the effects of Cryptocurrencies returns on the Weekly data of the Central Bank Digital Currency Uncertainty Index (CBDCUI) with lag = 1.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
CBDC Uncertainty Index	BTC	P-value	0.715	BTC	CBDC Uncertainty Index	P-value	0.357
		lag	1			lag	1
CBDC Uncertainty Index	ETH	P-value	0.032**	ETH	CBDC Uncertainty Index	P-value	0.877
		lag	1			lag	1
CBDC Uncertainty Index	XRP	P-value	0.003***	XRP	CBDC Uncertainty Index	P-value	0.510
		lag	1			lag	1
CBDC Uncertainty Index	LTC	P-value	0.025**	LTC	CBDC Uncertainty Index	P-value	0.251
		lag	1			lag	1
CBDC Uncertainty Index	BCH	P-value	0.058*	BCH	CBDC Uncertainty Index	P-value	0.441
		lag	1			lag	1
CBDC Uncertainty Index	EOS	P-value	0.023**	EOS	CBDC Uncertainty Index	P-value	0.533
		lag	1			lag	1
CBDC Uncertainty Index	XMR	P-value	0.105	XMR	CBDC Uncertainty Index	P-value	0.693
		lag	1			lag	1
CBDC Uncertainty Index	XLM	P-value	0.025**	XLM	CBDC Uncertainty Index	P-value	0.319
		lag	1			lag	1
CBDC Uncertainty Index	DASH	P-value	0.004***	DASH	CBDC Uncertainty Index	P-value	0.448
		lag	1			lag	1
CBDC Uncertainty Index	ETC	P-value	0.001***	ETC	CBDC Uncertainty Index	P-value	0.469
		lag	1			lag	1

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 23: The effects of the Weekly data of the Central Bank Digital Currency Uncertainty Index (CBDCUI) on Cryptocurrencies returns with lag = 6, and the effects of Cryptocurrencies returns on the Weekly data of the Central Bank Digital Currency Uncertainty Index (CBDCUI) with lag = 6.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
CBDC Uncertainty Index	BTC	P-value	0.071*	BTC	CBDC Uncertainty Index	P-value	0.067*
		lag	6			lag	6
CBDC Uncertainty Index	ETH	P-value	0.059*	ETH	CBDC Uncertainty Index	P-value	0.121
		lag	6			lag	6
CBDC Uncertainty Index	XRP	P-value	0.000***	XRP	CBDC Uncertainty Index	P-value	0.215
		lag	6			lag	6
CBDC Uncertainty Index	LTC	P-value	0.002***	LTC	CBDC Uncertainty Index	P-value	0.069*
		lag	6			lag	6
CBDC Uncertainty Index	BCH	P-value	0.014**	BCH	CBDC Uncertainty Index	P-value	0.276
		lag	6			lag	6
CBDC Uncertainty Index	EOS	P-value	0.001***	EOS	CBDC Uncertainty Index	P-value	0.087*
		lag	6			lag	6
CBDC Uncertainty Index	XMR	P-value	0.003***	XMR	CBDC Uncertainty Index	P-value	0.131
		lag	6			lag	6
CBDC Uncertainty Index	XLM	P-value	0.023**	XLM	CBDC Uncertainty Index	P-value	0.123
		lag	6			lag	6
CBDC Uncertainty Index	DASH	P-value	0.001***	DASH	CBDC Uncertainty Index	P-value	0.074*
		lag	6			lag	6
CBDC Uncertainty Index	ETC	P-value	0.000***	ETC	CBDC Uncertainty Index	P-value	0.034**
		lag	6			lag	6

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 24: The effects of the Weekly data of the Central Bank Digital Currency Attention Index on Cryptocurrencies returns with lag = 1, and the effects of Cryptocurrencies returns on the Weekly data of the Central Bank Digital Currency Attention Index with lag = 1.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
CBDC Attention Index	BTC	P-value	0.217	BTC	CBDC Attention Index	P-value	0.148
		lag	1			lag	1
CBDC Attention Index	ETH	P-value	0.063*	ETH	CBDC Attention Index	P-value	0.762
		lag	1			lag	1
CBDC Attention Index	XRP	P-value	0.000***	XRP	CBDC Attention Index	P-value	0.763
		lag	1			lag	1
CBDC Attention Index	LTC	P-value	0.058**	LTC	CBDC Attention Index	P-value	0.193
		lag	1			lag	1
CBDC Attention Index	BCH	P-value	0.083*	BCH	CBDC Attention Index	P-value	0.499
		lag	1			lag	1
CBDC Attention Index	EOS	P-value	0.019**	EOS	CBDC Attention Index	P-value	0.388
		lag	1			lag	1
CBDC Attention Index	XMR	P-value	0.085*	XMR	CBDC Attention Index	P-value	0.570
		lag	1			lag	1
CBDC Attention Index	XLM	P-value	0.011**	XLM	CBDC Attention Index	P-value	0.296
		lag	1			lag	1
CBDC Attention Index	DASH	P-value	0.007***	DASH	CBDC Attention Index	P-value	0.332
		lag	1			lag	1
CBDC Attention Index	ETC	P-value	0.000***	ETC	CBDC Attention Index	P-value	0.610
		lag	1			lag	1

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 25: The effects of the Weekly data of the Central Bank Digital Currency Attention Index on Cryptocurrencies returns with lag = 6, and the effects of Cryptocurrencies returns on the Weekly data of the Central Bank Digital Currency Attention Index with lag = 6.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
CBDC Attention Index	BTC	P-value	0.014**	BTC	CBDC Attention Index	P-value	0.261
		lag	6			lag	6
CBDC Attention Index	ETH	P-value	0.062*	ETH	CBDC Attention Index	P-value	0.226
		lag	6			lag	6
CBDC Attention Index	XRP	P-value	0.001***	XRP	CBDC Attention Index	P-value	0.002***
		lag	6			lag	6
CBDC Attention Index	LTC	P-value	0.009***	LTC	CBDC Attention Index	P-value	0.028**
		lag	6			lag	6
CBDC Attention Index	BCH	P-value	0.100	BCH	CBDC Attention Index	P-value	0.092*
		lag	6			lag	6
CBDC Attention Index	EOS	P-value	0.004***	EOS	CBDC Attention Index	P-value	0.035**
		lag	6			lag	6
CBDC Attention Index	XMR	P-value	0.003***	XMR	CBDC Attention Index	P-value	0.105
		lag	6			lag	6
CBDC Attention Index	XLM	P-value	0.030**	XLM	CBDC Attention Index	P-value	0.391
		lag	6			lag	6
CBDC Attention Index	DASH	P-value	0.001***	DASH	CBDC Attention Index	P-value	0.132
		lag	6			lag	6
CBDC Attention Index	ETC	P-value	0.001***	ETC	CBDC Attention Index	P-value	0.000***
		lag	6			lag	6

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 26: The effects of the Weekly data of the Cryptocurrency Environmental Attention (ICEA) index on Cryptocurrencies returns with lag = 1, and the effects of Cryptocurrencies returns on the Weekly data of the Cryptocurrency Environmental Attention (ICEA) index with lag = 1.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
CC Environmental Attention index	BTC	P-value	0.428	BTC	CC Environmental Attention index	P-value	0.257
		lag	1			lag	1
CC Environmental Attention index	ETH	P-value	0.025**	ETH	CC Environmental Attention index	P-value	0.733
		lag	1			lag	1
CC Environmental Attention index	XRP	P-value	0.095*	XRP	CC Environmental Attention index	P-value	0.701
		lag	1			lag	1
CC Environmental Attention index	LTC	P-value	0.018**	LTC	CC Environmental Attention index	P-value	0.186
		lag	1			lag	1
CC Environmental Attention index	BCH	P-value	0.051*	BCH	CC Environmental Attention index	P-value	0.416
		lag	1			lag	1
CC Environmental Attention index	EOS	P-value	0.002***	EOS	CC Environmental Attention index	P-value	0.337
		lag	1			lag	1
CC Environmental Attention index	XMR	P-value	0.053*	XMR	CC Environmental Attention index	P-value	0.532
		lag	1			lag	1
CC Environmental Attention index	XLM	P-value	0.101	XLM	CC Environmental Attention index	P-value	0.241
		lag	1			lag	1
CC Environmental Attention index	DASH	P-value	0.014	DASH	CC Environmental Attention index	P-value	0.358
		lag	1			lag	1
CC Environmental Attention index	ETC	P-value	0.000***	ETC	CC Environmental Attention index	P-value	0.766
		lag	1			lag	1

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 27: The Effects of the Weekly data of the Cryptocurrency Environmental Attention (ICEA) index on Cryptocurrencies returns with lag = 6, and the Effects of Cryptocurrencies returns on the Weekly data of the Cryptocurrency Environmental Attention (ICEA) index with lag = 6.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
CC Environmental Attention index	BTC	P-value	0.003***	BTC	CC Environmental Attention index	P-value	0.276
		lag	6			lag	6
CC Environmental Attention index	ETH	P-value	0.007***	ETH	CC Environmental Attention index	P-value	0.116
		lag	6			lag	6
CC Environmental Attention index	XRP	P-value	0.000***	XRP	CC Environmental Attention index	P-value	0.039**
		lag	6			lag	6
CC Environmental Attention index	LTC	P-value	0.002***	LTC	CC Environmental Attention index	P-value	0.090*
		lag	6			lag	6
CC Environmental Attention index	BCH	P-value	0.000***	BCH	CC Environmental Attention index	P-value	0.477
		lag	6			lag	6
CC Environmental Attention index	EOS	P-value	0.000***	EOS	CC Environmental Attention index	P-value	0.042**
		lag	6			lag	6
CC Environmental Attention index	XMR	P-value	0.000***	XMR	CC Environmental Attention index	P-value	0.132
		lag	6			lag	6
CC Environmental Attention index	XLM	P-value	0.020**	XLM	CC Environmental Attention index	P-value	0.241
		lag	6			lag	6
CC Environmental Attention index	DASH	P-value	0.000***	DASH	CC Environmental Attention index	P-value	0.686
		lag	6			lag	6
CC Environmental Attention index	ETC	P-value	0.000***	ETC	CC Environmental Attention index	P-value	0.395
		lag	6			lag	6

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 28: The Effects of the Weekly data of the Cryptocurrency Environmental Attention (ICEA) index on Cryptocurrencies returns with lag = 7, and the Effects of Cryptocurrencies returns on the Weekly data of the Cryptocurrency Environmental Attention (ICEA) index with lag = 7.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
CC Environmental Attention index	BTC	P-value	0.003***	BTC	CC Environmental Attention index	P-value	0.350
		lag	7			lag	7
CC Environmental Attention index	ETH	P-value	0.009***	ETH	CC Environmental Attention index	P-value	0.179
		lag	7			lag	7
CC Environmental Attention index	XRP	P-value	0.000***	XRP	CC Environmental Attention index	P-value	0.020**
		lag	7			lag	7
CC Environmental Attention index	LTC	P-value	0.001***	LTC	CC Environmental Attention index	P-value	0.159
		lag	7			lag	7
CC Environmental Attention index	BCH	P-value	0.000***	BCH	CC Environmental Attention index	P-value	0.577
		lag	7			lag	7
CC Environmental Attention index	EOS	P-value	0.000***	EOS	CC Environmental Attention index	P-value	0.082*
		lag	7			lag	7
CC Environmental Attention index	XMR	P-value	0.000***	XMR	CC Environmental Attention index	P-value	0.106
		lag	7			lag	7
CC Environmental Attention index	XLM	P-value	0.026**	XLM	CC Environmental Attention index	P-value	0.350
		lag	7			lag	7
CC Environmental Attention index	DASH	P-value	0.000***	DASH	CC Environmental Attention index	P-value	0.781
		lag	7			lag	7
CC Environmental Attention index	ETC	P-value	0.000***	ETC	CC Environmental Attention index	P-value	0.496
		lag	7			lag	7

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 29: The effects of the Monthly data of the Economic Policy Uncertainty Index for Europe index on Cryptocurrencies returns with lag = 1, and the effects of Cryptocurrencies returns on the Monthly data of the Economic Policy Uncertainty Index for Europe index with lag = 1.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
EUROEPU Index	BTC	P-value	0.826	BTC	EUROEPU Index	P-value	0.054*
		lag	1			lag	1
EUROEPU Index	ETH	P-value	0.810	ETH	EUROEPU Index	P-value	0.003***
		lag	1			lag	1
EUROEPU Index	XRP	P-value	0.336	XRP	EUROEPU Index	P-value	0.005***
		lag	1			lag	1
EUROEPU Index	LTC	P-value	0.964	LTC	EUROEPU Index	P-value	0.010***
		lag	1			lag	1
EUROEPU Index	BCH	P-value	0.632	BCH	EUROEPU Index	P-value	0.002***
		lag	1			lag	1
EUROEPU Index	EOS	P-value	0.723	EOS	EUROEPU Index	P-value	0.003***
		lag	1			lag	1
EUROEPU Index	XMR	P-value	0.612	XMR	EUROEPU Index	P-value	0.013**
		lag	1			lag	1
EUROEPU Index	XLM	P-value	0.829	XLM	EUROEPU Index	P-value	0.051*
		lag	1			lag	1
EUROEPU Index	DASH	P-value	0.151	DASH	EUROEPU Index	P-value	0.003***
		lag	1			lag	1
EUROEPU Index	ETC	P-value	0.641	ETC	EUROEPU Index	P-value	0.000***
		lag	1			lag	1

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 30: The effects of the Monthly data of the Economic Policy Uncertainty Index for Europe index on Cryptocurrencies returns with lag = 6, and the effects of Cryptocurrencies returns on the Monthly data of the Economic Policy Uncertainty Index for Europe index with lag = 6.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
EUROEPU Index	BTC	P-value	0.282	BTC	EUROEPU Index	P-value	0.000***
		lag	6			lag	6
EUROEPU Index	ETH	P-value	0.119	ETH	EUROEPU Index	P-value	0.000***
		lag	6			lag	6
EUROEPU Index	XRP	P-value	0.149	XRP	EUROEPU Index	P-value	0.000***
		lag	6			lag	6
EUROEPU Index	LTC	P-value	0.065*	LTC	EUROEPU Index	P-value	0.000***
		lag	6			lag	6
EUROEPU Index	BCH	P-value	0.432	BCH	EUROEPU Index	P-value	0.001***
		lag	6			lag	6
EUROEPU Index	EOS	P-value	0.653	EOS	EUROEPU Index	P-value	0.001***
		lag	6			lag	6
EUROEPU Index	XMR	P-value	0.405	XMR	EUROEPU Index	P-value	0.005***
		lag	6			lag	6
EUROEPU Index	XLM	P-value	0.011**	XLM	EUROEPU Index	P-value	0.000***
		lag	6			lag	6
EUROEPU Index	DASH	P-value	0.064*	DASH	EUROEPU Index	P-value	0.000***
		lag	6			lag	6
EUROEPU Index	ETC	P-value	0.834	ETC	EUROEPU Index	P-value	0.001***
		lag	6			lag	6

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 31: The Effects of the Monthly data of the Economic Policy Uncertainty Index for Europe index on Cryptocurrencies returns with lag = 10, and the Effects of Cryptocurrencies returns on the Monthly data of the Economic Policy Uncertainty Index for Europe index with lag = 10.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
EUROEPU Index	BTC	P-value	0.000***	BTC	EUROEPU Index	P-value	0.000***
		lag	10			lag	10
EUROEPU Index	ETH	P-value	0.033**	ETH	EUROEPU Index	P-value	0.000***
		lag	10			lag	10
EUROEPU Index	XRP	P-value	0.009***	XRP	EUROEPU Index	P-value	0.000***
		lag	10			lag	10
EUROEPU Index	LTC	P-value	0.013**	LTC	EUROEPU Index	P-value	0.000***
		lag	10			lag	10
EUROEPU Index	BCH	P-value	0.005***	BCH	EUROEPU Index	P-value	0.000***
		lag	10			lag	10
EUROEPU Index	EOS	P-value	0.279	EOS	EUROEPU Index	P-value	0.000***
		lag	10			lag	10
EUROEPU Index	XMR	P-value	0.000***	XMR	EUROEPU Index	P-value	0.000***
		lag	10			lag	10
EUROEPU Index	XLM	P-value	0.002***	XLM	EUROEPU Index	P-value	0.000***
		lag	10			lag	10
EUROEPU Index	DASH	P-value	0.003***	DASH	EUROEPU Index	P-value	0.000***
		lag	10			lag	10
EUROEPU Index	ETC	P-value	0.024**	ETC	EUROEPU Index	P-value	0.000***
		lag	10			lag	10

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Chapter Four: Covariance Forecasting in Cryptocurrency Market

1. ABSTRACT

The primary objective of this research is to identify the most effective model for forecasting the covariance matrix of cryptocurrency returns. Five models were extensively analyzed to pursue this goal: BEKK, Diagonal BEKK, DCC, Asymmetric DCC, and LRE. Three fundamental criteria were used to measure predicting accuracy and capability: Euclidean distance (LE), Frobenius distance (LF), and the multivariate quasi-likelihood loss function (LQ). The LRE model outperformed the other models, demonstrating superior predicting accuracy for daily and weekly frequencies. Also, further validation was performed using the Mean Squared Error (MSE) and Mean Absolute Error (MAE) loss functions. With the exception of LQ, the results were consistent with the forecasted criterion. These findings hold much potential for investors and portfolio managers looking to improve their risk management strategies. They may make better-educated decisions to reduce portfolio risk by exploiting the information given.

2. INTRODUCTION

Cryptocurrencies are often considered among the most innovative financial trading instruments since the turn of the millennium. As Chapter Two mentioned, Nakamoto (2008) proposed Bitcoin as a new financial asset. According to Nakamoto, Bitcoin is a peer-to-peer transaction that uses an electronic cash system permitting users to send online payments to each other directly without the need for intermediate financial institutions. Also, cryptocurrencies are not linked to regulators or authorities, and Bitcoin has no material representation. Bitcoin was first traded in 2009. Since then, Bitcoin has been the most prominent digital currency on the cryptocurrency market. Also, technological development has contributed to advancing cryptocurrency concepts and perspectives. A massive number of new cryptocurrencies have been introduced in the financial markets. As a result, many scholars have sought to simplify and clarify their behaviour.

To link the chapters of this thesis together, this chapter aims to close the circle of investigations. The second chapter focused on addressing the gap found in the literature of examining the best-fitted model to forecast the volatility of cryptocurrency returns, followed by the second gap found in the literature that chapter three aimed to examine the relationship effects of various uncertainty indices with cryptocurrency returns. Then, aiming to understand their risk connectedness and linkage among other cryptocurrencies, this chapter aims to close the gap found in the literature that investigates the best model that can accurately predict the covariance matrices of cryptocurrency returns.

3. LITERATURE REVIEW

Cryptocurrency markets have considerably advanced over the last decade, and cryptocurrencies' use has increased and gained immense public interest in response to the observed issues that the monetary and payment systems have. Those issues arose during the financial market crisis of 2008 (Weber, 2014). Besides, the notable price increases of cryptocurrencies have led individual investors to believe that the cryptocurrency markets can reach exceptionally high profits in simply a few weeks or months (Kristoufek, 2013). Though, cryptocurrencies as a new financial tool pose many challenges, such as legal, ethical, and regulatory challenges to central authorities (Fry and Cheah, 2016). Therefore, it is worth studying and exploring the cryptocurrency market's immatureness.

3.1.Cryptocurrencies Connectedness With Other Assets

The literature on interlinkages and volatility dynamics in cryptocurrency markets is still immature. Return and volatility spillovers quantify intermarket linkages, which are significant in international finance and have substantial consequences for portfolio and hedging choices. Empirical research has given this subject much attention, including greater market integration due to market openness, globalization, financialization, and technology advancements. Any indication of large return and volatility spillovers between Bitcoin and other asset classes has the potential to influence asset selection and allocation and regulators' policies aimed at maintaining the global financial system's stability. . Bouri et al. (2018a) examined the return and volatility spillover among Bitcoin, equities, currencies, stocks, bonds, and commodities and discovered empirical evidences that Bitcoin is mainly associated to commodities market and not really isolated, whereas Ji et al. (2018) reveal that the Bitcoin market is disconnected from other assets, as such no asset play an important role in the Bitcoin market but there appears to exist lagged and significant correlations. Bouri et al. (2018b) went on to say that Bitcoin price changes may be accurately anticipated using data from the aggregate commodities index and gold prices. However, these researchers demonstrate that, while bitcoin is linked to some investment alternatives such as commodities, it is not linked to other investment opportunities such as bonds and shares. Ji et al. (2019b) analyzed commodity links with key cryptocurrencies and discovered that cryptocurrency connectivity varies over time and gets more and more linked in the system. They also stated that the price dynamics of cryptocurrencies have an impact on energy commodities.

Likewise, Hayes (2017) demonstrates a considerable link between cryptocurrencies and the energy market (electricity market) in terms of the need for electricity for cryptocurrency mining. Also, according to Adebola et al. (2019), there are some considerable degrees of mean reversion movements in the prices of Gold and certain Cryptocurrencies with cointegrations. Bitcoin prices may be predicted using gold prices and aggregate commodity price information (Bouri et al., 2018a, 2018b). However, Shahzad et al., 2019, discovered that Bitcoin, gold, and the commodities index are poor safe haven investments for investors, although their performance varies over time across stock market indexes. Not only has Bitcoin demonstrated these characteristics, but it also has hedging capabilities with equities, Okorie, (2019). Furthermore, Al-Yahyaee et al. (2019) demonstrated that Bitcoin, and gold are capable of diversifying and hedging a portfolio when combined with crude oil and S&P GSCI, whereas Okorie (2019) demonstrated the importance of Bitcoin and the S&P500 for portfolio balancing and diversification. Consequently, Guesmi et al., (2019), show that considerable volatility spillovers exist between Bitcoin as well as other financial instruments such as gold and stocks, and an investment portfolio comprised of gold, oil, Bitcoin, and equities is capable of mitigating portfolio risk. Moreover, Cebrian-Hernandez and Jimenez-Rodriguez (2021) applied Engle's (2002) 's Dynamic Conditional Correlation (DCC) model to a diverse portfolio containing Bitcoin and 10 other assets.

3.2. Cryptocurrencies Connectedness within Cryptocurrency Market

Cryptocurrencies have recently been a prominent topic in academic study, despite the fact that Bitcoin and other cryptocurrencies are expected to be interdependent due to Bitcoin's market dominance and that most altcoin orders are traded in Bitcoin (Ciaian et al., 2018). It's also crucial for governments to consider Bitcoin as part of their foreign reserves or experiment with their own cryptocurrency equivalents. Therefore, Katsiampa et al. (2019) investigate the conditional volatility dynamics and conditional correlations of Bitcoin, Ethereum, and Litecoin using bivariate GARCH models. They demonstrate that their own current shocks and volatility impact the future volatility of returns. They show that there are two-way return flows between Bitcoin and Ether and Litecoin, as well as a one-way flow from Ether to Litecoin. Katsiampa et al. (2019) reveal evidence of two-way volatility flows across all pairings of cryptocurrencies under analysis, as well as positive pairwise conditional correlations that fluctuate over time.

Also, when it comes to research that looks at how efficient cryptocurrency markets are, Nadarajah and Chu (2017) employ eight different tests to show that the Bitcoin market is inefficient. Also, Caporale et al. (2018) take a similar approach and look at the markets for Bitcoin, Ripple, Litecoin, and Dash, finding evidence that they are inefficient since they are positively connected to past and future prices. In a similar vein, Charfeddine and Maouchi (2018) discover long-range reliance that leads to inefficiencies in Bitcoin, Litecoin, and Ripple markets, but not in the Ethereum market. Furthermore, Urquhart (2016), via a series of studies, concludes that Bitcoin is inefficient in the short term but tends to become efficient over time. Wei (2018) further claims that, despite the effectiveness of the Bitcoin markets, there are an enormous number of other cryptocurrencies whose present prices are based on their previous values. It has been discovered that greater liquidity leads to greater efficiency. Brauneis and Mestel (2018), on the other hand, look at a wide range of cryptocurrencies and conclude that liquid markets are much efficient.

Bouri et al. (2019) use a Granger causality technique in the frequency domain to discover that Bitcoin is not the only presenter of volatility, emphasizing the significance of other significant cryptocurrencies in the network of volatility spillovers. Koutmos (2018) discovers that the spillovers fluctuate over time and point to the rising interconnectedness of cryptocurrencies, indicating a larger level of contagion risk. The study also highlights Bitcoin's essential position in the return and volatility spillover network. Corbet et al. (2018) examine the return and volatility spillovers of three major cryptocurrencies (Bitcoin, Ripple, and Litecoin). Using time-domain connectivity measurements, they discover that Bitcoin returns greatly influence Ripple and Litecoin returns, whereas the response impact is minor. This result demonstrates Bitcoin's superiority in the network of return connectedness. The authors, however, present conclusions regarding volatility spillovers that differ from those of Koutmos (2018). They discover that Litecoin and Ripple have an impact on Bitcoin, whereas Bitcoin has little impact on Litecoin and Ripple. Additionally, Ripple and Litecoin are inseparably linked via both return and volatility channels. Corbet et al. (2018) further show that the three digital assets are differentiated from traditional assets, implying that they have the potential to operate as diversifiers.

Yi et al. (2018), for example, examined the volatility connections between the 52 cryptocurrencies and discovered a volatility transmission from Bitcoin to the others. Several other cryptocurrencies also transmit high levels of volatility; hence, Bitcoin is not the primary source of volatility for other cryptocurrencies. Ji et al. (2019a) examine the return and volatility of six major cryptocurrencies, and they show that Litecoin and Bitcoin are unquestionably the leaders in the network of returns. In contrast to the findings of Corbet et al. (2018), and in accordance with Koutmos (2018), they demonstrate that Bitcoin is important to the network of volatility spillovers. According to Yi, Xu, and Wang (2018), the connection within cryptocurrency markets fluctuates on a regular basis and has been rising since 2016. Kumar and Anandarao (2019) discovered consistent and same patterns, but with a focus on volatility spillovers after 2017.

These heated debates focus on the interconnectedness of cryptocurrencies (Bitcoin being the most prominent) with other investing alternatives. Nevertheless, Baur, Hong, and Lee (2018) discovered inconsistent findings where transaction data backed the product's status as a highly speculative asset. BEKK-GARCH models were utilized by Katsiampa, Corbet, and Lucey (2019) to demonstrate the existence of bi-directional positive shock transmission impacts between Bitcoin and both Ether and Litecoin as well as uni-directional shock transmission from Ether to Litecoin.

Also, the DCC model was applied to four cryptocurrencies by Mensi et al. (2020). They found that investors are encouraged to hold less BTC than LTC, ETH, and XRP in order to minimise risk while keeping consistent predicted portfolio returns. Katsiampa et al. (2019) tested eight cryptocurrencies using the Diagonal BEKK (Engle and Kroner 1995) and its asymmetric variation. Shi et al. (2020) studied the dynamic correlations among six cryptocurrencies using a multivariate factor stochastic volatility model in a Bayesian framework. They found a significant positive correlation between Bitcoin and Litecoin price volatility levels. Furthermore, Ethereum's volatility levels show a positive link with both Ripple and Stellar. Also, there is a positive correlation between Ripple and Dash volatility values. Garcia-Medina and Chaudary (2020) estimated the multivariate transfer entropy to investigate the interconnections of cryptocurrencies in a network environment. For each subperiod, they investigated the clustering coefficient and node degree distributions. The clustering coefficient increases considerably in March, coinciding with the most severe drop in the current global stock market meltdown. Furthermore, in all cases, the log-likelihood curved over a power law distribution, with a larger estimated power during the period of substantial financial contraction. Their findings imply that financial instability increases the flow of information on the bitcoin market, as measured by a higher clustering coefficient and network complexity. As a result, the complex features of the multivariate transfer entropy network may give early warning signs of increased systematic risk in cryptocurrency market turmoil.

Excitingly, anytime there have been "black swans" connected with geopolitical turbulence or an economic meltdown, such as the Greek debt crisis (2009), Cyprus bailout (2013), and Brexit (2016), the price of Bitcoin has consistently risen. Furthermore, in currency crises, Bitcoin is employed as an alternative store of economic value and a viable monetary alternative (Brandvold et al., 2015; Weber 2016; Luther and Salter 2017). Identifying instruments that are not reliant on the performance of other asset classes during periods of market volatility is critical from a portfolio risk viewpoint. The time-varying return and volatility links between various cryptocurrencies have significant consequences for asset allocations, option pricing, and risk management, particularly during a crisis (Kou et al., 2014; Caporin and Malik 2020).

Several researches in the relevant literature have looked at the return/volatility spillover between different cryptocurrencies. The diagonal BEKK model is used by Katsiampa (2019) to identify considerable volatility co-movement between Bitcoin and Ethereum. Canh et al. (2019) applied the DCC-MGARCH model to explore volatility dynamics among the seven main cryptocurrencies and find strong volatility transmission between all of them. Griffins and Shams (2018) investigated whether Tether affected Bitcoin and other cryptocurrency values and discovered that Tether purchases were timed to coincide with market downturns and resulted in considerable rises in Bitcoin price. Furthermore, less than 1% of the hours in which Tether had substantial transactions were linked to 50% of the increase in Bitcoin prices and 64% of the rise in other prominent cryptocurrencies, implying that Tether was utilized to offer price support and influence cryptocurrency prices.

To further this, it is a must to concentrate on the interdependencies that exist inside bitcoin marketplaces, which are yet primarily unexplored, despite the fact that the interconnectedness of cryptocurrencies has been studied by researchers such as Fry and Cheah (2016), Ciaian et al. (2018), Corbet et al. (2018b), Katsiampa (2017), Katsiampa et al. (2019), and Koutmos (2018). They all used daily data, and there has been little research on volatility interdependencies within cryptocurrency markets - especially when accounting for the asymmetric effects of a positive and negative shock. Although analyzing covariances and correlations is critical for estimating the risk of an investor's portfolio (Coudert et al., 2015), volatility modeling is vital for various option pricing, portfolio selection, and risk management applications (Fleming et al., 2003).

Kristoufek (2013) claims that Bitcoin and search information such as Google Trends and Wikipedia have a substantial association. However, Kristoufek (2015) claims that typical basic elements such as use in trade, money supply, and price level have a role in Bitcoin pricing over time. Furthermore, Ciaian et al. (2018) 's major findings suggest that Bitcoin market fundamentals and the attractiveness of Bitcoin to investors have a considerable influence on Bitcoin price. Furthermore, using a quantiles-based method, Balcilar et al. (2017) show that while volume may be used to forecast returns, it cannot be used to estimate volatility. In a similar vein, Koutmos (2018) shows that while larger Bitcoin transactions lead to better profits, this impact is only transitory, and any gains eventually fade away.

High degrees of volatility co-movements among cryptocurrencies can restrict the benefits of diversification, therefore, knowing covariances and correlation coefficients is critical for investors in order to estimate the risk of their portfolios (Coudert et al., 2015). As a result, analyzing volatility dynamics in cryptocurrency markets is critical for cryptocurrency users and traders to increase their awareness of interdependencies and make more educated decisions, especially when cryptocurrency consumers confront undifferentiated risks (Gkillas and Katsiampa, 2018).

3.3.Predicting Covariance Matrices In The Equity Market:

The focus on forecasting the covariance matrix for the equity market returns has been widely noticed. Many studies have been published recently. Usually, the multivariate GARCH models have been used to model and predict the covariance matrices for any market, especially equity markets. However, using high-frequency data has not been the main focus of scholars. The covariance matrix forecasting is essential to the portfolio design and strategy. With the availability of high-frequency asset price data, covariance measurement has gotten better (Sharma and Vipul, 2016). The realized estimators take advantage of this rich dataset to produce strong model-free estimates of the integrated variance and covariance. These estimators can yield exact estimates of the covariance matrix by increasing the sampling frequency (Sharma and Vipul, 2016). The authors applied three estimators to anticipate the daily realized covariance matrix, namely the two-scale realized covariance estimator (TSC), the jump-resistant two-scale realized covariance estimator (RTSC), and the realized bi-power covariance estimator (BPC). They built three risk-based portfolios based on these covariance matrix forecasts; the global minimal variance portfolio, the equal risk contribution portfolio, and the most diversified portfolio. They found evidence that utilizing TSC or RTSC estimators enhances portfolio performance compared to the daily returns-based estimator. The performance benefits are robust to the risk-based portfolio strategy, time interval selection, market circumstances, and the degree of investor risk aversion.

Nevertheless, Callot et al. (2017) applied the penalized vector autoregressive models for modeling and predicting large realized covariance matrices. They consider the Lasso-type estimators to minimize dimensionality. They produced strong theoretical assurances on their procedure's prediction capacity of the 30 Dow Jones equities. As the data is aggregated from daily to lower frequency, they indicated that the dynamics are unstable. Furthermore, they outperform their benchmark by a large amount. Examine the economic worth of their forecasting portfolio selection operation, and discover that, in some situations, an investor is prepared to pay a significant expanse to access their projections.

Also, Anatolyev and Kobotaev (2018) claimed that the existing dynamic models for realized covariance matrices ignore the price direction asymmetry. To account for the leverage effect, they reformed the previously presented conditional autoregressive Wishart (CAW) model. The parameters influencing each asset's volatility and covolatility dynamics in the conditional threshold autoregressive Wishart (CTAW) model and its variants are susceptible to switches that rely on the signs of past asset returns or prior market returns. They assessed the CTAW model's predictive performance and its limited and extended specifications from statistical and economic perspectives. They found evidence that numerous CTAW variants outperform the original CAW model and its alterations in terms of in-sample and out-of-sample predictive capabilities.

Furthermore, while many academics have focused on developing more accurate volatility models, asset interdependence and consequent co-movements are extremely important in practice, e.g., asset allocation, risk management, and portfolio management. Based on covering and reading the literature review, the volatility models naturally extend to model the entire covariance structure of the provided assets. This leads to the creation of multivariate GARCH models. Although the shift from univariate to multivariate GARCH models appears simple, it is not without difficulties. Multivariate volatility modeling provides several research possibilities in the form of extending or innovating current procedures, as well as inventing ways to address the limitations of present approaches. Also, recent developments in financial econometrics and the availability of high-frequency intraday data have permitted the direct measurement and modeling of covariance matrices. Barndorff-Nielsen and Shephard (2004) introduced the realized covariance (RC) matrix as the sum of the external products of intraday return vectors, making the covariance matrix visible for the first time. Christensen et al. (2010) proposed the pre-averaging method-based modulated realized covariance (MRC) estimator for high-dimensional applications with assets of varying liquidity.

This model is favored since it assures positive definiteness, accuracy, and robustness to non-synchronous trading and market microstructure noise. Corsi et al. (2015) treated non-synchronicity as a data lack problem. They proposed a positive-definite estimator based on Kalman smoother and expectation maximization (KEM) that takes into account all available intraday prices and is robust to non-synchronous trading and market microstructure noise. Using high-dimensional applications on US equities and comprehensive Monte Carlo simulations that simulate the liquidity and market microstructure features of the S&P 500, they demonstrated the performance of the KEM estimator. They found that KEM delivers extremely precise covariance matrix estimations and substantially exceeds competing methodologies recently proposed in the literature.

Correspondingly, the multivariate heterogeneous autoregressive (MHAR) model is frequently used among the models that use high-frequency data to forecast the covariance matrix (Bauer and

Vorkink, 2011; Chiriac and Voev, 2011; Varneskov and Voev, 2013; Hautsch et al., 2015). The MHAR is a multivariate variant of the HAR-RV model proposed by Corsi (2009). The model can accurately characterize the long memory quality of the covariance matrix using a basic linear regression framework. It is worth noticing that before developing the MHAR model, the matrix logarithm transformation of Bauer and Vorkink (2011) and the Cholesky factorization of Chiriac and Voev (2011) can be applied to the covariance matrix estimator to confirm its positive-definiteness. Furthermore, Qu and Zhang (2022) proposed the idea of incorporating asymmetry in the MHAR models. They wanted to examine if the volatility timing investors could achieve higher economic gains. They tested their concept on China's stock markets and found that they reached the highest economic values out-of-sample under various market conditions. Also, they found that the portfolios with diversified strategies are more effective when the market is calm, but the global minimal variance strategy is more effective when the market is unstable.

Additionally, Chou et al. (2009) introduced the range-based dynamic conditional correlation (DCC) model that is combined with the return-based DCC model and the conditional autoregressive range (CARR) model. They stated that the significant improvement in volatility estimation efficiency can improve the accuracy of estimating time-varying covariances. Including MA100, EWMA, BEKK, CCC, range-based DCC, and return-based DCC, using the S&P 500 stock index and 10-year government bond futures, they analyzed the in-sample and out-of-sample results for six models. The range-based DCC model outperforms all other models in terms of estimating and forecasting covariance matrices. However, Fiszeder et al. (2019) stated that the dynamic conditional correlation (DCC) model by Engle (2002) is based only on closing prices. As a result, they proposed a model that combines high and low prices into the DCC framework. Using the currencies, equities, and commodities exchange-traded funds datasets, they applied the new model. Their findings show that the new model approach beats the traditional DCC model and the range-based DCC model in the three tests: in-sample fit, covariance predictions, or value-at-risk forecasts.

Furthermore, Bauwens et al. (2012) proposed a corresponding DCC technique to realize covariance modeling using the Wishart density. The mechanism utilized to update the time-varying parameters varies in the suggested methodology. However, Vassallo et al. (2021) added to their framework the conditional density score that determines the update rule (Creal, Koopman, &

Lucas, 2013). If the score is scaled by the inverse of the Fisher information matrix in the case of the Wishart density, our technique yields the same updating rule as Bauwens et al. (2012).

On the other hand, the two-scale sub-sampler proposed by Zhang et al. (2005), the multi-scale version proposed by Zhang (2006), the realized kernel introduced by Barndorff-Nielsen et al. (2008), which depends on autocovariance-based corrections, and the pre-averaging estimator proposed by Podolskij and Vetter (2009) and Jacob et al. (2009) are the main univariate approaches that the damage triggered by the noise is fixed.

4. Research Gap and Contribution

Because cryptocurrencies are still relatively new compared to traditional financial instruments, there remains limited empirical research concerning the linkage between their returns and risk. Although some research studies emphasize the additional risk such investments might pose to investors in developing economies, numerous researchers recognize the various benefits of cryptocurrencies. Thus, understanding and forecasting the covariance matrices of cryptocurrency returns using high-frequency data will reveal the usefulness and benefits of improving the decision-making for potential investors. It was also inspired by Symitsi, Symeonidis, Kourtis, and Markellos's (2018) study that investigated the ability of different models to forecast the covariance matrices of equity markets. Therefore, this research contribution aims to find the best-fitted model to forecast the covariance matrices for ten cryptocurrency returns using five models. It also focuses on applying the most prominent volatility forecasting models based on previous studies, aiming to compare models across models to identify the models that outperform in predicting the covariance matrices of cryptocurrency returns. Also, more contributions go towards using high-frequency data of the dominant cryptocurrency returns that have the highest market cap and less dominant cryptocurrency returns to provide valuable insights to investors, portfolio managers, financial firms, and regulators.

4.1. Research Questions:

What is the best-fitted model to forecast the covariance matrix of the cryptocurrency returns?

4.2. Research objectives:

1. Identify the best-fitted model to forecast the covariance matrix of the cryptocurrency returns.
2. Forecast the covariance matrices of both the dominant and less dominant cryptocurrency returns.
3. Forecast the covariance matrices of the cryptocurrency returns using high-frequency data.

5. METHODOLOGY

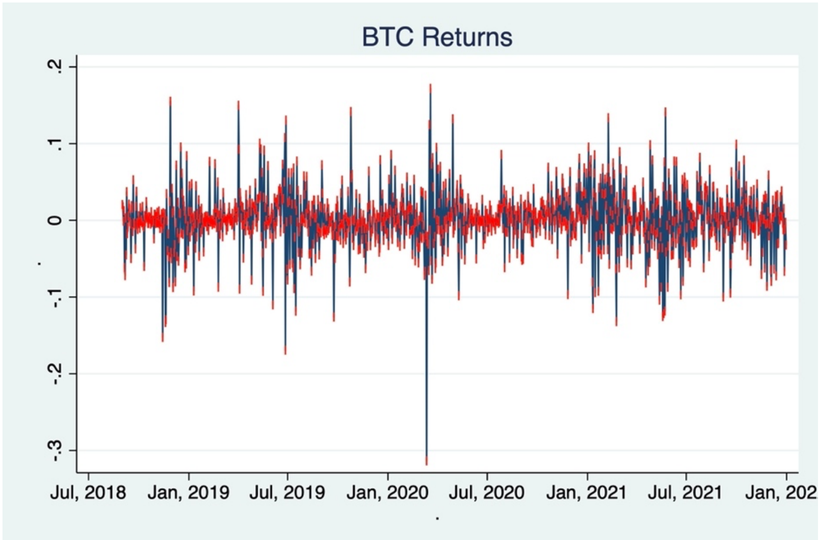
5.1. Research Design

Forecasting cryptocurrency covariance using high-frequency data depends on selecting a suitable methodology that produces valuable and accurate findings. The extensive use of academic resources that support analytical approaches contributes to producing and communicating the results that can be used in the real world. Specifically, Lagged Realized Volatility model (LRE), the BEKK model (BEKK), the Diagonal BEKK model (D-BEKK), the Dynamic Conditional Correlations model (DCC), and the Asymmetric DCC model (A-DCC) are the frameworks applied in the current study. These models have been chosen based on previous literature and the contribution of Symitsi, Symeonidis, Kourtis, and Markellos's (2018) study. Their study has inspired the research's methodology design. Although their analysis has been applied to five major European equity indices, some of the models they used apply to the research dataset and field. Some models they used do not apply to our study since they used option prices. Therefore, the Lagged Realized Volatility (LRE) model has been adapted from Kourtis, Markellos, and Symeonidis's (2016) study. Also, the BEKK model has been chosen based on Katsiampa, Corbet, and Lucey's (2019) study. Each model has advantages and characteristics that improve the research's primary aim to find the best-fitted model to forecast the covariance matrix of cryptocurrency returns. Each model will be explained in detail in the following sections.

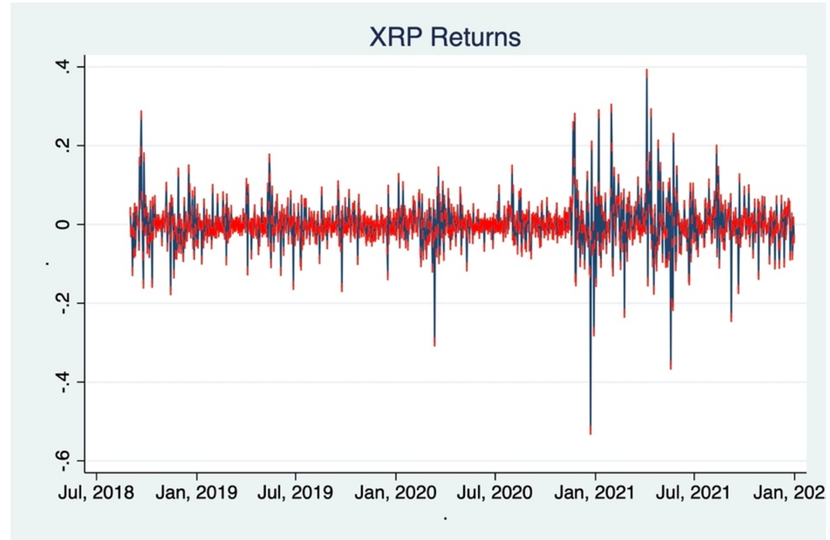
5.2. Data Collection

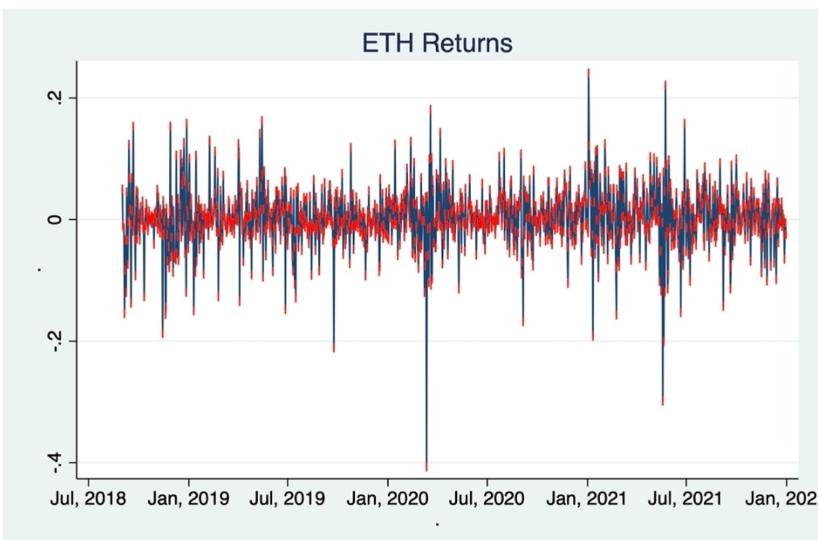
This research uses daily and weekly historical data computed from 5-minute log returns for the following 10 cryptocurrency returns: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), Bitcoin Cash (BTH), Eos (EOS), Monero (XMR), Stellar (XLM), Dash (DASH), and Ethereum Classic (ETC) between 1st September 2018 to 31st December 2021 (Table A). These cryptocracies have different market capitalizations that vary from dominant and less dominant cryptos. The data were obtained from https://www.kraken.com. Here are the visual figures of the cryptocurrency returns .

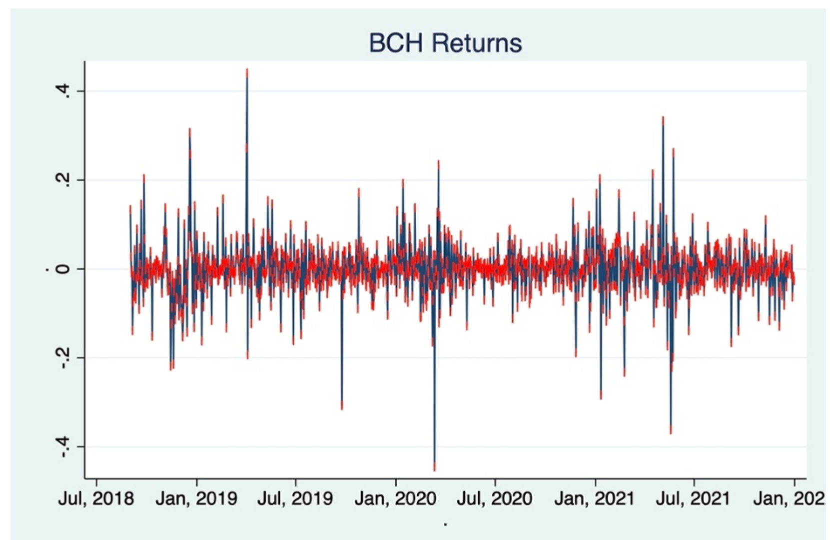
Cryptocurrency Returns



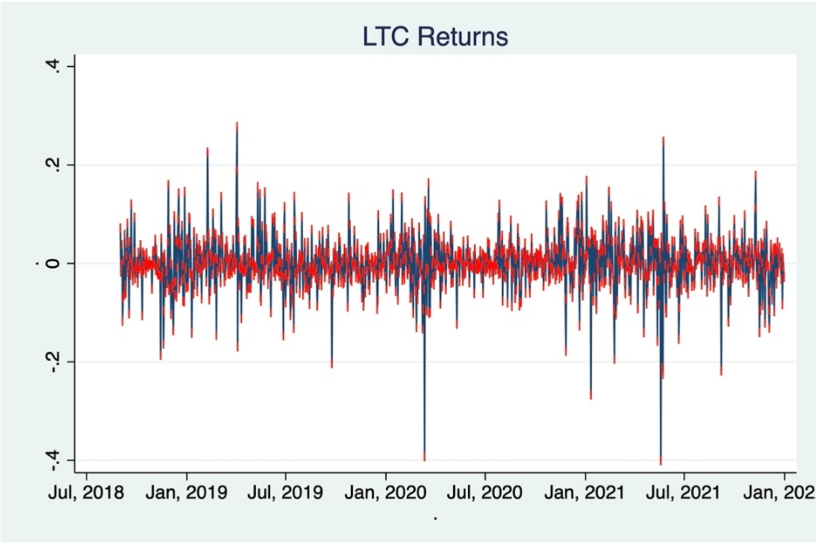
Cryptocurrency Returns



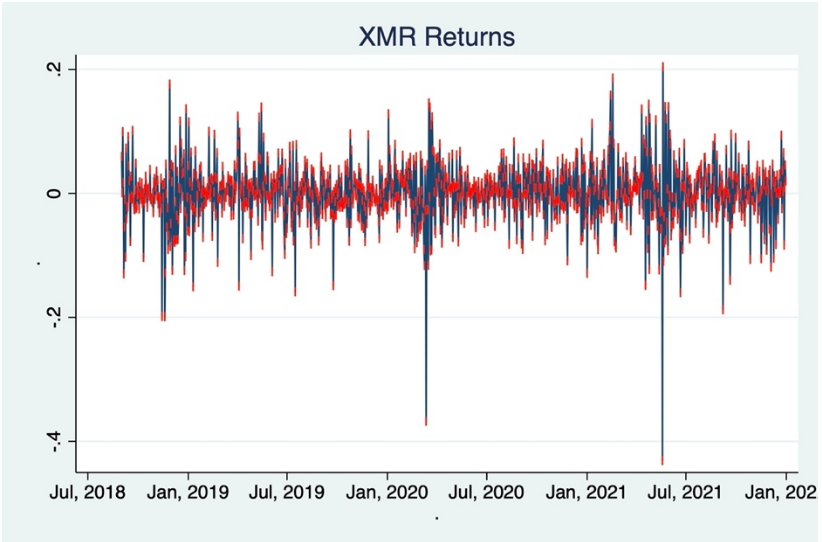


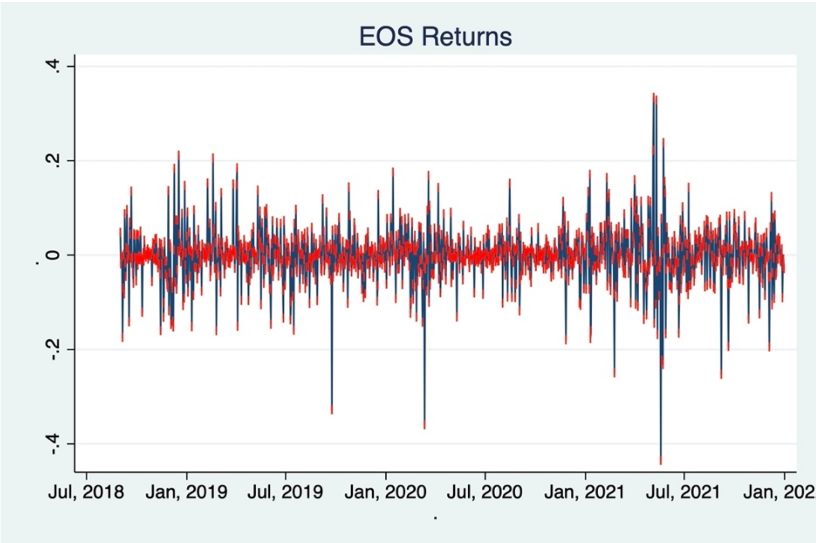


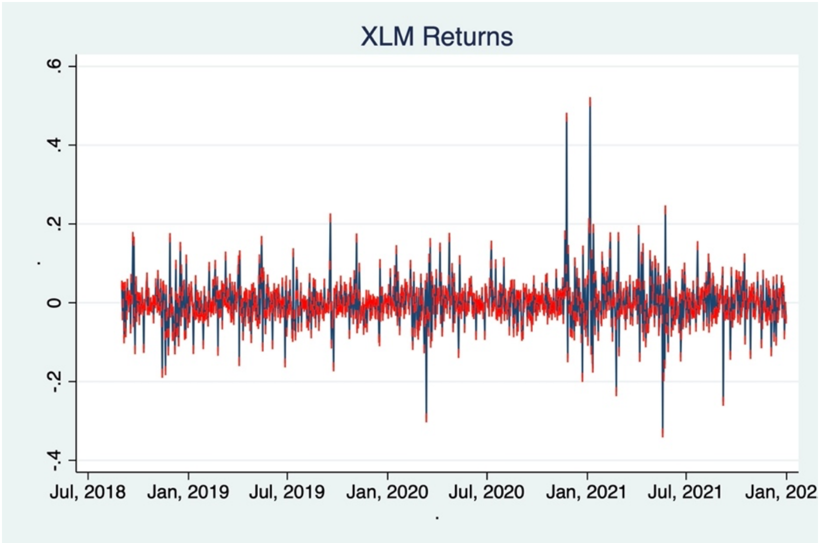
Cryptocurrency Returns



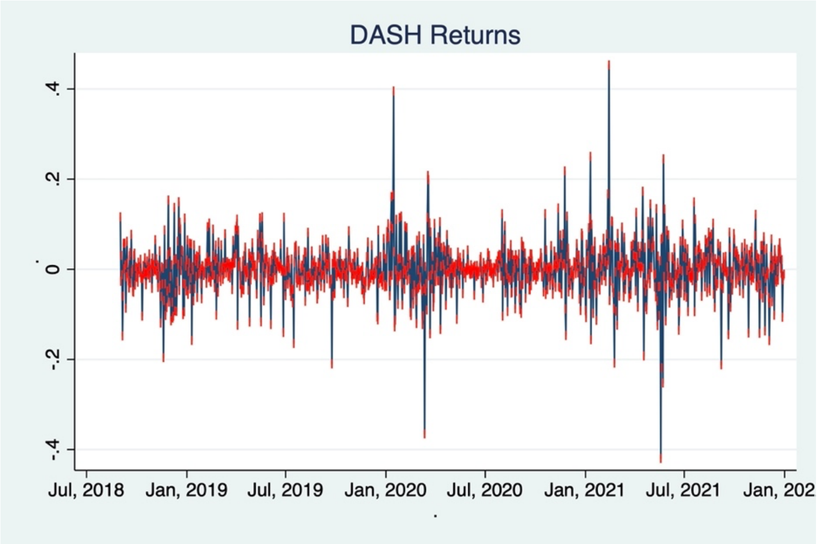
Cryptocurrency Returns



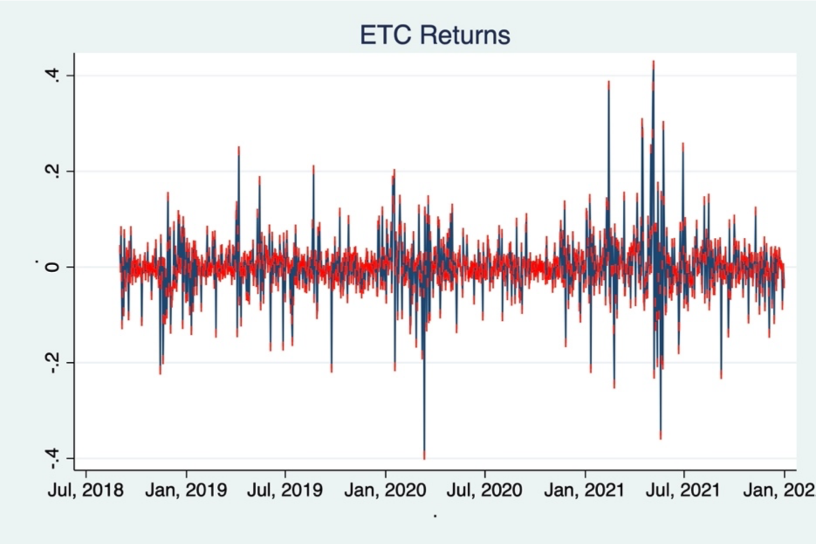




Cryptocurrency Returns



Cryptocurrency Returns



5.3. Covariance Proxy

The approach of producing the covariance matrix, since the true covariance matrix is not observable by Symitsi, Symeonidis, Kourtis, and Markellos (2018), has been adapted. The realized covariance matrices for intraday have been calculated by computing the intraday returns sample at equally-spaced intervals. The calculations of the covariance matrix can be expressed as follows. Presume that on day t a grid of $M + 1$ equally-distant intraday prices is observed at times $t_0, t_1, t_2, \dots, t_M$ with the p_{t_j} is the logarithmic price at time t_j. The equivalent asset return for the r_{t_j} in the j^{th} intraday interval of day t is calculated as $r_{t_j} = p_{t_j} - p_{t_{j-1}}$. We denote the N X 1 vector demeaned asset returns for the j^{th} interval of day t, by $r_{j,t}$. The realized daily covariance matrix can be expressed as follows:

$$\sum t = \sum_{j=1}^{M} r_{j,t} \quad r'_{j,t} \qquad (1)$$

From Equation (1), it can be indicated that the equation consistently estimates the true unobserved covariance as the sampling frequency goes to in infinity (Andersen et al., 2003). As the comment standard practice that Andersen et al., 2001, used, this research relies on the 5-minute returns for the calculation of t . Then, covariance over horizons of k days is given by the sum of daily realized covariances.

5.4. Research Models

5.4.1. BEKK (BEKK) and Diagonal BEKK (DBEKK) Model

This model has been developed by Engle and Kroner (1995). This model is widely utilized in the literature, particularly for modeling volatility spillovers. This is because the model's complete form permits conditional volatilities to be determined by their own historical values as well as the volatilities of other markets (Symitsi, Symeonidis, Kourtis, and Markellos, 2018). The BEKK model allows the conditional variances and covariances of several time series to interact (Katsiampa et al., 2019). As a result, we can discover volatility transmission effects. The BEKK model ensures that the three-parameter matrices of the diagonal elements are restricted to be positive (Bekiros, 2014). The BEKK(1,1) model is described below (Katsiampa et al., 2019):

$$H_t = W'W + A'e_{t-1}\, e'_{t-1}A + B'H_{t-1}\, B \qquad (2)$$

Where W, A, and B are matrices of parameters with appropriate dimensions, with W being an upper triangular matrix and A and B being restricted to be diagonal. The diagonal components of matrices A and B represent the influence of the asset's own previous shocks and volatility, whereas the off-diagonal elements of matrices A and B record the cross-market impacts of shocks and volatility (Li and Majerowska, 2008). These cross-market impacts are sometimes referred to as shock transmission and volatility spillover.

5.4.2. Dynamic Conditional Correlations (DCC) Model

Engle's dynamic conditional correlation model differs from Bollerslev's constant conditional correlation model only in that R has a structure that can change over time. In Engle's (2002) DCC model, the *H* matrix is as follows:

$$H_t = D_t R_t D_t \qquad (3)$$

Where R_t denotes the correlation matrix containing dynamic conditional correlations and can be expressed as follows:

$$R_t = diag\ (\sqrt{q_{11t}} \ldots\ldots \sqrt{q_{NNt}}\ )\ Q_t\ \mathrm{diag}\ (\sqrt{q_{11t}} \ldots\ldots \sqrt{q_{NNt}}\ ) \qquad (4)$$

Where Q_t is a N x N symmetric positive definite matrix, $Q_t = q_{ii}$ and can be expressed as follows (Symitsi, Symeonidis, Kourtis, and Markellos, 2018):

$$Q_t = (\ 1 - a - \beta\ )\ \overline{Q} + a u_{t-1} u_{t-1} + \beta Q_{t-1} \qquad (5)$$

Where u_t = (u_{1t} u_{2t} … u_{Nt}) and u_{it} = ε_{it} / $\sqrt{h_{iij}}$. $\overline{Q}$ is the unconditional variance matrix of standardized residuals u_t. a and β are non-negative parameters. Providing the condition that $a + \beta < 1$ is fulfilled, the model would be mean-reverting. The quasi-correlations are represented by the $q_{ij,t}$ element of the Q_t . Like the CCC model, the DCC model may be estimated using a two-step maximum likelihood technique that involves estimating univariate GARCH processes first, followed by estimating correlation parameters using Equation (4). As a result, the method is applicable in huge systems. One disadvantage of the typical DCC model is that, in order to decrease estimate complexity, parameters a and β in Equation (8) are vectors, implying that all correlations follow the same dynamics (Symitsi et al., (2018).

5.4.3. Asymmetric DCC (A-DCC) Model

The Asymmetric Dynamic Conditional Correlations are the extension of the DCC model. The A-DCC model permits leverage effects on dynamic conditional correlations. The A-DCC model can be expressed as follows:

$$Q_t = [(1 - a - \beta)\, \overline{Q} - \gamma\overline{N}] + a u_{t-1}u_{t-1} + \beta Q_{t-1} + \gamma z_{t-1}z'_{t-1} \qquad (6)$$

Where $\overline{N}$ is the unconditional covariance matrix of the negative innovations ($z'_t s$) (Symitsi, et al, 2018).

5.4.4. Lagged Realized Volatility (LRE) Model

LRE is one of the methods used for the purpose of financial instrument predictions. For this reason, its consideration in the present research is justified by the necessity to predict the volatility of cryptocurrencies. Kaminska and Roberts-Sklar (2018) explained that the LRE model considers the regular array of short-term predictive aspects, including a variable representing volatility persistence. Also, Sensoy and Omole (2018) point out that volatility becomes persistent when lagged realized volatility is significant.

Moreover, the ability of LRE to explain high-frequency data has been confirmed in recent academic research. Huang, Tong, and Wang (2019) emphasized that the findings of their study supported the hypothesis that taking into account realized volatility contributes to the production of superior predictions. In particular, quarterly and yearly data on lagged realized volatility describe the long-term dynamics of volatility. Periods of high volatility are particularly well explained with the help of the LRE framework. Given that the model is gaining momentum among financial academics, its use for the analysis of cryptocurrency behaviour is likely to improve our understanding of innovative currencies. Because the cryptocurrency market experiences high levels of volatility, the capacity of LRE to analyze such data makes the model a relevant and justifiable approach to employ. According to Kourtis, Markellos, and Symeonidis (2016), the realized volatility is calculated as follows:

$$\mathrm{RVt} = \sqrt{\sum_{j=1}^{m} r_{tj}^{2}} \tag{7}$$

Therefore, the lagged realized volatility can be calculated:

$$\mathrm{LRE} = \sqrt{\sum_{j=1}^{m} r_{t-1}^{2}} \tag{8}$$

As Kourtis, Markellos, and Symeonidis (2016) explained, these variables are crucial because they assume that volatility occurs within a Markov process, which signifies that its period is predictive of future data.

6. FORECASTING EVALUATION CRITERIA:

The forecast evaluation is adapted from the Symitsi et al., (2018) study. The forecast evaluation ability is based on combining three criteria multivariate loss functions. The Euclidean distance (Le), Frobenius distance (Lf), and the multivariate quasi-likelihood loss function (Lq) are the three loss functions that will be applied to evaluate the forecasting ability of the four models used in this research. Symitsi et al. (2018) and Laurent et al. (2012) used and applied the Euclidean distance (Le). Also, Symitsi et al. (2018) and Bollerslev et al. (2016) used and applied the Frobenius distance (Lf) and the multivariate quasi-likelihood loss function (Lq).

These loss functions can be expressed as follows (Symitsi et al. 2018):

$$L_e = vech(\sum t - H_t)' vech(\sum t - H_t) \tag{9}$$

$$L_f = T_r[(\sum t - H_t)'(\sum t - H_t)] \tag{10}$$

$$L_q = log|H_t| + T_r[H_r^{-1} \sum t] \tag{11}$$

The $vech$ is the operator that accumulates all lower fractions of the covariance matrices to a vector. Also, the T_r denotes the trace of a square matrix, which is the sum of all diagonal elements.

6.1. Statistical Comparison of the Forecasts

Based on the forecasting criteria chosen above, further evaluation will be carried out to evaluate the forecast and determine the best model that could provide accurate forecasting ability. The Mean Squared Error (MSE) and Mean Absolute Error (MAE) forecasting measures have been applied. The Mean Squared Error measures the mean of the differences between the actual values and the forecasted values (Arnerić et al., 2018).

These estimators provide more evidence on the best model to predict the covariance matrix for the cryptocurrency returns in the study. Mensi et al. (2014) applied these measures to evaluate the forecasting performance and compare the forecasts of several models.

The Mean Squared Error measure can be expressed as follows (Mensi et al., 2014):

$$\text{MSE} = \frac{1}{T}\sum_{t=1}^{T}(F_t - A_t)^2, \qquad (12)$$

The Mean Absolute Error measure can be expressed as follows (Mensi et al., 2014):

$$\text{MAE} = \frac{1}{T}\sum_{t=1}^{T}|F_t - A_t|, \qquad (13)$$

6.2.Model Fit:

The assessment started by evaluating the models' forecasting ability by three multivariate loss functions, namely Euclidean Distance (LE), Frobenius Distance (LF), and the multivariate quasi-likelihood loss function (LQ). The Euclidean distance loss function results show that the Lagged Realized Volatility model is the best-fitted model among the five models to forecast the covariance matrix. This findings supports the findings of Huang et al. (2019) study. Also, it supports the fact that obtained from several empirical evidence that historical volatility estimators derived from daily data are inferior than their high frequency-based data (Andersen and Bollerslev, 1998; Andersen, Bollerslev, and Diebold, 2007; Blair et al., 2001). The Diagonal BEKK and DCC models are the second best-fitted models for the daily returns, followed by the BEKK and Asymmetric DCC models, respectively. This results contradict the findings of Lai, (2021)'s study. Based on the model specification that he stated, the BEKK model outperformed the DCC model in forecasting accuracy. It also supports the findings of Balter et al. (2015)'s study regarding the Diagonal BEKK model. When using the multivariate Realized GARCH model to forecast the covariance of exchange rates, the multivariate Realized GARCH model outperformed the traditional CCC, cDCC and diagonal BEKK models for 10 periods-ahead.

Similarly, the weekly returns' Euclidean distance loss function results reveal that the Lagged Realized Volatility model is the best-fitted model among the five models. Also, this result is alignment with the results of Huang et al. (2019) study. However, the Asymmetric DCC model is the second best-fitted model that forecasts the covariance matrix of the weekly cryptocurrency returns, followed by the Diagonal BEKK, BEKK, and DCC models, respectively. This results disagree with the findings of Yu and Huang, (2022)'s study. They found that among their forecasting model, the BEKK model has the highest turnover with a weekly rebalancing frequency. Furthermore, throughout weekly and monthly investment intervals, the DCC model is one of the top models in terms of portfolio concentration and selling position. They have tested these model for covariance forecasting. However, regarding the Asymmetric DCC model, the results of Asai and McAleer, (2015)'s study are confirmed by the results of the forecasts of the covariance matrix of the weekly cryptocurrency returns. Their empirical evidence of 7 financial asset returns for the US stock returns shows that the new fMSV models are superior to the current dynamic conditional correlation models when forecasting future covariances. They applied the DCC and Asymmetric DCC models in their study.

Corresponding, the daily and weekly Euclidean Distance loss function results, the Frobenius Distance loss function results show that the Lagged Realized Volatility model is the best-fitted model among the five models to forecast the daily returns covariance matrix. This is align with the findings of Huang et al. (2019) study as well. The Diagonal BEKK and DCC models are the second best-fitted models for daily returns.

Similarly, the weekly returns' Frobenius Distance loss function results uncover that the Lagged Realized Volatility model is the best-fitted model among the five models. However, the Asymmetric DCC model is the second best-fitted model that forecasts the covariance matrix of the weekly cryptocurrency returns, followed by the Diagonal BEKK, BEKK, and DCC models, respectively. these results contradict the findings of Yu and Huang, (2022)'s study as mentioned above. It also support the findings of Han and Park, (2022)'s study. The BEKK and DCC models were outperformed by their developed model named Geometric Covariance Dynamics (GCD). Furthermore, it supports the result of the Callot et al. (2017)'s study. They concluded that given their weak forecasts, the DCC and EWMA models performed profoundly.

Likewise, the results of the multivariate quasi-likelihood loss function reveal a different pattern than the previous two loss functions. The best-fitted model to forecast the covariance matrix for the daily cryptocurrency returns is Lagged Realized Volatility model. The Asymmetric DCC is the second best-fitted model for daily returns, followed by the BEKK, Diagonal BEKK, and DCC models, respectively. Regarding the DCC model being the least favourite model to forecast the covariance matrix, this result supports the findings of the Fiszeder and Orzeszko, (2021)'s study. Their empirical evidence of their proposed procedure suggested that the forecast of the entire covariance matrix and each individual covariance are more accurate than those provided by the DCC model. Alike, the best-fitted model to forecast the covariance matrix for the weekly cryptocurrency returns is Lagged Realized Volatility model. The Asymmetric DCC is the second best-fitted model for daily returns, followed by the BEKK, Diagonal BEKK, and DCC models, respectively.

Then, the Mean Squared Error and Mean Absolute Error measures were applied to evaluate the loss function outcomes and compare the five models based on the three loss function criteria. The Mean Squared Error measures of the Euclidean Distance loss function results of the daily cryptocurrency returns reveal that the Lagged Realized Volatility model is the best-fitted model to forecast the covariance matrix among the five models which confirms the results of the forecasting criteria and support the findings of Huang et al. (2019). The Asymmetric DCC is the second best-fitted model for daily returns. However, the Mean Absolute Error measures show that the Asymmetric DCC model is the best-fitted model for daily returns, and the BEKK model is the second best-fitted model. this contradict the results of Huang et al. (2019) for the Asymmetric DCC model and Lai, (2021)'s study for the BEKK model.

Correspondingly, the Mean Squared Error measures of the Euclidean Distance loss function results of the weekly cryptocurrency returns discover that the Lagged Realized Volatility model is the best-fitted model to forecast the covariance matrix among the five models. The Asymmetric DCC is the second best-fitted model for weekly returns. The Mean Absolute Error measures also show that the Asymmetric DCC model is the best-fitted model for daily returns. Yet, the Lagged Realized Volatility model is the second best-fitted model for weekly returns which supports the findings of Huang et al. (2019).

Furthermore, similar to the Euclidean Distance loss function daily and weekly results, the Mean Squared Error measures of the Frobenius Distance loss function results of the daily cryptocurrency returns indicate that the Lagged Realized Volatility model is the best-fitted model to forecast the covariance matrix among the five models. The Asymmetric DCC model is the second best-fitted model for daily returns. However, the Mean Absolute Error measures show that the Asymmetric DCC model is the best-fitted model for daily returns, and the BEKK model is the second best-fitted model. Correspondingly, the Mean Squared Error measures of the Frobenius Distance loss function results of the weekly cryptocurrency returns show that the Lagged Realized Volatility model is the best-fitted model to forecast the covariance matrix among the five models. The Asymmetric DCC is the second best-fitted model for weekly returns. The Mean Absolute Error measures also show that the Asymmetric DCC model is the best-fitted model for weekly returns. Still, the Lagged Realized Volatility model is the second best-fitted model for weekly returns.

Finally, the Mean Squared Error measures of the multivariate quasi-likelihood loss function results of the daily cryptocurrency returns show that the Lagged Realized Volatility model is the best-fitted model to forecast the covariance matrix among the five models. The Asymmetric DCC model is the second best-fitted model for daily returns. However, the Mean Absolute Error measures show that the Lagged Realized Volatility model is the best-fitted model for daily returns, and the Asymmetric DCC model is the second best-fitted model.

Also, the Mean Squared Error measures of the multivariate quasi-likelihood loss function results of the weekly cryptocurrency returns exhibit that the Asymmetric DCC model is the best-fitted model to forecast the covariance matrix among the five models. The LRE is the second best-fitted model for weekly returns. Also, the Mean Absolute Error measures reveal that the Asymmetric DCC model is the best-fitted model for weekly returns due to permitting leverage effects on dynamic conditional correlations. Nevertheless, the Lagged Realized Volatility, BEKK, and DCC models are the second best-fitted model for weekly returns.

Based on these results, it can be concluded that the best-fitted model to forecast the daily covariance matrix is the Lagged Realized Volatility model when applying the Mean

Squared Error measures. This finding supports the forecast evaluation criteria results for the daily returns. It also supports the results of Huang et al. (2019)'s study along with the supporting the fact that obtained from several empirical evidence mentioned before (Andersen and Bollerslev, 1998; Andersen, Bollerslev, and Diebold, 2007; Blair et al., 2001). However, when using the Mean Absolute Error measures, only the multivariate quasi-likelihood loss function endorses the finding of the forecast evaluation criteria results for the daily returns. The other two loss functions reveal different conclusions than the forecast evaluation criteria results for the daily returns.

Also, based on the LE and LF loss functions, it can be determined that the best-fitted model to forecast the weekly covariance matrix is the Lagged Realized Volatility model when applying the Mean Squared Error measures. This finding supports the forecast evaluation criteria results for the weekly returns. However, the LQ loss function reveals different results than the forecast evaluation criteria for weekly returns. It shows that the Asymmetric DCC model is the best-fitted model, and the Lagged Realized Volatility model is the second-fitted model for the daily returns. Nonetheless, when applying the Mean Absolute Error measures, the Asymmetric DCC model is the best-fitted model to forecast the covariance matrix for weekly returns. This finding does not support the weekly results of the forecast evaluation criteria.

7. Limitations

Chapter Four research has certain limitations that should be considered. The empirical findings included five models only. Therefore, future researchers should broaden their scope beyond these models to explore more models and seek better accuracy in forecasting the covariance matrices for cryptocurrency returns. Furthermore, the research included only cryptocurrency returns. Therefore, future researchers might widen their reach by including additional financial assets and examining their influence on forecasting cryptocurrency return covariance matrices.

Furthermore, the empirical findings of this research did not include the COVID-19 pandemic period. Therefore, examining the impact of the COVID-19 pandemic on cryptocurrency returns at various stages, including pre-COVID-19, during-COVID-19, and post-COVID-19, is an exciting field for research. Extending the dataset to include this more prolonged period can give valuable insights into the implications of the pandemic on cryptocurrency returns. Finally, as noted in Chapter Three restrictions, future academics could investigate integrating data from 2022 and 2023 to expand these findings and ensure a more thorough study.

8. CONCLUSION

This research evaluates the forecasting ability to forecast the covariance matrix of five models: BEKK, Diagonal BEKK, DCC, Asymmetric DCC, and Lagged Realized Volatility. The evaluation process was obtained in two phases. The first phase contains the evaluation of the forecasting ability based on three multivariate loss functions: Euclidean Distance (LE), Frobenius Distance (LF), and the multivariate quasi-likelihood loss function (LQ). The second phase includes using two measures to evaluate the five models based on the findings of the first phase. These two measures are the Mean Squared Error and Mean Absolute Error measures.

The results of the first phase reveal that the Lagged Realized Volatility model is the best-fitted model across all three multivariate loss functions for the daily and weekly cryptocurrency returns. This result is supported by most of the second-phase findings. The second phase findings reveal that the best-fitted model to forecast the daily covariance matrix is the Lagged Realized Volatility model when applying the Mean Squared Error measures.

However, when using the Mean Absolute Error measures, only the multivariate quasi-likelihood loss function endorses the finding of the forecast evaluation criteria results for the daily returns. The other two loss functions reveal that the Asymmetric DCC model is the best-fitted model to forecast the daily covariance matrix.

Also, when applying the Mean Squared Error measures, the best-fitted model to forecast the weekly covariance matrix is the Lagged Realized Volatility model based on the LE and LF loss functions. This finding supports the forecast evaluation criteria results for the weekly returns. However, the LQ loss function reveals different results than the forecast evaluation criteria for weekly returns. It shows that the Asymmetric DCC model is the best-fitted model. However, when applying the Mean Absolute Error measures, the Asymmetric DCC model is the best-fitted model to forecast the covariance matrix for weekly returns. This finding does not support the weekly results of the forecast evaluation criteria across all three multivariate loss functions. Instead, the Asymmetric DCC is the best-fitted model to forecast the covariance matrix for weekly cryptocurrency returns.

References

Adebola, S.S., Gil-Alana, L., Madigu, G., 2019. Gold prices and the cryptocurrencies: evidence of convergence and cointegration. *Physica A: Statistical Mechanics and its Applications 523, 1227–1236.*

Al-Yahyaee, K.H., Mensi,W., Al-Jarrah, I.M., Hamdi, A., Kang, S.H., 2019. Volatility forecasting, downside risk, and diversification benefits of bitcoin and oil and international commodity markets: a comparative analysis with yellow metal. *The North American Journal of Economics and Finance 49, 104–120.*

Anatolyev, S. and Kobotaev, N., 2018. Modeling and forecasting realized covariance matrices with accounting for leverage. *Econometric Reviews*, *37*(2), pp.114-139.

Andersen, T. G., & Bollerslev, T. (1998). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *International Economic Review, 39*, 885–905.

Andersen, T. G., Bollerslev, T., & Diebold, F. X. (2007). Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility. Review of Economics and Statistics, 89, 701–720.

Arnerić, J., Poklepović, T. and Teai, J.W., 2018. Neural network approach in forecasting realized variance using high-frequency data. *Business Systems Research: International journal of the Society for Advancing Innovation and Research in Economy*, *9*(2), pp.18-34.

Asai, M. and McAleer, M., 2015. Forecasting co-volatilities via factor models with asymmetry and long memory in realized covariance. *Journal of Econometrics*, *189*(2), pp.251-262.

Asteriou, D, and S Hall (2011). “Vector autoregressive (VAR) models and causality tests. *Applied Econometrics.”*

Audrino, F. and Knaus, S.D., 2016. Lassoing the HAR model: A model selection perspective on realized volatility dynamics. *Econometric Reviews, 35(8-10),* pp.1485-1521.

Baillie, R.T. and Bollerslev, T., 1990. A multivariate generalized ARCH approach to modeling risk premia in forward foreign exchange rate markets. *Journal of International Money and Finance*, *9*(3), pp.309-324

Balcilar, M., Bouri, E., Gupta, R., Roubaud, D., 2017. Can volume predict Bitcoin returns and volatility? A quantiles-based approach. *Econ. Model.* 64, 74–81.

Balter, A., Dumitrescu, E.I. and Hensen, P.R., 2015. Exchange rate volatility forecasting: a multivariate Realized-GARCH approach.

Barndorff-Nielsen, O.E. and Shephard, N., 2004. Econometric analysis of realized covariation: High frequency based covariance, regression, and correlation in financial economics. *Econometrica*, *72*(3), pp.885-925.

Barndorff-Nielsen, O.E., Hansen, P.R., Lunde, A. and Shephard, N., 2008. Designing realized kernels to measure the ex post variation of equity prices in the presence of noise. *Econometrica*, *76*(6), pp.1481-1536.

Bauer, G.H. and Vorkink, K., 2011. Forecasting multivariate realized stock market volatility. *Journal of Econometrics*, *160*(1), pp.93-101.

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

Bauwens, L., Storti, G. and Violante, F., 2012. Dynamic conditional correlation models for realized covariance matrices. *CORE DP*, *60*, pp.104-108.

Bekiros, S.D., 2014. Contagion, decoupling and the spillover effects of the US financial crisis: evidence from the BRIC markets. Int. Rev. Financ. Anal. 33, 58–69.

Blair, B. J., Poon, S. H., & Taylor, S. J. (2001). Forecasting S&P 100 volatility: The incremental information content of implied volatilities and high-frequency index returns. *Journal of Econometrics,* 105, 5–26.

Blau, B.M., 2018. Price dynamics and speculative trading in Bitcoin. *Res. Int. Bus. Finance*. 43, 15–21.

Bollerslev, T., Patton, A.J. and Quaedvlieg, R., 2018. Modeling and forecasting (un) reliable realized covariances for more reliable financial decisions. *Journal of Econometrics, 207(1),* pp.71-91.

Bouri, E., Das, M., Gupta, R. and Roubaud, D., 2018a. Spillovers between Bitcoin and other assets during bear and bull markets. *Applied Economics*, *50*(55), pp.5935-5949.

Bouri, E., Gupta, R., Lahiani, A., Shahbaz, M., 2018b. Testing for asymmetric nonlinear short- and long-run relationships between bitcoin, aggregate commodity and gold prices. *Resource Policy 57*, 224–235.

Bouri, E., Lucey, B. and Roubaud, D., 2020. The volatility surprise of leading cryptocurrencies: Transitory and permanent linkages. *Finance Research Letters, 33*, p.101188.

Brandvold, M., Moln r, P., Vagstad, K., & Valstad, O. C. A. (2015). Price discovery on Bitcoin exchanges. *Journal of International Financial Markets, Institutions, and Money, 36,* 18 35.

Brauneis, A., Mestel, R., 2018. Price discovery of cryptocurrencies: bitcoin and beyond. *Econ. Lett.* 165, 58–61.

Callot, L.A., Kock, A.B. and Medeiros, M.C., 2017. Modeling and forecasting large realized covariance matrices and portfolio choice. *Journal of Applied Econometrics, 32(1)*, pp.140-158.

Canh NP, Wongchoti U, Thanh SD, Thong NT (2019) Systematic risk in cryptocurrency market: evidence from DCCMGARCH model. *Finance Res Lett 29:90–100*

Caporale, G.M., Gil-Alana, L., Plastun, A., 2018. Persistence in the cryptocurrency market. *Res. Int. Bus. Finance. 46, 141–148.*

Caporin M, Malik F (2020) Do structural breaks in volatility cause spurious volatility transmission? *J Empire Finance 55:60–82*

Cebrian-Hernandez, Angeles, and Enrique Jimenez-Rodriguez. 2021. Modeling of the Bitcoin Volatility through Key Financial Environment Variables: An Application of Conditional Correlation MGARCH Models. *Mathematics 9: 267.*

Charfeddine, L., Maouchi, Y., 2018. Are shocks on the returns and volatility of cryptocurrencies really persistent? Finance. *Res. Lett*. https://doi.org/10.1016/j.frl.2018. 06.017.

Cheah, E.-T., Mishra, T., Parhi, M., Zhang, Z., 2018. Long memory interdependency and inefficiency in bitcoin markets. *Econ. Lett.* 167, 18–25.

Cheah, E.T. and Fry, J., 2015. Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economics letters, 130*, pp.32-36.

Chiriac, R. and Voev, V., 2011. Modelling and forecasting multivariate realized volatility. *Journal of Applied Econometrics*, *26*(6), pp.922-947

Chiriac, R. and Voev, V., 2011. Modelling and forecasting multivariate realized volatility. *Journal of Applied Econometrics*, *26*(6), pp.922-947.

Chou, R.Y., Wu, C.C. and Liu, N., 2009. Forecasting time-varying covariance with a range-based dynamic conditional correlation model. *Review of Quantitative Finance and Accounting*, *33*, pp.327-345.

Christensen, K., Kinnebrock, S. and Podolskij, M., 2010. Pre-averaging estimators of the ex-post covariance matrix in noisy diffusion models with non-synchronous data. *Journal of econometrics*, *159*(1), pp.116-133.

Ciaian, P., Rajcaniova, M., Kancs, d., 2018. Virtual relationships: short- and long-run evidence from BitCoin and Altcoin markets. *J. Int. Financ. Mark. Inst. Money 52,173–195.*

Corbet, S., Meegan, A., Larkin, C., Lucey, B., Yarovaya, L., 2018. Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economic. Lett.* 165, 28-34.

Corsi, F., 2009. A simple approximate long-memory model of realized volatility. *Journal of Financial Econometrics*, *7*(2), pp.174-196.

Corsi, F., Peluso, S. and Audrino, F., 2015. Missing in asynchronicity: a Kalman-em approach for multivariate realized covariance estimation. *Journal of Applied Econometrics*, *30*(3), pp.377-397.

Coudert, V., Herv , K., Mabille, P., 2015. Internationalization versus regionalization in the emerging stock markets. *Int. J. Finance. Econ. 20 (1),* 16–27. doi.org/10.1016/j.ribaf.2007.06.001.

Creal, D., Koopman, S.J. and Lucas, A., 2013. Generalized autoregressive score models with applications. *Journal of Applied Econometrics*, *28*(5), pp.777-795.

Engle, R.F., Lilien, D.M. & Robins, R.P. 1987. Estimating time varying risk premia in the term structure : The ARCH-M model. The Econometric Society 55(2): 391–407.

Engle, Robert F. 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics 20:* 339–50.

Engle, Robert F., and Kennett F. Kroner. 1995. Multivariate simultaneous generalized ARCH. *Econometric Theory 11*: 122–50.

Fiszeder, P. and Orzeszko, W., 2021. Covariance matrix forecasting using support vector regression. *Applied intelligence*, *51*(10), pp.7029-7042.

Fiszeder, P., Fałdziński, M. and Molnár, P., 2019. Range-based DCC models for covariance and value-at-risk forecasting. *Journal of Empirical Finance*, *54*, pp.58-76.

Fleming, J., Kirby, C., Ostdiek, B., 2003. The economic value of volatility timing using 'realized' volatility. *J. Finance. Econ.* 67 (3), 473–509.

Fry, J., Cheah, E.T., 2016. Negative bubbles and shocks in cryptocurrency markets. *Int. Rev. Finance. Anal. 47,* 343–352.

Garcia-Medina, Andres, and Jose B.Hernandez Chaudary. 2020. Network analysis of multivariate transfer entropy of cryptocurrencies in times of turbulence. *Entropy 22*: 760.

Gkillas, K., Katsiampa, P., 2018. An application of extreme value theory to cryptocurrencies. *Econ. Lett. 164,* 109–111.

Glosten, L.R., Jagannathan, R. & Runkle, D.E. 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. The Journal of Finance 48(5): 1779–1801.

Griffins, J., Shams, A., 2018. Is bitcoin really un-tethered. Available at SSRN 13 June 2018.

Guesmi, K., Saadi, S., Abid, I., Ftiti, Z., 2019. Portfolio diversification with virtual currency: evidence from bitcoin. *Int. Rev. Financ. Anal. 63, 431–437.*

Han, C. and Park, F.C., 2022. A geometric framework for covariance dynamics. *Journal of Banking & Finance*, *134*, p.106319.

Hautsch, N., Kyj, L.M. and Malec, P., 2015. Do high-frequency data improve high-dimensional portfolio allocations?. *Journal of Applied Econometrics*, *30*(2), pp.263-290.

Hayes, A.S., 2017. Cryptocurrency value formation: an empirical study leading to a cost of production model for valuing bitcoin. *Telematics Inform. 34 (7), 1308–1321.*

Hossain, M.J., Akter, S. and Ismail, M.T., 2021. Performance analysis of GARCH family models in three time-frames. *Malaysian Economic Journal*, *55*(2), pp.15-28. https://doi.org/10.1016/j.irfa.2013.07.007.

Huang, Z., Tong, C. and Wang, T., 2019. VIX term structure and VIX futures pricing with realized volatility. *Journal of Futures Markets, 39(1),* pp.72-93.

Jacod, J., Li, Y., Mykland, P.A., Podolskij, M. and Vetter, M., 2009. Microstructure noise in the continuous case: the pre-averaging approach. *Stochastic processes and their applications*, *119*(7), pp.2249-2276.

Ji, Q., Bouri, E., Gupta, R., Roubaude, D., 2018. Network causality structures among bitcoin and other financial assets: a directed acyclic graph approach. *The Quarterly Review of Economics and Finance 70,* 203–213.

Ji, Q., Bouri, E., Lau, C.K.M., Roubaud, D., 2019a. Dynamic connectedness and integration in cryptocurrency markets. *Int. Rev. Financ. Anal. 63*, 257–272.

Ji, Q., Bouri, E., Roubaud, D., Kristoufek, L., 2019b. Information interdependence among energy, cryptocurrency and major commodity markets. *Energy Econ. 81, 1042–1055.*

Kaminska, I. and Roberts-Sklar, M., 2018. Volatility in equity markets and monetary policy rate uncertainty. *Journal of Empirical Finance, 45,* pp.68-83.

Katsiampa P (2019) Volatility co-movement between Bitcoin and Ether. Finance Res Lett 30:221–227

Katsiampa, P., 2017. Volatility estimation for bitcoin: a comparison of garch models. *Econ. Lett. 158, 3–6.*

Katsiampa, P., 2018. An empirical investigation of volatility dynamics in the cryptocurrency market. Available at SSRN.

Katsiampa, P., Corbet, S. and Lucey, B., 2019. Volatility spillover effects in leading cryptocurrencies: A BEKK-MGARCH analysis. *Finance Research Letters*, *29*, pp.68-74

Kou G, Peng Y, Wang G (2014) Evaluation of clustering algorithms for financial risk analysis using MCDM methods. *Inf Sci 275*:1–12

Kourtis, A., Markellos, R.N. and Symeonidis, L., 2016. An international comparison of implied, realized, and GARCH volatility forecasts. *Journal of Futures Markets, 36(12),* pp.1164-1193.

Koutmos, D., 2018. Return and volatility spillovers among cryptocurrencies. *Econ. Lett*. 173, 122–127.

Kristoufek, L., 2013. BitCoin meets Google Trends and Wikipedia: Quantifying the Relationship Between Phenomena of the Internet Era. Scientific Reports. *Nature Publisher Group* https://doi.org/10.1038/srep03415.

Kristoufek, L., 2015. What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis. *PLoS One*. https://doi.org/10.1371/journal.pone. 0123923.

Kumar, A.S. and Anandarao, S., 2019. Volatility spillover in crypto-currency markets: Some evidences from GARCH and wavelet analysis. *Physica A: Statistical Mechanics and its Applications*, *524*, pp.448-458.

Kyriazis, N.A., Daskalou, K., Arampatzis, M., Prassa, P. and Papaioannou, E., 2019. Estimating the volatility of cryptocurrencies during bearish markets by employing GARCH models. *Heliyon, 5(8),* p.e02239.

Lai, Y.S., 2022. Use of high‐frequency data to evaluate the performance of dynamic hedging strategies. *Journal of Futures Markets*, *42*(1), pp.104-124.

Laurent, S., J. V. Rombouts, and F. Violante (2012). On the forecasting accuracy of multivariate GARCH models. *Journal of Applied Econometrics 27 (6),* 934-955.

Li, H., Majerowska, E., 2008. Testing stock market linkages for poland and hungary: a multivariate GARCH approach. Res. Int. Bus. Finance 22 (3), 247–266.

Luther, W. J., & Salter, A. W. (2017). Bitcoin and the bailout. *The Quartely Review of Economics and Finance,* 66, 50–56.

Malladi, R.K. and Dheeriya, P.L., 2021. Time series analysis of Cryptocurrency returns and volatilities. Journal of Economics and Finance, 45(1), pp.75-94.

McAleer, M. and Medeiros, M.C., 2008. Realized volatility: A review. *Econometric reviews*, *27*(1-3), pp.10-45

Mensi, W., Hammoudeh, S. and Yoon, S.M., 2014. Structural breaks and long memory in modeling and forecasting volatility of foreign exchange markets of oil exporters: The importance of scheduled and unscheduled news announcements. *International Review of Economics & Finance, 30, pp.101-119.*

Mensi, Walid, Khamis Hamed Al-Yahyaee, Idries Mohammad Wanas Al-Jarrah, Xuan Vinh Vo, and Sang Hoon Kang. 2020. Dynamic volatility transmission and portfolio management across major cryptocurrencies: Evidence from hourly data. *The North American Journal of Economics and Finance* 54: 1–14.

Nadarajah, S., Chu, J., 2017. On the inefficiency of Bitcoin. *Econ. Lett*. 150, 6–9.

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

Okorie, D.I., 2019. Could stock hedge bitcoin risk(s) and vice versa? Digital Finance, 1–20 https://doi.org/10.1007/s42521-019-00011-0.

Podolskij, M. and Vetter, M., 2009. Estimation of volatility functionals in the simultaneous presence of microstructure noise and jumps.

Qu, H. and Zhang, Y., 2022. Asymmetric multivariate HAR models for realized covariance matrix: A study based on volatility timing strategies. *Economic Modelling*, *106*, p.105699.

Sensoy, A. and Omole, J., 2018. Implied volatility indices: A review and extension in the Turkish case. *International Review of Financial Analysis, 60,* pp.151-161.

Shahzad, S.J., Bouri, E., Roubaud, D., Kristoufek, L., Lucey, B., 2019. Is Bitcoin a better safe haven investment than gold and commodities? *International Review of Financial Analysis 63, 322–330.*

Sharma, P. and Vipul, 2016. Economic benefits of using realized covariance forecasts in risk-based portfolios. *Applied Economics*, *48*(6), pp.502-516.

Shi, Yongjing, Aviral Kumar Tiwari, Giray Gozgor, and Zhou Lu. 2020. Correlations among cryptocurrencies: Evidence from multivariate factor stochastic volatility model. *Research in International Business and Finance 5*3: 1–11.

Sims, Christopher A (1980). “Macroeconomics and reality.” Econometrica : 1–48

Symitsi, E., Symeonidis, L., Kourtis, A. and Markellos, R., 2018. Covariance forecasting in equity markets. *Journal of Banking & Finance*, *96*, pp.153-168

Terrell, D., Fomby, T.B., 2006. Econometric Analysis of Financial and Economic Time Series. *Emerald Group Publishing.*

Tiwari, A.K., Kumar, S. and Pathak, R., 2019. Modelling the dynamics of Bitcoin and Litecoin: GARCH versus stochastic volatility models. *Applied Economics*, *51*(37), pp.4073-4082

Urquhart, A., 2016. The inefficiency of Bitcoin. *Econ. Lett. 148*, 80–82.

Varneskov, R. and Voev, V., 2013. The role of realized ex-post covariance measures and dynamic model choice on the quality of covariance forecasts. *Journal of Empirical Finance*, *20*, pp.83-95.

Vassallo, D., Buccheri, G. and Corsi, F., 2021. A DCC-type approach for realized covariance modeling with score-driven dynamics. *International Journal of Forecasting*, *37*(2), pp.569-586.

Weber, B., 2016. Bitcoin and the legitimacy crisis of money. *Cambridge J. Econ*. 40 (1), 17–41.

Wei, W.C., 2018. Liquidity and market efficiency in cryptocurrencies. *Econ. Lett. 168,* 21–24.

Yi S, Xu Z, Wang GJ (2018) Volatility connectedness in the cryptocurrency market: is Bitcoin a dominant cryptocurrency? *Int Rev Financ Anal 60:98–114.*

Yu, L. and Huang, Z., 2022. Do high-frequency data improve multivariate volatility forecasting for investors with different investment horizons (No. E2022018).

Zhang, L., 2006. Efficient estimation of stochastic volatility using noisy observations: A multi-scale approach. *Bernoulli*, *12*(6), pp.1019-1043.

Zhang, L., Mykland, P.A. and Aït-Sahalia, Y., 2005. A tale of two time scales: Determining integrated volatility with noisy high-frequency data. *Journal of the American Statistical Association*, *100*(472), pp.1394-1411.

Chapter Four Research Tables

Table A: Cryptocurrencies List: Start and End dates, Number of observations in 5-min, days, and Weeks

Cryptocurrency	Symbol	Start Date	End Date	Number of observations in 5-min	Number of observations in days	Number of observations in Weeks
Bitcoin	BTC	9/1/2018	12/31/2021	350,786	1218	174
Ethereum	ETH	9/1/2018	12/31/2021	350,786	1218	174
Ripple	XRP	9/1/2018	12/31/2021	350,786	1218	174
Litecoin	LTC	9/1/2018	12/31/2021	350,786	1218	174
Bitcoin Cash	BCH	9/1/2018	12/31/2021	350,786	1218	174
EOS	EOS	9/1/2018	12/31/2021	350,786	1218	174
Monero	XMR	9/1/2018	12/31/2021	350,786	1218	174
Stellar	XLM	9/1/2018	12/31/2021	350,786	1218	174
Dash	DASH	9/1/2018	12/31/2021	350,786	1218	174
Ethereum Classic	ETC	9/1/2018	12/31/2021	350,786	1218	174

Table B: Descriptive Analysis of the Daily Data and Index

	Mean	Median	SD	Kurtosis	Skewness	Range
BTC	0.002	0.001	0.04	6.19	-0.52	0.49
ETH	0.002	0.001	0.05	6.86	-0.72	0.65
XRP	0.001	-0.001	0.06	11.73	-0.22	0.91
LTC	0.001	-0.001	0.05	6.85	-0.63	0.68
BCH	0.000	0.001	0.06	9.84	-0.04	0.89
EOS	-0.001	0.000	0.06	7.28	-0.49	0.77
XMR	0.001	0.001	0.05	8.77	-1.00	0.64
XLM	0.000	-0.001	0.06	11.38	0.88	0.84
DASH	0.000	0.000	0.06	9.38	0.10	0.87
ETC	0.001	0.000	0.06	9.41	0.46	0.82

Table C: Descriptive Analysis of the Weekly Data and Indices

	Mean	Median	SD	Kurtosis	Skewness	Range
BTC	0.011	0.012	0.100	3.893	-0.828	0.789
ETH	0.015	0.022	0.133	4.530	-0.953	1.055
XRP	0.005	-0.009	0.152	4.277	0.666	1.186
LTC	0.005	0.013	0.140	3.362	-0.672	1.026
BCH	-0.001	0.000	0.175	6.112	-0.205	1.536
EOS	-0.004	0.008	0.155	4.485	-0.978	1.184
XMR	0.004	0.015	0.124	5.057	-1.230	0.935
XLM	0.001	-0.005	0.151	7.444	1.249	1.268
DASH	-0.002	0.001	0.165	5.778	0.033	1.441
ETC	0.006	0.003	0.174	13.797	1.999	1.699

Table 1: The correlations as pairwise correlations using daily and weekly returns.

	BTC	*ETH*	*XRP*	*LTC*	*BCH*	*EOS*	*XMR*	*XLM*	*DASH*	*ETC*
					Panel A: Daily Returns					
BTC										
ETH	0.820									
XRP	0.596	0.655								
LTC	0.806	0.832	0.660							
BCH	0.765	0.791	0.644	0.823						
EOS	0.729	0.782	0.694	0.806	0.808					
XMR	0.750	0.746	0.586	0.743	0.710	0.702				
XLM	0.637	0.704	0.732	0.693	0.674	0.725	0.623			
DASH	0.702	0.722	0.621	0.755	0.761	0.744	0.736	0.648		
ETC	0.637	0.700	0.580	0.721	0.753	0.753	0.637	0.634	0.722	
					Panel A: Weekly Returns					
	BTC	*ETH*	*XRP*	*LTC*	*BCH*	*EOS*	*XMR*	*XLM*	*DASH*	*ETC*
BTC										
ETH	0.786									
XRP	0.511	0.600								
LTC	0.819	0.803	0.563							
BCH	0.769	0.777	0.598	0.840						
EOS	0.719	0.820	0.654	0.829	0.837					
XMR	0.767	0.731	0.592	0.770	0.825	0.762				
XLM	0.578	0.689	0.755	0.624	0.676	0.695	0.585			
DASH	0.720	0.707	0.606	0.796	0.845	0.806	0.832	0.654		
ETC	0.591	0.686	0.552	0.726	0.756	0.782	0.684	0.598	0.757	

Table 2: The descriptive statistics of the daily (panel A) and weekly (panel B) returns.

	Panel A: Daily Returns					
	Mean	**Range**	**Median**	**Standard Deviation**	**Kurtosis**	**Skewness**
BTC	0.0016	0.4854	0.0013	0.0378	6.1944	-0.5205
ETH	0.0021	0.6480	0.0015	0.0495	6.8644	-0.7185
XRP	0.0007	0.9056	-0.0011	0.0584	11.7265	-0.2184
LTC	0.0007	0.6787	-0.0008	0.0550	6.8506	-0.6300
BCH	-0.0002	0.8863	0.0007	0.0597	9.8360	-0.0367
EOS	-0.0006	0.7692	0.0004	0.0592	7.2789	-0.4853
XMR	0.0006	0.6354	0.0014	0.0489	8.7702	-0.9976
XLM	0.0001	0.8408	-0.0014	0.0573	11.3846	0.8779
DASH	-0.0003	0.8732	-0.0001	0.0583	9.3755	0.0988
ETC	0.0008	0.8160	-0.0001	0.0609	9.4067	0.4602
	Panel A: Weekly Returns					
	Mean	**Median**	**Range**	**Standard Deviation**	**Kurtosis**	**Skewness**
BTC	0.0109	0.0120	0.7888	0.1001	3.8926	-0.8281
ETH	0.0148	0.0216	1.0547	0.1325	4.5297	-0.9528
XRP	0.0052	-0.0090	1.1856	0.1522	4.2767	0.6657
LTC	0.0050	0.0131	1.0261	0.1403	3.3617	-0.6722
BCH	-0.0014	-0.0001	1.5362	0.1753	6.1122	-0.2050
EOS	-0.0042	0.0075	1.1842	0.1552	4.4852	-0.9783
XMR	0.0040	0.0153	0.9355	0.1236	5.0573	-1.2304
XLM	0.0010	-0.0050	1.2681	0.1514	7.4445	1.2485
DASH	-0.0021	0.0005	1.4406	0.1654	5.7782	0.0330
ETC	0.0057	0.0035	1.6991	0.1741	13.7970	1.9987

Table 3: Report of the forecasts of the loss functions for daily and weekly returns. LE is the Euclidean distance, LF is the Frobenius distance, and LQ is the multivariate quasi-likelihood loss function. The LE and LF values are multiplied by 1000 to simplify the readability. An asterisk (*) means that the model is the best fit for cryptocurrency returns.

	Panel A: Daily Returns			**Panel A: Weekly Returns**		
	LE	**LF**	**LQ**	**LE**	**LF**	**LQ**
BEKK	0.397	0.10057	-0.14090	0.0411	0.0138	-0.19901
D-BEKK	0.390	0.09748	-0.14096	0.0401	0.0132	-0.19929
DCC	0.390	0.09748	-0.14096	0.0411	0.0138	-0.19901
ADCC	0.434	0.10178	-0.13989	0.0370	0.0126	-0.19610
LRE	0.262*	0.02975*	-0.11915*	0.0175*	0.0028*	-0.13724*

Table 4: Report of the MSE and MAE of the LE Loss function for the daily and weekly returns. An asterisk (**) means that model best fits cryptocurrency returns. An asterisk (*) means that the model is the second-best model that fits cryptocurrency returns.

	Panel A: Daily Returns	
	Mean Squared Error	**Mean Absolute Error**
BEKK	0.046399	0.213684*
DBEKK	0.046401	0.213691
DCC	0.046401	0.213691
ADCC	0.046383*	0.213648**
LRE	0.045719**	0.213819
	Panel A: Weekly Returns	
	Mean Squared Error	**Mean Absolute Error**
BEKK	0.024750	0.016693
DBEKK	0.022772	0.015941
DCC	0.024750	0.016693
ADCC	0.019509*	0.015542**
LRE	0.001232**	0.015672*

Table 5: Report of the MSE and MAE of the LF Loss function for the daily and weekly returns. An asterisk (**) means that model best fits cryptocurrency returns. An asterisk (*) means that the model is the second-best model that fits cryptocurrency returns.

	Panel A: Daily Returns	
	Mean Squared Error	**Mean Absolute Error**
BEKK	0.046524	0.213981*
DBEKK	0.046525	0.213984
DCC	0.046525	0.213984
ADCC	0.046523*	0.213979**
LRE	0.045818**	0.214051
	Panel A: Weekly Returns	
	Mean Squared Error	**Mean Absolute Error**
BEKK	0.004181	0.016693
DBEKK	0.003879	0.015941
DCC	0.004181	0.016693
ADCC	0.003360*	0.015542**
LRE	0.000060**	0.015672*

Table 6: Report of the MSE and MAE of the LQ loss function for the daily and weekly returns. An asterisk (**) means that model best fits cryptocurrency returns. An asterisk (*) means that the model is the second-best model that fits cryptocurrency returns.

	Panel A: Daily Returns	
	Mean Squared Error	**Mean Absolute Error**
BEKK	0.126860	0.354982
DBEKK	0.126901	0.355040
DCC	0.126901	0.355040
ADCC	0.126114*	0.353972*
LRE	0.111042**	0.333230**
	Panel A: Weekly Returns	
	Mean Squared Error	**Mean Absolute Error**
BEKK	0.0426041	0.2050540*
DBEKK	0.0427302	0.2053296
DCC	0.0426041	0.2050540*
ADCC	0.0413876**	0.2021404**
LRE	0.0420472*	0.2050540*

Chapter Five: Conclusion

This thesis comprises three chapters investigating the cryptocurrency market's risk and uncertainty. The first chapter compares six models' ability to predict the volatility of cryptocurrency returns. At the same time, the second chapter focuses on examining the relationships and effects of eight uncertainty indices on cryptocurrency market returns. Focusing on the risk and connectedness among cryptocurrency returns, the third chapter examined the ability to forecast the covariance matrices of five models. High-frequency data have been used when conducting those studies. The dataset span from 09/01/2018 to 30/09/2020 for chapter two and to 12/31/2021 for chapters two and three. The data was obtained from 5-minute historical data and computed to daily, weekly, and monthly data.

Chapter Two reveals the capability and features of different models to predict cryptocurrency volatility. The Mincer-Zarnowitz Regression with Newey-West Standard Errors has been applied in two phases: univariate and encompassing regressions. The empirical evidence shows different effects of univariate regression and compassing regressions. Also, the empirical evidence confirms the different data frequencies' additional findings. To illustrate, the findings of the univariate regressions for 1-day horizons reveal that the HAR model outperforms the other models. The univariate regressions for 7-day horizons, on the other hand, show that the EGARCH model had the most significant explanatory power of all the models tested.

Furthermore, the EGARCH model had the greatest significant explanatory power of all the research models in univariate regressions for 30-day horizons. Furthermore, the study revealed the results of the encompassing regressions. The encompassing regressions allow for a direct comparison of two sets of predictions to assess if one's useful information outweighs the other, rendering it obsolete (Cook, 2014). According to the comprehensive regressions with Newey-West Standard Errors for a 1-day prediction horizon., the HAR + EGARCH models had the most significant explanatory power among the various model combinations.

Similarly, the encompassing regressions with Newey-West Standard Errors reveal that the HAR + EGARCH duo has the highest explanatory power among the other model pairs over the 7-day prediction horizon. Furthermore, for the 30-day prediction horizon, the encompassing regressions with Newey-West Standard Errors show that the HAR + EGARCH models have the most significant explanatory power of the other model combinations. The out-of-sample analysis was carried out.

Chapter Three provides empirical evidence for investigating the relationships and effects of eight different indices, namely the daily and weekly Twitter-based Economic Uncertainty (TEU) index, the UCRY Policy Index, the UCRY Price Index, the Central Bank Digital Currency Uncertainty Index (CBDCUI), the Central Bank Digital Currency Attention Index (CBDCAI), the Cryptocurrency Environmental Attention (ICEA) index, and the Economic Policy Uncertainty Index for Europe index on cryptocurrency returns. The quantile regressions, multivariate quantile regressions, and Granger causality tests were applied.

The study looks at the link between numerous indices of economic uncertainty and cryptocurrency returns. The daily and weekly data from the Twitter-based Economic Uncertainty (TEU) index demonstrate minimal effects on the virtual currency returns across quantiles. Weekly data from the Cryptocurrency Policy Uncertainty index substantially impact bear periods for particular quantiles. The Cryptocurrency Price Uncertainty index has fewer implications for cryptocurrency returns. These findings are supported by during the crisis period evidence, particularly for the Cryptocurrency Policy Uncertainty index.

The Multivariate Quantile Regression model demonstrates that the analyzed indices have little influence during bull markets, except the 95% quantile when the UCRY Price Index and the Cryptocurrency Environmental Attention (ICEA) index exhibit significance. Pairings effects analysis finds the most significant and least influential pairings throughout bear and bull market waves, with the UCRY Policy Index + Central Bank Digital Currency Attention Index being the most and least effective, respectively.

The Granger Causality Test reveals different correlations between indices and cryptocurrency returns. The TEU index exhibits long-term impacts. The UCRY Policy Index and UCRY Price Index have the most significant impact on returns. However, several cryptocurrencies also impact these indices. At lagged order = 6, the Central Bank Digital Currency Uncertainty Index (CBDCUI) has considerable implications. The Central Bank Digital Currency Attention Index and the Cryptocurrency Environmental Attention (ICEA) index significantly influence returns. However, the CBDCUI and the Economic Policy Uncertainty Index for Europe have a lesser impact. Ultimately, the study investigates the effect of several economic uncertainty indices on digital currency returns. While some indices have a considerable impact, their impact varies depending on quantile and market conditions, shedding insight into the complicated link between economic uncertainty and cryptocurrency performance.

Chapter Four provides empirical evidence of different models' capability to forecast the covariance matrices of cryptocurrency returns. This study assesses the efficacy of five models for predicting the covariance matrix: BEKK, Diagonal BEKK, DCC, Asymmetric DCC, and Lagged Realized Volatility. The examination was completed in two stages. The forecasting ability is evaluated in the first phase using three multivariate loss functions: Euclidean Distance (LE), Frobenius Distance (LF), and the multivariate quasi-likelihood loss function (LQ). Based on the findings of the first phase, the second step comprises applying two measures to evaluate the five models. The Mean Squared Error and Mean Absolute Error are the two metrics.

The first phase findings show that the Lagged Realized Volatility model fits the daily and weekly cryptocurrency returns the best across all three multivariate loss functions. The majority of the second-phase outcomes corroborate this conclusion. When the Mean Squared Error measurements are used, the Lagged Realized Volatility model is shown to be the best-fitted model for forecasting the daily covariance matrix for all three loss functions. However, only the multivariate quasi-likelihood loss function supports discovering the forecast assessment criteria outcomes for the daily returns when the Mean Absolute Error measurements are used. The other two loss functions show that the Asymmetric DCC model is the best match for forecasting the daily covariance matrix.

Also, when applying the Mean Squared Error measures, the best-fitted model to forecast the weekly covariance matrix is the Lagged Realized Volatility model based on the LE and LF loss functions. This finding supports the forecast evaluation criteria results for the weekly returns. However, the LQ loss function reveals different results than the forecast evaluation criteria for weekly returns. It shows that the Asymmetric DCC model is the best-fitted model. However, when applying the Mean Absolute Error measures, the Asymmetric DCC model is the best-fitted model to forecast the covariance matrix for weekly returns for the three loss functions. This finding does not support the weekly results of the forecast evaluation criteria across all three multivariate loss functions. Instead, the Asymmetric DCC is the best-fitted model to forecast the covariance matrix for weekly cryptocurrency returns.

1. Limitations and Directions for Future Research:

The limitations of each chapter were mentioned in each chapter, but it is worth mentioning and expanding for future researchers. When examining the breadth of chapter two research, it is critical to recognize some limitations. While the dataset is extensive, it does not include data from the during-COVID-19 and post-COVID-19 periods. A dataset containing the COVID-19 pandemic would acquire a more thorough understanding of how the COVID-19 pandemic, as an external factor, affects the volatility of cryptocurrency returns. Therefore, future scholars should consider this limitation and expand the dataset to obtain better and accurate findings. These findings could draw better understanding for investors and portfolio managers when they make educated-decisions regarding their portfolio assets choices. Additionally, for analyzing realized volatility, the research focused on six models from the GARCH family, HAR model, and LRE model. Future studies might go beyond this selection, possibly revealing innovative methods for more accurate prediction of cryptocurrency return volatility. Likewise, future scholars should apply simpler models and test such as Random Walk model as well. It is also worth noting that the research looked particularly at 10 cryptocurrency results only. In fact, the large amount of the original data before the cleaning and screening process, which exceeded 100 million observations, created considerable time limitations. As a consequence, only 10 cryptocurrency returns were chosen for the research. Therefore, future scholars should expand the dataset to cover a larger spectrum of cryptocurrency returns. Adding more cryptocurrency returns to the dataset offers the potential to improve the precision of research findings.

In Chapter Three, the research encounters specific limitations. the dataset lacks information for the years 2022 and 2023 due to data unavailability during the study's conclusion. Furthermore, due to time limits in this chapter, as well as the additional effort necessary for data cleaning and filtering, it was difficult to expand the dataset to include 2022. As a result, future researchers should investigate increasing the dataset in order to obtain more thorough results. They also, should include more than 10 cryptocurrency returns as in chapter three research. Including more cryptocurrency returns will lead to more accurate and comprehensive findings. Additionally, future examination should extend on this work by investigating the impact of the COVID-19 pandemic period on these indices and their impact on cryptocurrency returns. Furthermore, future scholars could investigate how these uncertainty indices impact cryptocurrency returns before, during, and after COVID-19 pandemic period. Moreover, the research did not include other economic uncertainty indices, especially those used by important nations such as China. Therefore, investigating other economic uncertainty indices could provide useful information. Furthermore, the research only used three regressions approach. Therefore, future research should look at the link between uncertainty indices and cryptocurrency returns using a wide range of models that take into account a variety of elements and viewpoints. Exploring new uncertainty indices may also help us better understand bitcoin markets and the external forces that influence their performance.

Chapter Four research has certain limitations that should be considered. The empirical findings included five models only. Therefore, future researchers should broaden their scope beyond these models to explore more models and seek better accuracy in forecasting the covariance matrices for cryptocurrency returns. Furthermore, the research included only 10 cryptocurrency returns. Including more cryptocurrency returns will lead to more accurate and comprehensive findings. Therefore, future research should investigate increasing the dataset variables in order to obtain more thorough results. Also, the research included only cryptocurrency returns. Therefore, future researchers might widen their reach by including additional financial assets and examining their influence on forecasting cryptocurrency return covariance matrices.

Furthermore, the empirical findings of this research did not include the COVID-19 pandemic period. Therefore, examining the impact of the COVID-19 pandemic on cryptocurrency returns at various stages, including pre-COVID-19, during-COVID-19, and post-COVID-19, is an exciting field for research. Extending the dataset to include this more prolonged period can give valuable insights into the implications of the pandemic on cryptocurrency returns. Finally, as noted in Chapter Three restrictions, future academics could investigate integrating data from 2022 and 2023 to expand these findings and ensure a more thorough study.

2. Practical Implications:

Investigating and examining the risk and uncertainty of the cryptocurrency market offers significant benefits to a wide range of stakeholders, such as investors, portfolio managers, policymakers, and the broader economy.

Making informed decisions requires investors to understand the risk and uncertainty of the cryptocurrency market. The HAR model could help the investors to predict the volatility of cryptocurrency returns for one day ahead while the EGARCH model could help them to predict the volatility of cryptocurrency returns for seven and thirty days ahead. Also, the HAR + EGARCH models together could yield accurate results in predicting the volatility of cryptocurrency returns for one day, seven, and thirty days ahead. Also, the Lagged Realized Volatility model could help the investors to forecast the covariance matrix and risk spillover among cryptocurrency retunes. These models offer the opportunity for investors to evaluate risk-reward profiles, and they can adjust their portfolios accordingly and potentially avoid significant losses. Also, by understanding the risk and uncertainty of the cryptocurrency market, they can apply the risk assessments to diversify their portfolios efficiently, reducing overall portfolio risk. Besides, by understanding the risks and uncertainty of the cryptocurrency market, the investors will identify risks that are imposed by security vulnerabilities or regulatory changes. Therefore, investors will be able to implement risk mitigation strategies, such as hedging strategies.

Furthermore, by understanding the risk and uncertainty of the cryptocurrency market and using the HAR and EGARCH models in their risk analysis, portfolio managers can include cryptocurrency risk assessments into their inclusive risk management strategies to make sure that their portfolios are well-balanced and resilient to market fluctuations. Similarly, the Lagged Realized Volatility model could help the investors to forecast the covariance matrix and risk spillover among cryptocurrency retunes. Also, they should pay attention to the uncertainty such as the UCRY Policy Index + Central Bank Digital Currency Attention Index when the bull wave hit the cryptocurrency market. Also, the should consider the UCRY Policy Index + the Cryptocurrency Environmental Attention (ICEA) index when the bear wave hit the cryptocurrency market. Moreover, the portfolio managers can decide the appropriate allocation of cryptocurrency into a broader investment portfolio. Similarly, they can make timely adjustments to optimize portfolio performance and minimize potential losses by monitoring the risks and uncertainties of the cryptocurrency market.

Moreover, policymakers can develop and improve more effective regulatory frameworks to help reduce market manipulation, protect investors, and promote market integrity by considering the the UCRY Policy Index and the UCRY Price Index along with the other uncertainty indices. However, these two indices show stronger connectedness with cryptocurrency returns. Also, they can foster trust in the financial system by using insights into market risks to implement measures that prevent high-risk cryptocurrency schemes and protect consumers against fraudulent. Correspondingly, by assessing systemic risks associated with cryptocurrency markets, policymakers can identify and address the potential threats to financial stability. Also, they can help preventing market crashes and protecting the broader economy through timely interventions.

Finally, job creation, increased economic activity in the blockchain and crypto-related sectors, and economic growth require a well-regulated and understood cryptocurrency market that attracts and interests innovative businesses and investments. Additionally, by providing access to financial services for underserved populations, cryptocurrencies have the potential to increase financial inclusion, which will lead to economic development by increasing economic participation and expanding the consumer base. Also, to help restrict fraudulent and illegal activities in the cryptocurrency sector, practical risk assessment and regulatory measures are required. These measures will protect the economy from reputational damage and financial crimes.

In conclusion, investigating and examining the risk and uncertainty of the cryptocurrency market offers significant benefits and advantages to investors, portfolio managers, policymakers, and the broader economy. It promotes a more secure and stable financial ecosystem, encourages responsible innovation, and supports informed decision-making. By controlling and reducing the risks connected with cryptocurrencies, stakeholders may secure the potential advantages while avoiding adverse outcomes, eventually contributing to the economy's long-term viability and growth.

Appendices

Chapter Tow Out-of-Sample Forecasting Performance:

Table 7: Out-of-Sample Forecasting Performance: 1-Day Horizon

	Panel A: RMSE						Panel B: QLIKE					
	GARCH	IGARCH	EGARCH	GJR-GARCH	LRE	HAR	GARCH	IGARCH	EGARCH	GJR-GARCH	LRE	HAR
BTC	0.0178	0.4248***	**0.0172**	0.0180	0.0212	0.0188	-2.526	-0.982***	-2.511	-2.510	-2.523	**-2.543**
ETH	0.0207	0.2998***	**0.0195**	0.0255	0.0229	0.0200	-2.253	-1.463***	-2.257	-2.224**	-2.266	**-2.282**
XRP	**0.0229**	0.3778***	0.0230	0.0258	0.0274	0.0233	-2.326	-1.120***	-2.332	-2.203	-2.314**	**-2.339**
LTC	0.0242***	0.2731***	0.0224	0.0222	0.0246	**0.0214**	-2.182***	-1.388***	-2.187	-2.184	-2.197	**-2.211**
BCH	0.0306**	0.3446***	0.0304*	0.0318**	0.0332	**0.0291**	-2.142**	-1.223***	-2.130*	-2.050**	-2.160	**-2.189**
EOS	0.0315	0.2226***	0.0304	0.0331	0.0338**	**0.0290**	-2.144	-1.510***	-2.149	-2.062	-2.167**	**-2.189**
XMR	0.0179**	0.3029***	**0.0166**	0.0176	0.0201	0.0177	-2.252	-1.359***	-2.256	-2.247	-2.258	**-2.269**
XLM	0.0246**	0.3031***	0.0218	0.0258**	0.0248	**0.0216**	-2.140**	-1.339***	-2.160	-2.127**	-2.160	**-2.171**
DASH	0.0221	0.3828***	0.0231	0.0297***	0.0241	**0.0216**	-2.190	-1.028***	-2.188	-2.163***	-2.194	**-2.207**
ETC	0.0278***	0.2971***	0.0271***	0.0297***	0.0276	**0.0244**	-2.078***	-1.229***	-2.073***	-2.056***	-2.098	**-2.116**

This table presents out-of-sample forecasting errors for the 10 cryptocurrencies using the root mean squared error (RMSE) and the quasi-likelihood (QLIKE) loss functions for 1-day forecast horizon. Each columns resemble the forecasting models. The model with the lowest forecast errors is highlighted in bold. Forecasting is based on GARCH(1,1) model, IGARCH model, the EGARCH model, the GJR-GARCH model, the lagged realized volatility (LRE), and the Heterogeneous Autoregressive (HAR) model. All forecasts are obtained from 5-minutes returns. Also, based on the DM test, the models that have higher forecast errors and are more statistically significant than the best models are signaled with one, two, and three asterisks at 10%, 5%, and 1% significant levels.

Table 8: Out-of-Sample Forecasting Performance: 7-Day Horizon

Panel A: RMSE

	GARCH	IGARCH	EGARCH	GJR-GARCH	LRE	HAR
BTC	**0.0476**	1.1230***	0.0508**	0.0508***	0.0592***	0.0492
ETH	0.0554***	0.7935***	0.0558*	0.0601***	0.0605***	**0.0509**
XRP	0.0521	0.9958***	0.0539	0.0575**	0.0644***	**0.0519**
LTC	0.0561***	0.7219***	**0.0525**	0.0565**	0.0645***	0.0541
BCH	0.0692***	0.9077***	0.0694**	0.0726***	0.0731***	**0.0655**
EOS	0.0663**	0.5845***	**0.0637**	0.0683*	0.0796***	0.0659
XMR	0.0470***	0.8015***	**0.0441**	0.0492**	0.0528***	0.0444
XLM	0.0540**	0.7980***	0.0540*	0.0561***	0.0645***	**0.0513**
DASH	0.0635**	1.0105***	0.0611**	0.0757***	0.0681***	**0.0569**
ETC	0.0654***	0.7804***	0.0670***	0.0647***	0.0710***	**0.0580**

Panel B: QLIKE

	GARCH	IGARCH	EGARCH	GJR-GARCH	LRE	HAR
BTC	**-1.469**	0.019***	-1.434**	-1.445***	-1.425***	-1.464
ETH	-1.210***	-0.458***	-1.213*	-1.196***	-1.200***	**-1.223**
XRP	-1.252	-0.115***	-1.248	-1.131**	-1.217***	**-1.257**
LTC	-1.146***	-0.385***	**-1.153**	-1.148**	-1.127***	-1.147
BCH	-1.112***	-0.227***	-1.099**	-1.032***	-1.102***	**-1.126**
EOS	-1.086	-0.491***	-1.091	-1.050	-1.066***	**-1.097**
XMR	-1.227**	-0.362***	-1.232	-1.222***	-1.219***	**-1.234**
XLM	-1.097**	-0.340***	-1.097*	-1.089***	-1.066***	**-1.105**
DASH	-1.138**	-0.035***	-1.143**	-1.121***	-1.131***	**-1.148**
ETC	-1.026***	-0.232***	-1.006***	-1.017***	-1.025***	**-1.050**

This table presents out-of-sample forecasting errors for the 10 cryptocurrencies using the root mean squared error (RMSE) and the quasi-likelihood (QLIKE) loss functions for 7-days forecast horizon. Each columns resemble the forecasting models. The model with the lowest forecast errors is highlighted in bold. Forecasting is based on GARCH(1,1) model, IGARCH model, the EGARCH model, the GJR-GARCH model, the lagged realized volatility (LRE), and the Heterogeneous Autoregressive (HAR) model. All forecasts are obtained from 5-minutes returns. Also, based on the DM test, the models that have higher forecast errors and are more statistically significant than the best models are signaled with one, two, and three asterisks at 10%, 5%, and 1% significant levels.

Table 9: Out-of-Sample Forecasting Performance: 30-Day Horizon

	Panel A: RMSE						Panel B: QLIKE					
	GARCH	IGARCH	EGARCH	GJR-GARCH	LRE	HAR	GARCH	IGARCH	EGARCH	GJR-GARCH	LRE	HAR
BTC	0.1013**	2.3338***	0.1103**	0.1137***	0.1253***	**0.0942**	**-0.682**	0.782***	-0.646	-0.652***	-0.636***	-0.679***
ETH	0.1178***	1.6518***	0.1156	0.1096***	0.1164***	**0.0972**	-0.433***	0.298***	-0.441	-0.441***	-0.434***	**-0.451**
XRP	0.0946***	2.0638***	0.0970***	0.0952***	0.1009***	**0.0847**	-0.464***	0.641***	-0.456***	-0.393***	-0.462***	**-0.476**
LTC	0.1091***	1.5041***	**0.0988**	0.1124**	0.1161***	0.1069**	-0.380	0.373***	-0.389**	**-0.390**	-0.379	-0.379
BCH	0.1259	1.8871***	0.1251	**0.1245**	0.1289	0.1521***	-0.347	0.527***	-0.329	-0.307	**-0.348**	-0.314***
EOS	0.1091**	1.2146***	0.1096**	**0.1041**	0.1266***	0.1092**	-0.316	0.271***	-0.312	-0.309**	-0.303***	**-0.319**
XMR	0.1047***	1.6699***	0.0959**	0.1063**	0.1083***	**0.0826**	-0.467***	0.392***	-0.476**	-0.473**	-0.468***	**-0.484**
XLM	0.0917**	1.6530***	0.0993***	0.0930**	0.1023***	**0.0852**	-0.329**	0.412***	-0.326***	-0.328**	-0.320***	**-0.336**
DASH	0.1373**	2.0922***	0.1262**	0.1471***	0.1356***	**0.1133**	-0.355**	0.713***	-0.359**	-0.343***	-0.340***	**-0.362**
ETC	0.1211***	1.6137***	0.1256***	0.1057	0.1343***	**0.1027**	-0.250***	0.516***	-0.230***	-0.257	-0.235***	**-0.269**

This table presents out-of-sample forecasting errors for the 10 cryptocurrencies using the root mean squared error (RMSE) and the quasi-likelihood (QLIKE) loss functions for 30-days forecast horizon. Each columns resemble the forecasting models. The model with the lowest forecast errors is highlighted in bold. Forecasting is based on GARCH(1,1) model, IGARCH model, the EGARCH model, the GJR-GARCH model, the lagged realized volatility (LRE), and the Heterogeneous Autoregressive (HAR) model. All forecasts are obtained from 5-minutes returns. Also, based on the DM test, the models that have higher forecast errors and are more statistically significant than the best models are signaled with one, two, and three asterisks at 10%, 5%, and 1% significant levels.

Chapter Three: Quantile Regression Results During Crisis Period

Table 32: The effects of during crisis period daily data (Covid-19 period) of the Twitter-based Economic Uncertainty (TEU) index on Cryptocurrencies returns.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
10	**Estimate**	-0.00002	-0.00002	0.00005	0.00001	0.00001	0.00004	-0.00001	0.00000	0.00002	0.00002
	P-value	0.614	0.506	0.345	0.850	0.858	0.276	0.798	0.993	0.577	0.540
20	**Estimate**	0.00001	0.00000	0.00004	0.00002	-0.00001	0.00003	0.00001	0.00002	0.00002	0.00003
	P-value	0.825	0.757	0.466	0.715	0.966	0.360	0.323	0.270	0.739	0.088*
30	**Estimate**	0.00000	0.00001	0.00002	0.00001	0.00001	0.00002	0.00001	0.00003	0.00001	0.00003
	P-value	0.997	0.665	0.353	0.534	0.587	0.261	0.671	0.088*	0.626	0.116
40	**Estimate**	0.00000	0.00000	0.00001	0.00000	0.00000	0.00001	0.00002	0.00002	0.00001	0.00000
	P-value	0.825	0.757	0.466	0.715	0.966	0.360	0.323	0.270	0.739	0.985
50	**Estimate**	-0.00001	-0.00002	0.00000	-0.00001	0.00000	-0.00001	0.00001	0.00002	-0.00001	-0.00001
	P-value	0.435	0.263	0.812	0.187	0.997	0.413	0.548	0.349	0.773	0.574
60	**Estimate**	-0.00001	-0.00002	-0.00001	-0.00002	-0.00002	-0.00004	0.00000	0.00001	-0.00002	-0.00002
	P-value	0.749	0.313	0.560	0.164	0.296	0.009***	0.933	0.667	0.385	0.255
70	**Estimate**	-0.00002	-0.00002	-0.00003	-0.00005	-0.00002	-0.00004	-0.00001	-0.00001	-0.00005	-0.00003
	P-value	0.281	0.390	0.273	0.007***	0.379	0.010***	0.591	0.682	0.000***	0.036**
80	**Estimate**	-0.00003	-0.00001	-0.00005	-0.00003	-0.00002	-0.00003	0.00001	-0.00001	-0.00005	-0.00002
	P-value	0.263	0.786	0.087*	0.181	0.437	0.243	0.688	0.618	0.061*	0.362
90	**Estimate**	0.00001	0.00001	-0.00007	-0.00001	0.00003	-0.00002	0.00002	0.00000	-0.00001	0.00000
	P-value	0.709	0.731	0.122	0.782	0.371	0.461	0.485	0.961	0.870	0.908

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 33: The effects of during crisis period weekly data (Covid-19 period) of the Cryptocurrency policy uncertainty index on Cryptocurrencies returns.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
10	Estimate	-0.02774	-0.03141	-0.03455	-0.03903	-0.03715	-0.04877	-0.04150	-0.03368	-0.04581	-0.03237
	P-value	0.001***	0.010***	0.002***	0.020**	0.079*	0.013**	0.001***	0.002***	0.002***	0.024**
20	Estimate	-0.01944	-0.01401	-0.02225	-0.02696	-0.01748	-0.02806	-0.01429	-0.01313	-0.02338	-0.01967
	P-value	0.301	0.942	0.401	0.296	0.385	0.964	0.415	0.410	0.928	0.088*
30	Estimate	-0.01084	-0.01013	-0.01188	-0.01895	-0.01108	-0.01504	-0.01112	-0.00753	-0.01756	-0.01498
	P-value	0.134	0.402	0.234	0.002***	0.166	0.276	0.078*	0.402	0.142	0.343
40	Estimate	-0.00645	-0.00085	-0.00833	-0.01020	-0.00799	0.00056	-0.00609	-0.00674	-0.00111	-0.00570
	P-value	0.301	0.942	0.401	0.296	0.385	0.964	0.415	0.410	0.928	0.672
50	Estimate	-0.00082	0.00471	-0.00525	-0.00349	0.00232	0.00545	-0.00474	-0.00357	0.00529	0.00106
	P-value	0.911	0.592	0.614	0.717	0.837	0.592	0.500	0.594	0.503	0.908
60	Estimate	0.00373	0.00251	0.00324	0.00281	0.00200	0.00264	0.00034	0.00335	0.00396	0.00959
	P-value	0.661	0.677	0.743	0.690	0.832	0.786	0.965	0.466	0.460	0.284
70	Estimate	0.00349	0.00701	0.00993	0.01120	0.00465	0.01151	0.00693	0.00390	0.01171	0.01128
	P-value	0.766	0.141	0.361	0.282	0.535	0.120	0.334	0.531	0.245	0.301
80	Estimate	0.00879	0.01035	0.03645	0.03255	0.01560	0.01544	0.01517	0.00834	0.01927	0.00936
	P-value	0.559	0.179	0.011**	0.003***	0.071*	0.008***	0.097*	0.643	0.043**	0.413
90	Estimate	0.00645	0.00652	0.04893	0.03760	0.03211	0.02198	0.02055	0.01098	0.04461	0.02886
	P-value	0.556	0.577	0.002***	0.023**	0.001***	0.212	0.249	0.553	0.000***	0.143

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 34: The effects of during crisis period weekly data (Covid-19 period) of the Cryptocurrency Price Uncertainty Index on Cryptocurrencies returns.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
10	Estimate	-0.02990	-0.02292	-0.03207	-0.04637	-0.03887	-0.05129	-0.04431	-0.03461	-0.06088	-0.02815
	P-value	0.000***	0.240	0.000***	0.000***	0.073*	0.006***	0.022**	0.000***	0.005***	0.035**
20	Estimate	-0.02158	-0.01307	-0.02242	-0.02317	-0.01706	-0.02658	-0.01360	-0.01001	-0.01962	-0.02158
	P-value	0.553	0.926	0.252	0.390	0.418	0.944	0.530	0.880	0.858	0.144
30	Estimate	-0.01053	-0.00791	-0.01005	-0.01879	-0.01269	-0.01054	-0.01095	-0.00756	-0.01653	-0.01022
	P-value	0.299	0.469	0.230	0.127	0.089*	0.269	0.138	0.493	0.257	0.384
40	Estimate	-0.00528	0.00082	-0.00882	-0.00884	-0.00641	0.00053	-0.00470	-0.00142	0.00236	-0.00509
	P-value	0.553	0.926	0.252	0.390	0.418	0.944	0.530	0.880	0.858	0.684
50	Estimate	-0.00088	0.00463	-0.00490	-0.00414	0.00279	0.00656	-0.00597	-0.00319	0.00725	0.00094
	P-value	0.918	0.465	0.576	0.728	0.810	0.487	0.259	0.706	0.428	0.944
60	Estimate	0.00413	0.00203	0.00251	0.00210	0.00224	0.00503	-0.00182	0.00190	0.00524	0.00961
	P-value	0.478	0.744	0.797	0.764	0.812	0.431	0.722	0.825	0.186	0.506
70	Estimate	0.00380	0.00746	0.01121	0.01073	0.00651	0.01160	0.00409	0.00404	0.01137	0.01604
	P-value	0.597	0.130	0.350	0.344	0.543	0.006***	0.449	0.769	0.136	0.310
80	Estimate	0.00869	0.00985	0.03873	0.02633	0.01559	0.01486	0.01224	0.00882	0.02047	0.01197
	P-value	0.434	0.244	0.010***	0.000***	0.155	0.003***	0.186	0.596	0.113	0.491
90	Estimate	0.00708	0.00976	0.03630	0.04113	0.02872	0.02404	0.02083	0.01762	0.04147	0.02608
	P-value	0.534	0.643	0.099*	0.000***	0.000***	0.121	0.113	0.608	0.000***	0.155

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 35: The effects of during crisis period weekly data (Covid-19 period) of the Twitter-based Economic Uncertainty (TEU) index on Cryptocurrencies returns.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
10	Estimate	0.00014	0.00017	0.00037	0.00028	0.00036	0.00046	0.00039	0.00028	0.00033	0.00030
	P-value	0.386	0.067*	0.223	0.188	0.094*	0.423	0.221	0.232	0.569	0.600
20	Estimate	0.00016	0.00011	0.00020	0.00020	0.00026	0.00032	0.00017	0.00015	0.00031	0.00016
	P-value	0.253	0.508	0.307	0.181	0.369	0.655	0.662	0.513	0.694	0.088*
30	Estimate	0.00009	0.00003	0.00013	0.00016	0.00017	0.00016	0.00011	0.00012	0.00020	0.00010
	P-value	0.307	0.787	0.255	0.008***	0.012**	0.060*	0.268	0.162	0.097*	0.470
40	Estimate	0.00010	0.00007	0.00008	0.00009	0.00009	0.00004	0.00004	0.00005	0.00005	0.00002
	P-value	0.253	0.508	0.307	0.181	0.369	0.655	0.662	0.513	0.694	0.876
50	Estimate	0.00004	-0.00001	0.00004	0.00002	-0.00002	0.00006	0.00000	-0.00001	-0.00011	0.00001
	P-value	0.593	0.841	0.584	0.740	0.853	0.546	0.949	0.924	0.149	0.943
60	Estimate	0.00000	-0.00001	-0.00004	-0.00004	0.00004	0.00000	0.00005	-0.00002	-0.00007	-0.00006
	P-value	0.958	0.889	0.572	0.424	0.667	0.986	0.524	0.806	0.295	0.612
70	Estimate	0.00005	-0.00009	-0.00010	-0.00010	0.00000	-0.00010	-0.00002	-0.00008	-0.00012	-0.00014
	P-value	0.669	0.185	0.133	0.089*	0.957	0.216	0.707	0.438	0.137	0.112
80	Estimate	0.00004	-0.00014	-0.00019	-0.00024	-0.00003	-0.00010	-0.00003	0.00000	-0.00028	-0.00017
	P-value	0.711	0.077*	0.131	0.001***	0.824	0.031**	0.469	0.997	0.013**	0.213
90	Estimate	-0.00004	-0.00023	-0.00046	-0.00035	0.00005	-0.00015	-0.00008	-0.00012	-0.00028	-0.00038
	P-value	0.631	0.068*	0.022**	0.175	0.812	0.096*	0.609	0.576	0.381	0.038**

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 36: The effects of during crisis period weekly data (Covid-19 period) of the Central Bank Digital Currency Uncertainty Index on Cryptocurrencies returns.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
10	**Estimate**	-0.027	-0.023	-0.046	-0.034	-0.032	-0.059	-0.045	-0.042	-0.054	-0.037
	P-value	0.024**	0.469	0.002***	0.200	0.320	0.042**	0.031**	0.048**	0.018**	0.126
20	**Estimate**	-0.026	-0.015	-0.024	-0.038	-0.018	-0.049	-0.025	-0.032	-0.037	-0.024
	P-value	0.244	0.674	0.126	0.100	0.458	0.844	0.283	0.370	0.271	0.088*
30	**Estimate**	-0.015	-0.009	-0.023	-0.017	-0.018	-0.018	-0.021	-0.015	-0.023	-0.023
	P-value	0.086*	0.465	0.065*	0.247	0.159	0.360	0.095*	0.313	0.057*	0.073*
40	**Estimate**	-0.010	-0.005	-0.022	-0.016	-0.011	-0.003	-0.013	-0.012	-0.017	-0.020
	P-value	0.244	0.674	0.126	0.100	0.458	0.844	0.283	0.370	0.271	0.063*
50	**Estimate**	-0.007	0.001	-0.014	-0.006	-0.015	-0.003	-0.007	-0.005	0.002	-0.008
	P-value	0.310	0.942	0.317	0.658	0.220	0.864	0.526	0.513	0.847	0.590
60	**Estimate**	-0.0003	0.0028	0.0041	0.0001	0.0021	0.0055	-0.0025	0.0019	-0.0002	0.0127
	P-value	0.966	0.729	0.803	0.990	0.870	0.682	0.817	0.825	0.981	0.374
70	**Estimate**	-0.004	0.012	0.019	0.013	0.002	0.012	0.011	0.003	0.007	0.015
	P-value	0.673	0.026**	0.136	0.089*	0.885	0.229	0.254	0.806	0.652	0.166
80	**Estimate**	0.007	0.016	0.041	0.020	0.020	0.017	0.017	-0.004	0.027	0.009
	P-value	0.576	0.018**	0.010***	0.291	0.010***	0.056*	0.137	0.806	0.077*	0.616
90	**Estimate**	-0.005	0.004	0.040	0.029	0.032	0.027	0.023	0.006	0.037	0.071
	P-value	0.722	0.517	0.096*	0.200	0.251	0.215	0.043**	0.696	0.113	0.217

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 37: The effects of during crisis period weekly data (Covid-19 period) of the Central Bank Digital Currency Attention Index on Cryptocurrencies returns.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
10	**Estimate**	-0.018	-0.018	-0.027	-0.021	-0.025	-0.035	-0.022	-0.022	-0.034	-0.023
	P-value	0.175	0.033**	0.112	0.361	0.266	0.018**	0.343	0.153	0.001***	0.037**
20	**Estimate**	-0.017	-0.010	-0.020	-0.022	-0.018	-0.032	-0.017	-0.005	-0.020	-0.019
	P-value	0.211	0.279	0.122	0.199	0.222	0.987	0.259	0.519	0.754	0.088*
30	**Estimate**	-0.010	-0.008	-0.017	-0.013	-0.008	-0.013	-0.009	-0.006	-0.017	-0.013
	P-value	0.236	0.349	0.021**	0.183	0.384	0.318	0.092*	0.621	0.059*	0.237
40	**Estimate**	-0.009	-0.009	-0.013	-0.012	-0.008	0.000	-0.007	-0.006	-0.004	-0.011
	P-value	0.211	0.279	0.122	0.199	0.222	0.987	0.259	0.519	0.754	0.247
50	**Estimate**	-0.007	-0.003	-0.009	-0.007	-0.009	-0.004	-0.006	0.001	0.002	-0.005
	P-value	0.262	0.720	0.174	0.446	0.135	0.701	0.389	0.925	0.892	0.617
60	**Estimate**	-0.0056	0.0017	0.0021	-0.0001	-0.0025	0.0043	-0.0017	-0.0023	-0.0002	0.0056
	P-value	0.441	0.855	0.750	0.991	0.730	0.677	0.806	0.769	0.978	0.667
70	**Estimate**	-0.006	0.006	0.010	0.006	0.002	0.012	0.003	0.002	0.003	0.011
	P-value	0.454	0.394	0.470	0.576	0.763	0.147	0.603	0.814	0.798	0.287
80	**Estimate**	-0.007	0.007	0.012	0.012	0.011	0.010	0.008	-0.010	0.016	0.009
	P-value	0.347	0.253	0.653	0.385	0.257	0.212	0.249	0.534	0.241	0.561
90	**Estimate**	-0.007	0.005	0.041	0.019	0.025	0.026	0.017	0.006	0.019	0.029
	P-value	0.395	0.533	0.042**	0.282	0.288	0.281	0.194	0.719	0.166	0.442

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 38: The effects of during crisis period weekly data (Covid-19 period) of the Cryptocurrency Environmental Attention (ICEA) index on Cryptocurrencies returns.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
10	**Estimate**	-0.008	-0.015	-0.023	-0.017	-0.017	-0.019	-0.025	-0.012	-0.027	-0.021
	P-value	0.258	0.262	0.128	0.291	0.307	0.210	0.034	0.385	0.143	0.078*
20	**Estimate**	-0.011	-0.007	-0.011	-0.014	-0.012	-0.019	-0.011	-0.003	-0.015	-0.009
	P-value	0.114	0.937	0.135	0.227	0.435	0.964	0.220	0.575	0.922	0.088*
30	**Estimate**	-0.008	-0.005	-0.009	-0.007	-0.006	-0.007	-0.009	-0.004	-0.009	-0.010
	P-value	0.041**	0.570	0.119	0.240	0.329	0.440	0.073*	0.469	0.221	0.107
40	**Estimate**	-0.005	-0.001	-0.008	-0.006	-0.003	0.000	-0.006	-0.003	-0.001	-0.009
	P-value	0.114	0.937	0.135	0.227	0.435	0.964	0.220	0.575	0.922	0.144
50	**Estimate**	-0.0037	0.0020	-0.0032	-0.0041	-0.0060	-0.0012	-0.0008	0.0004	0.0028	-0.0026
	P-value	0.121	0.719	0.587	0.416	0.204	0.847	0.870	0.941	0.564	0.699
60	**Estimate**	-0.0029	0.0012	0.0011	-0.0001	-0.0017	0.0021	-0.0022	0.0001	-0.0001	0.0047
	P-value	0.532	0.758	0.869	0.984	0.715	0.676	0.566	0.988	0.976	0.487
70	**Estimate**	-0.0043	0.0040	0.0056	0.0014	-0.0002	0.0067	0.0007	0.0015	0.0006	0.0061
	P-value	0.372	0.379	0.310	0.807	0.969	0.050**	0.874	0.765	0.913	0.212
80	**Estimate**	-0.008	0.002	0.007	0.008	0.005	0.007	0.001	-0.006	0.010	0.004
	P-value	0.301	0.677	0.588	0.551	0.352	0.082*	0.887	0.404	0.219	0.349
90	**Estimate**	-0.004	0.003	0.027	0.004	0.017	0.015	0.010	0.001	0.015	0.020
	P-value	0.652	0.576	0.057*	0.742	0.144	0.242	0.250	0.938	0.194	0.402

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 39: The effects of during crisis period monthly data (Covid-19 period) of the Economic Policy Uncertainty Index for Europe index on Cryptocurrencies returns.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
10	**Estimate**	-0.002	-0.003	-0.003	-0.006	-0.004	-0.003	-0.006	-0.001	-0.007	-0.007
	P-value	0.467	0.384	0.464	0.200	0.268	0.409	0.159	0.681	0.112	0.144
20	**Estimate**	-0.0007	-0.0003	0.0022	-0.0005	-0.0006	0.0001	-0.0023	0.0005	-0.0024	-0.0024
	P-value	0.647	0.525	0.928	0.202	0.256	0.562	0.837	0.763	0.053*	0.088*
30	**Estimate**	-0.0006	-0.0002	0.0009	-0.0012	-0.0008	-0.0002	0.0000	-0.0006	-0.0021	-0.0021
	P-value	0.716	0.870	0.801	0.602	0.532	0.870	0.991	0.867	0.194	0.271
40	**Estimate**	-0.0005	-0.0010	0.0004	-0.0010	-0.0016	-0.0010	-0.0003	-0.0009	-0.0022	-0.0022
	P-value	0.647	0.525	0.928	0.202	0.256	0.562	0.837	0.763	0.053*	0.165
50	**Estimate**	-0.00049	-0.00035	-0.00096	0.00002	-0.00212	-0.00035	-0.00049	-0.00124	-0.00151	-0.00151
	P-value	0.593	0.830	0.799	0.982	0.201	0.854	0.702	0.615	0.213	0.179
60	**Estimate**	-0.00009	0.00062	-0.00232	0.00011	0.00002	0.00108	-0.00054	-0.00017	-0.00169	-0.00169
	P-value	0.905	0.717	0.532	0.921	0.990	0.666	0.510	0.949	0.048**	0.084*
70	**Estimate**	-0.00005	0.00140	-0.00207	0.00066	0.00074	0.00163	0.00036	0.00014	-0.00044	-0.00044
	P-value	0.944	0.420	0.498	0.565	0.652	0.550	0.661	0.951	0.632	0.646
80	**Estimate**	-0.0004	0.0016	-0.0023	0.0003	0.0006	-0.0020	0.0005	-0.0006	-0.0006	-0.0006
	P-value	0.681	0.367	0.370	0.830	0.756	0.368	0.610	0.701	0.507	0.582
90	**Estimate**	-0.0015	0.0002	-0.0020	-0.0006	-0.0010	-0.0007	0.0005	-0.0016	-0.0002	-0.0002
	P-value	0.271	0.924	0.295	0.521	0.680	0.654	0.738	0.224	0.828	0.822

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Chapter Three: Multivariate Quantile Regressions Results During Crisis Period.

Table 40: The effects of during crisis period weekly data (Covid-19 period) of the UCRY Policy Index, the UCRY Price Index, the Central Bank Digital Currency Uncertainty Index (CBDCUI), the Cryptocurrency Environmental Attention (ICEA) index, the Cryptocurrency Environmental Attention (ICEA) index, and the Twitter-based Economic Uncertainty (TEU) index on Cryptocurrencies returns of the 5, 25, 50, 75, and 95 quantiles.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
5	UCRY Policy Index	-0.036	0.076	-0.338	-0.020	0.013	-0.049	-0.003	-0.086	-0.033	-0.036
		0.534	0.521	0.009***	0.806	0.904	0.694	0.972	0.321	0.732	0.770
	UCRY Price Index	0.019	-0.101	0.205	-0.037	-0.032	0.033	-0.048	0.017	0.004	0.019
		0.740	0.331	0.018**	0.662	0.757	0.801	0.552	0.828	0.965	0.866
	CBDC Uncertainty Index	-0.036	-0.008	0.035	-0.020	-0.066	-0.103	0.041	-0.004	-0.083	-0.031
		0.505	0.925	0.667	0.794	0.233	0.338	0.452	0.947	0.356	0.572
	CBDC Attention Index	0.033	0.077	0.060	0.054	0.089	0.093	0.063	0.011	0.085	0.051
		0.356	0.251	0.222	0.536	0.137	0.216	0.242	0.861	0.326	0.250
	Cryptocurrency Environmental Attention Index	-0.014	-0.054	0.000	-0.025	-0.049	-0.038	-0.051	0.009	-0.033	-0.039
		0.474	0.236	0.991	0.523	0.165	0.400	0.153	0.795	0.439	0.087
	TEU Index	-0.0005	-0.0002	-0.0001	-0.0006	-0.0007	-0.0004	-0.0004	-0.0008	-0.0002	-0.0005
		0.494	0.827	0.841	0.392	0.470	0.635	0.719	0.171	0.809	0.552
25	UCRY Policy Index	0.004	-0.078	-0.010	-0.063	-0.030	-0.107	-0.003	-0.037	-0.035	-0.057
		0.953	0.126	0.916	0.513	0.618	0.352	0.968	0.643	0.680	0.432
	UCRY Price Index	-0.016	0.074	0.006	0.048	0.014	0.083	0.000	0.032	0.028	0.048
		0.804	0.116	0.952	0.581	0.834	0.465	0.995	0.666	0.724	0.510
	CBDC Uncertainty Index	-0.045	-0.002	-0.018	-0.038	-0.041	-0.011	-0.031	-0.052	-0.082	-0.039
		0.276	0.954	0.767	0.371	0.352	0.886	0.411	0.372	0.164	0.249
	CBDC Attention Index	0.032	0.002	-0.003	-0.004	0.007	-0.028	0.024	0.024	0.025	0.030
		0.166	0.969	0.957	0.939	0.897	0.472	0.501	0.663	0.721	0.462
	Cryptocurrency Environmental Attention Index	-0.004	-0.007	0.001	0.018	0.018	0.024	-0.010	0.006	0.017	-0.008
		0.801	0.804	0.952	0.356	0.546	0.159	0.560	0.787	0.585	0.763
	TEU Index	0.0000	0.0000	0.0000	0.0001	0.0002	0.0002	0.0000	0.0001	0.0002	0.0000
		0.880	0.937	0.827	0.495	0.583	0.550	0.982	0.752	0.219	0.976

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
50	UCRY Policy Index	0.015	-0.014	0.035	-0.039	0.027	-0.019	0.004	-0.003	-0.020	-0.032
		0.719	0.688	0.608	0.578	0.701	0.759	0.911	0.958	0.672	0.554
	UCRY Price Index	-0.003	0.024	-0.030	0.058	-0.008	0.037	-0.007	0.005	0.057	0.056
		0.957	0.482	0.665	0.443	0.920	0.593	0.885	0.931	0.239	0.367
	CBDC Uncertainty Index	0.015	-0.024	-0.013	-0.018	-0.028	-0.005	-0.001	-0.032	-0.037	-0.033
		0.614	0.544	0.799	0.511	0.505	0.907	0.975	0.564	0.330	0.421
	CBDC Attention Index	-0.024	-0.003	0.015	-0.004	0.003	-0.006	-0.007	-0.008	0.014	-0.018
		0.122	0.882	0.745	0.920	0.919	0.843	0.792	0.823	0.529	0.443
	Cryptocurrency Environmental Attention Index	-0.006	0.010	-0.013	-0.008	-0.001	0.005	-0.001	0.016	-0.018	0.007
		0.692	0.643	0.512	0.781	0.930	0.803	0.964	0.406	0.340	0.668
	TEU Index	-0.0001	0.0001	0.0000	0.0000	0.0000	0.0002	-0.0001	0.0000	0.0000	0.0001
		0.511	0.405	0.804	0.747	0.836	0.172	0.631	0.961	0.851	0.682
75	UCRY Policy Index	-0.006	-0.005	0.085	-0.001	-0.026	-0.034	0.028	0.020	0.055	-0.049
		0.874	0.902	0.217	0.984	0.400	0.447	0.245	0.825	0.415	0.249
	UCRY Price Index	0.040	0.004	-0.016	0.046	0.052	0.039	-0.012	0.028	-0.024	0.050
		0.383	0.940	0.793	0.403	0.073*	0.433	0.698	0.762	0.725	0.163
	CBDC Uncertainty Index	0.013	0.023	-0.015	-0.009	-0.014	0.002	0.020	-0.028	0.007	0.013
		0.582	0.363	0.758	0.649	0.731	0.951	0.448	0.598	0.875	0.763
	CBDC Attention Index	-0.015	0.004	0.036	0.031	0.037	0.024	0.018	0.009	0.024	0.016
		0.436	0.864	0.385	0.514	0.034**	0.443	0.317	0.772	0.603	0.717
	Cryptocurrency Environmental Attention Index	-0.018	-0.008	-0.058	-0.041	-0.024	-0.010	-0.022	-0.015	-0.028	-0.020
		0.330	0.731	0.056	0.118	0.104	0.526	0.057*	0.592	0.216	0.477
	TEU Index	0.0000	-0.0001	-0.0003	-0.0002	0.0001	0.0000	0.0000	0.0000	-0.0001	-0.0002
		0.943	0.692	0.211	0.060*	0.706	0.588	0.953	0.866	0.852	0.234

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
95	UCRY Policy Index	0.033	-0.080	0.086	0.115	0.040	-0.034	0.014	-0.081	0.019	-0.106
		0.600	0.290	0.351	0.276	0.607	0.592	0.874	0.585	0.894	0.079*
	UCRY Price Index	0.011	0.110	0.047	-0.053	0.007	0.084	0.037	0.180	0.104	0.087
		0.844	0.256	0.567	0.458	0.937	0.216	0.625	0.134	0.519	0.285
	CBDC Uncertainty Index	0.038	0.003	-0.090	0.005	0.009	-0.023	-0.005	-0.033	-0.019	0.105
		0.334	0.935	0.280	0.918	0.911	0.820	0.914	0.553	0.757	0.610
	CBDC Attention Index	-0.031	-0.003	0.154	0.064	0.096	0.101	0.029	0.035	0.018	0.084
		0.270	0.901	0.183	0.095*	0.139	0.098*	0.575	0.579	0.704	0.459
	Cryptocurrency Environmental Attention Index	-0.024	-0.025	-0.123	-0.085	-0.056	-0.041	-0.030	-0.064	-0.031	-0.047
		0.374	0.296	0.022**	0.041**	0.023**	0.216	0.349	0.353	0.501	0.154
	TEU Index	-0.0001	-0.0004	-0.0002	-0.0006	0.0002	0.0000	0.0004	0.0000	0.0004	-0.0003
		0.466	0.126	0.464	0.002***	0.389	0.822	0.225	0.978	0.305	0.069*

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 41: The effects of during crisis period weekly data (Covid-19 period) of the UCRY Policy Index and CBDC Attention Index on Cryptocurrencies returns.

τ = quantile		**BTC**	**ETH**	**XRP**	**LTC**	**BCH**	**EOS**	**XMR**	**XLM**	**DASH**	**ETC**
5	UCRY Policy Index	-0.042	-0.089	-0.134	-0.103	-0.117	-0.098	-0.083	-0.058	-0.101	-0.073
		0.007***	0.025**	0.000***	0.001***	0.008***	0.004***	0.063*	0.000***	0.010***	0.024**
	CBDC Attention Index	0.016	0.047	0.084	0.059	0.074	0.033	0.042	0.018	0.042	0.036
		0.303	0.131	0.055**	0.120	0.030**	0.363	0.489	0.358	0.194	0.159
25	UCRY Policy Index	-0.012	-0.010	-0.004	-0.018	-0.024	-0.018	-0.009	-0.010	-0.013	-0.010
		0.505	0.598	0.835	0.453	0.449	0.476	0.686	0.576	0.616	0.693
	CBDC Attention Index	-0.003	0.002	-0.012	-0.001	0.009	-0.006	-0.002	0.004	-0.007	-0.009
		0.854	0.909	0.526	0.959	0.738	0.770	0.918	0.724	0.737	0.676
50	UCRY Policy Index	0.015	0.009	0.001	0.014	0.010	0.010	-0.005	-0.005	0.013	0.017
		0.264	0.410	0.953	0.580	0.589	0.549	0.694	0.786	0.256	0.192
	CBDC Attention Index	-0.016	-0.013	-0.010	-0.017	-0.013	-0.008	-0.001	0.004	-0.009	-0.023
		0.169	0.462	0.528	0.429	0.410	0.542	0.954	0.786	0.554	0.049**
75	UCRY Policy Index	0.032	-0.001	0.020	0.044	0.011	0.016	0.011	0.029	0.033	0.020
		0.021**	0.963	0.549	0.054*	0.651	0.308	0.467	0.170	0.071*	0.482
	CBDC Attention Index	-0.030	0.009	0.001	-0.026	0.001	-0.005	-0.004	-0.024	-0.014	-0.004
		0.008***	0.662	0.966	0.321	0.979	0.753	0.818	0.247	0.375	0.867
95	UCRY Policy Index	0.056	0.027	0.103	0.012	0.032	0.014	0.032	0.052	0.060	0.013
		0.001***	0.609	0.139	0.820	0.076*	0.613	0.271	0.405	0.376	0.707
	CBDC Attention Index	-0.035	-0.006	-0.014	-0.006	0.028	0.071	-0.015	-0.044	-0.007	0.088
		0.002***	0.866	0.815	0.886	0.389	0.100	0.485	0.323	0.895	0.407

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 42: The effects of during crisis period weekly data (Covid-19 period) of the UCRY Policy Index and the Cryptocurrency Environmental Attention (ICEA) index on Cryptocurrencies returns.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
5	UCRY Policy Index	-0.046	-0.037	-0.081	-0.057	-0.053	-0.079	-0.039	-0.072	-0.072	-0.032
		0.007***	0.235	0.110	0.123	0.114	0.079*	0.064*	0.000***	0.046**	0.205
	Cryptocurrency Environmental Index	0.010	0.002	0.027	0.010	0.006	0.014	-0.014	0.021	0.013	-0.012
		0.168	0.901	0.323	0.618	0.708	0.698	0.308	0.043**	0.529	0.363
25	UCRY Policy Index	-0.013	-0.010	-0.003	-0.031	-0.023	-0.018	-0.007	-0.011	-0.014	-0.011
		0.411	0.520	0.899	0.117	0.166	0.560	0.715	0.591	0.546	0.626
	Cryptocurrency Environmental Index	-0.001	0.002	-0.009	0.008	0.004	-0.003	-0.005	0.005	-0.003	-0.005
		0.913	0.866	0.429	0.501	0.666	0.826	0.709	0.705	0.801	0.638
50	UCRY Policy Index	0.022	0.008	0.009	0.020	0.010	0.011	-0.006	-0.005	0.013	0.013
		0.286	0.652	0.677	0.261	0.619	0.602	0.739	0.827	0.632	0.435
	Cryptocurrency Environmental Index	-0.013	-0.003	-0.009	-0.014	-0.008	-0.005	0.000	0.003	-0.006	-0.010
		0.201	0.770	0.463	0.157	0.338	0.650	0.965	0.841	0.669	0.355
75	UCRY Policy Index	0.039	0.017	0.062	0.049	0.021	0.018	0.015	0.025	0.037	0.022
		0.001***	0.343	0.042**	0.002***	0.147	0.345	0.142	0.467	0.175	0.408
	Cryptocurrency Environmental Index	-0.025	-0.005	-0.024	-0.019	-0.010	-0.005	-0.007	-0.013	-0.013	-0.004
		0.002***	0.603	0.132	0.018**	0.188	0.665	0.271	0.488	0.428	0.807
95	UCRY Policy Index	0.059	0.034	0.124	0.013	0.048	0.061	0.043	0.145	0.137	0.016
		0.001***	0.496	0.173	0.743	0.127	0.031**	0.080*	0.011**	0.041**	0.588
	Cryptocurrency Environmental Index	-0.024	-0.015	-0.050	-0.006	-0.013	-0.004	-0.023	-0.068	-0.047	0.036
		0.026**	0.494	0.386	0.832	0.721	0.905	0.206	0.025**	0.110	0.550

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 43: The effects of during crisis period weekly data (Covid-19 period) of the UCRY Price Index and the CBDC Attention Index on Cryptocurrencies returns.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
5	UCRY Price Index	-0.031	-0.068	-0.058	-0.078	-0.095	-0.079	-0.067	-0.049	-0.081	-0.038
		0.379	0.012**	0.328	0.001***	0.041**	0.003***	0.065*	0.085*	0.020**	0.130
	CBDC Attention Index	0.004	0.025	0.002	0.033	0.050	0.013	0.032	0.012	0.019	-0.012
		0.926	0.199	0.976	0.084*	0.316	0.519	0.545	0.638	0.693	0.735
25	UCRY Price Index	-0.019	0.001	-0.003	-0.018	-0.023	-0.015	-0.008	-0.009	-0.011	-0.009
		0.345	0.966	0.867	0.466	0.344	0.588	0.774	0.586	0.724	0.687
	CBDC Attention Index	0.004	-0.009	-0.015	0.000	0.007	-0.006	-0.003	0.002	-0.010	-0.011
		0.836	0.697	0.364	0.997	0.720	0.822	0.908	0.869	0.692	0.538
50	UCRY Price Index	0.010	0.008	0.000	0.018	0.011	0.010	-0.006	-0.004	0.010	0.017
		0.559	0.560	0.989	0.373	0.544	0.634	0.500	0.807	0.439	0.100
	CBDC Attention Index	-0.016	-0.012	-0.009	-0.023	-0.013	-0.010	0.000	0.004	-0.007	-0.023
		0.214	0.438	0.555	0.201	0.320	0.615	0.997	0.833	0.546	0.025**
75	UCRY Price Index	0.032	-0.001	0.016	0.036	0.018	0.016	0.008	0.029	0.019	0.019
		0.002***	0.953	0.436	0.108	0.182	0.332	0.586	0.150	0.374	0.256
	CBDC Attention Index	-0.034	0.009	0.002	-0.019	-0.011	-0.003	-0.002	-0.024	-0.011	-0.005
		0.001***	0.625	0.892	0.461	0.461	0.812	0.896	0.261	0.608	0.798
95	UCRY Price Index	0.036	0.067	0.005	0.007	0.026	0.034	0.031	0.117	0.061	0.011
		0.063*	0.102	0.944	0.826	0.126	0.267	0.323	0.017	0.310	0.761
	CBDC Attention Index	-0.032	-0.040	0.034	-0.003	0.026	0.061	-0.007	-0.075	-0.011	0.089
		0.036**	0.152	0.538	0.923	0.452	0.153	0.744	0.094	0.809	0.439

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 44: The effects of during crisis period weekly data (Covid-19 period) of the UCRY Price Index and the Cryptocurrency Environmental Attention (ICEA) index on Cryptocurrencies returns.

τ = quantile		BTC	ETH	XRP	LTC	BCH	EOS	XMR	XLM	DASH	ETC
5	UCRY Price Index	-0.038	-0.064	-0.078	-0.073	-0.084	-0.079	-0.030	-0.052	-0.081	-0.033
		0.016**	0.013**	0.002***	0.002***	0.016**	0.032**	0.358	0.001***	0.008***	0.109
	Cryptocurrency Environmental Index	0.007	0.007	0.039	0.008	0.014	0.007	-0.012	0.009	0.009	-0.012
		0.496	0.522	0.036**	0.621	0.619	0.808	0.659	0.504	0.537	0.386
25	UCRY Price Index	-0.019	-0.001	-0.003	-0.019	-0.024	-0.015	-0.006	-0.009	-0.014	-0.010
		0.305	0.969	0.865	0.302	0.170	0.523	0.771	0.686	0.363	0.627
	Cryptocurrency Environmental Index	0.004	-0.007	-0.009	0.003	0.007	-0.004	-0.005	0.002	-0.002	-0.005
		0.762	0.601	0.458	0.737	0.573	0.760	0.705	0.908	0.799	0.659
50	UCRY Price Index	0.022	0.006	0.010	0.023	0.013	0.014	-0.006	-0.005	0.010	0.018
		0.324	0.637	0.626	0.336	0.518	0.518	0.731	0.836	0.521	0.383
	Cryptocurrency Environmental Index	-0.014	-0.003	-0.008	-0.016	-0.009	-0.005	0.001	0.003	-0.003	-0.014
		0.231	0.794	0.497	0.260	0.296	0.574	0.956	0.836	0.798	0.308
75	UCRY Price Index	0.036	0.009	0.046	0.042	0.029	0.016	0.016	0.035	0.040	0.030
		0.010***	0.639	0.035**	0.002***	0.029**	0.481	0.239	0.373	0.044**	0.301
	Cryptocurrency Environmental Index	-0.022	-0.002	-0.015	-0.017	-0.012	-0.002	-0.006	-0.019	-0.017	-0.009
		0.016**	0.866	0.241	0.073*	0.021**	0.828	0.410	0.371	0.216	0.579
95	UCRY Price Index	0.034	0.068	0.168	0.008	0.046	0.051	0.058	0.126	0.128	0.025
		0.006***	0.127	0.053*	0.894	0.052*	0.186	0.041**	0.027**	0.048**	0.559
	Cryptocurrency Environmental Index	-0.013	-0.028	-0.074	-0.003	-0.010	0.002	-0.028	-0.067	-0.044	0.018
		0.216	0.198	0.220	0.931	0.721	0.956	0.108	0.018	0.169	0.818

Note: the table contains the coefficient and p-value for each quantile. Also, the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Chapter Three: Results of the Granger Causality Test During Crisis Period.

Table 45: The effects of during crisis period daily data of the Twitter-based Economic Uncertainty (TEU) index on Cryptocurrencies returns with lag = 1, and the effects of Cryptocurrencies returns on the Daily data of the Twitter-based Economic Uncertainty (TEU) index with lag = 1.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
TEPU	BTC	P-value	0.753	BTC	TEPU	P-value	0.394
		lag	1			lag	1
TEPU	ETH	P-value	0.756	ETH	TEPU	P-value	0.854
		lag	1			lag	1
TEPU	XRP	P-value	0.374	XRP	TEPU	P-value	0.918
		lag	1			lag	1
TEPU	LTC	P-value	0.492	LTC	TEPU	P-value	0.930
		lag	1			lag	1
TEPU	BCH	P-value	0.978	BCH	TEPU	P-value	0.849
		lag	1			lag	1
TEPU	EOS	P-value	0.833	EOS	TEPU	P-value	0.876
		lag	1			lag	1
TEPU	XMR	P-value	0.622	XMR	TEPU	P-value	0.360
		lag	1			lag	1
TEPU	XLM	P-value	0.686	XLM	TEPU	P-value	0.550
		lag	1			lag	1
TEPU	DASH	P-value	0.372	DASH	TEPU	P-value	0.791
		lag	1			lag	1
TEPU	ETC	P-value	0.499	ETC	TEPU	P-value	0.456
		lag	1			lag	1

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 46: The effects of during crisis period daily data of the Twitter-based Economic Uncertainty (TEU) index on Cryptocurrencies returns with lag = 6, and the Effects of Cryptocurrencies returns on the Daily data of the Twitter-based Economic Uncertainty (TEU) index with lag = 6.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
TEPU	BTC	P-value	0.030**	BTC	TEPU	P-value	0.481
		lag	6			lag	6
TEPU	ETH	P-value	0.056*	ETH	TEPU	P-value	0.358
		lag	6			lag	6
TEPU	XRP	P-value	0.239	XRP	TEPU	P-value	0.077
		lag	6			lag	6
TEPU	LTC	P-value	0.123	LTC	TEPU	P-value	0.327
		lag	6			lag	6
TEPU	BCH	P-value	0.078*	BCH	TEPU	P-value	0.534
		lag	6			lag	6
TEPU	EOS	P-value	0.386	EOS	TEPU	P-value	0.785
		lag	6			lag	6
TEPU	XMR	P-value	0.017**	XMR	TEPU	P-value	0.769
		lag	6			lag	6
TEPU	XLM	P-value	0.802	XLM	TEPU	P-value	0.376
		lag	6			lag	6
TEPU	DASH	P-value	0.158	DASH	TEPU	P-value	0.483
		lag	6			lag	6
TEPU	ETC	P-value	0.505	ETC	TEPU	P-value	0.831
		lag	6			lag	6

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 47: The effects of during crisis period weekly data of the UCRY Policy Index on Cryptocurrencies returns with lag = 1, and the effects of Cryptocurrencies returns on the Weekly data of the UCRY Policy Index with lag = 1.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
UCRY Policy Index	BTC	P-value	0.211	BTC	UCRY Policy Index	P-value	0.880
		lag	1			lag	1
UCRY Policy Index	ETH	P-value	0.001***	ETH	UCRY Policy Index	P-value	0.587
		lag	1			lag	1
UCRY Policy Index	XRP	P-value	0.060**	XRP	UCRY Policy Index	P-value	0.939
		lag	1			lag	1
UCRY Policy Index	LTC	P-value	0.004***	LTC	UCRY Policy Index	P-value	0.931
		lag	1			lag	1
UCRY Policy Index	BCH	P-value	0.002***	BCH	UCRY Policy Index	P-value	0.792
		lag	1			lag	1
UCRY Policy Index	EOS	P-value	0.000***	EOS	UCRY Policy Index	P-value	0.583
		lag	1			lag	1
UCRY Policy Index	XMR	P-value	0.078*	XMR	UCRY Policy Index	P-value	0.566
		lag	1			lag	1
UCRY Policy Index	XLM	P-value	0.072*	XLM	UCRY Policy Index	P-value	0.412
		lag	1			lag	1
UCRY Policy Index	DASH	P-value	0.002***	DASH	UCRY Policy Index	P-value	0.640
		lag	1			lag	1
UCRY Policy Index	ETC	P-value	0.002***	ETC	UCRY Policy Index	P-value	0.206
		lag	1			lag	1

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 48: The effects of during crisis period weekly data of the UCRY Policy Index on Cryptocurrencies returns with lag = 6, and the effects of Cryptocurrencies returns on the Weekly data of the UCRY Policy Index with lag = 6.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
UCRY Policy Index	BTC	P-value	0.133	BTC	UCRY Policy Index	P-value	0.099*
		lag	6			lag	6
UCRY Policy Index	ETH	P-value	0.000***	ETH	UCRY Policy Index	P-value	0.168
		lag	6			lag	6
UCRY Policy Index	XRP	P-value	0.000***	XRP	UCRY Policy Index	P-value	0.052*
		lag	6			lag	6
UCRY Policy Index	LTC	P-value	0.001***	LTC	UCRY Policy Index	P-value	0.083*
		lag	6			lag	6
UCRY Policy Index	BCH	P-value	0.000***	BCH	UCRY Policy Index	P-value	0.188
		lag	6			lag	6
UCRY Policy Index	EOS	P-value	0.000***	EOS	UCRY Policy Index	P-value	0.280
		lag	6			lag	6
UCRY Policy Index	XMR	P-value	0.316	XMR	UCRY Policy Index	P-value	0.012**
		lag	6			lag	6
UCRY Policy Index	XLM	P-value	0.013**	XLM	UCRY Policy Index	P-value	0.230
		lag	6			lag	6
UCRY Policy Index	DASH	P-value	0.004***	DASH	UCRY Policy Index	P-value	0.033**
		lag	6			lag	6
UCRY Policy Index	ETC	P-value	0.001***	ETC	UCRY Policy Index	P-value	0.037**
		lag	6			lag	6

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 49: The effects of during crisis period weekly data of the UCRY Price Index on Cryptocurrencies returns with lag = 1, and the effects of Cryptocurrencies returns on the Weekly data of the UCRY Price Index with lag = 1.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
UCRY Price Index	BTC	P-value	0.209	BTC	UCRY Price Index	P-value	0.800
		lag	1			lag	1
UCRY Price Index	ETH	P-value	0.002***	ETH	UCRY Price Index	P-value	0.843
		lag	1			lag	1
UCRY Price Index	XRP	P-value	0.121	XRP	UCRY Price Index	P-value	0.897
		lag	1			lag	1
UCRY Price Index	LTC	P-value	0.008***	LTC	UCRY Price Index	P-value	0.602
		lag	1			lag	1
UCRY Price Index	BCH	P-value	0.004***	BCH	UCRY Price Index	P-value	0.961
		lag	1			lag	1
UCRY Price Index	EOS	P-value	0.001***	EOS	UCRY Price Index	P-value	0.940
		lag	1			lag	1
UCRY Price Index	XMR	P-value	0.265	XMR	UCRY Price Index	P-value	0.809
		lag	1			lag	1
UCRY Price Index	XLM	P-value	0.229	XLM	UCRY Price Index	P-value	0.244
		lag	1			lag	1
UCRY Price Index	DASH	P-value	0.009***	DASH	UCRY Price Index	P-value	0.712
		lag	1			lag	1
UCRY Price Index	ETC	P-value	0.007***	ETC	UCRY Price Index	P-value	0.425
		lag	1			lag	1

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 50: The effects of during crisis period weekly data of the UCRY Price Index on Cryptocurrencies returns with lag = 6, and the effects of Cryptocurrencies returns on the Weekly data of the UCRY Price Index with lag = 6.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
UCRY Price Index	BTC	P-value	0.040**	BTC	UCRY Price Index	P-value	0.099*
		lag	6			lag	6
UCRY Price Index	ETH	P-value	0.000***	ETH	UCRY Price Index	P-value	0.263
		lag	6			lag	6
UCRY Price Index	XRP	P-value	0.001***	XRP	UCRY Price Index	P-value	0.176
		lag	6			lag	6
UCRY Price Index	LTC	P-value	0.000***	LTC	UCRY Price Index	P-value	0.149
		lag	6			lag	6
UCRY Price Index	BCH	P-value	0.000***	BCH	UCRY Price Index	P-value	0.258
		lag	6			lag	6
UCRY Price Index	EOS	P-value	0.000***	EOS	UCRY Price Index	P-value	0.369
		lag	6			lag	6
UCRY Price Index	XMR	P-value	0.130	XMR	UCRY Price Index	P-value	0.055*
		lag	6			lag	6
UCRY Price Index	XLM	P-value	0.006***	XLM	UCRY Price Index	P-value	0.207
		lag	6			lag	6
UCRY Price Index	DASH	P-value	0.006***	DASH	UCRY Price Index	P-value	0.024**
		lag	6			lag	6
UCRY Price Index	ETC	P-value	0.000***	ETC	UCRY Price Index	P-value	0.096*
		lag	6			lag	6

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 51: The effects of during crisis period weekly data of the Twitter-based Economic Uncertainty (TEU) index on Cryptocurrencies returns with lag = 1, and the effects of Cryptocurrencies returns on the Daily data of the Twitter-based Economic Uncertainty (TEU) index with lag = 1.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
TEPU	BTC	P-value	0.022**	BTC	TEPU	P-value	0.610
		lag	1			lag	1
TEPU	ETH	P-value	0.009***	ETH	TEPU	P-value	0.896
		lag	1			lag	1
TEPU	XRP	P-value	0.116	XRP	TEPU	P-value	0.903
		lag	1			lag	1
TEPU	LTC	P-value	0.045**	LTC	TEPU	P-value	0.924
		lag	1			lag	1
TEPU	BCH	P-value	0.018**	BCH	TEPU	P-value	0.953
		lag	1			lag	1
TEPU	EOS re	P-value	0.039**	EOS	TEPU	P-value	0.900
		lag	1			lag	1
TEPU	XMR	P-value	0.047**	XMR	TEPU	P-value	0.380
		lag	1			lag	1
TEPU	XLM	P-value	0.223	XLM	TEPU	P-value	0.521
		lag	1			lag	1
TEPU	DASH	P-value	0.062*	DASH	TEPU	P-value	0.927
		lag	1			lag	1
TEPU	ETC	P-value	0.242	ETC	TEPU	P-value	0.523
		lag	1			lag	1

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 52: The effects of during crisis period weekly data of the Twitter-based Economic Uncertainty (TEU) index on Cryptocurrencies returns with lag = 6, and the Effects of Cryptocurrencies returns on the Daily data of the Twitter-based Economic Uncertainty (TEU) index with lag = 6.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
TEPU	BTC	P-value	0.736	BTC	TEPU	P-value	0.965
		lag	6			lag	6
TEPU	ETH	P-value	0.959	ETH	TEPU	P-value	0.911
		lag	6			lag	6
TEPU	XRP	P-value	0.683	XRP	TEPU	P-value	0.856
		lag	6			lag	6
TEPU	LTC	P-value	0.491	LTC	TEPU	P-value	0.975
		lag	6			lag	6
TEPU	BCH	P-value	0.667	BCH	TEPU	P-value	0.917
		lag	6			lag	6
TEPU	EOS	P-value	0.968	EOS	TEPU	P-value	0.940
		lag	6			lag	6
TEPU	XMR	P-value	0.907	XMR	TEPU	P-value	0.978
		lag	6			lag	6
TEPU	XLM	P-value	0.588	XLM	TEPU	P-value	0.707
		lag	6			lag	6
TEPU	DASH	P-value	0.909	DASH	TEPU	P-value	0.900
		lag	6			lag	6
TEPU	ETC	P-value	0.950	ETC	TEPU	P-value	0.812
		lag	6			lag	6

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 53: The effects of during crisis period weekly data of the Central Bank Digital Currency Uncertainty Index (CBDCUI) on Cryptocurrencies returns with lag = 1, and the effects of Cryptocurrencies returns on the Weekly data of the Central Bank Digital Currency Uncertainty Index (CBDCUI) with lag = 1.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
CBDC Uncertainty Index	BTC	P-value	0.739	BTC	CBDC Uncertainty Index	P-value	0.159
		lag	1			lag	1
CBDC Uncertainty Index	ETH	P-value	0.065*	ETH	CBDC Uncertainty Index	P-value	0.717
		lag	1			lag	1
CBDC Uncertainty Index	XRP	P-value	0.016**	XRP	CBDC Uncertainty Index	P-value	0.460
		lag	1			lag	1
CBDC Uncertainty Index	LTC	P-value	0.046**	LTC	CBDC Uncertainty Index	P-value	0.243
		lag	1			lag	1
CBDC Uncertainty Index	BCH	P-value	0.015**	BCH	CBDC Uncertainty Index	P-value	0.394
		lag	1			lag	1
CBDC Uncertainty Index	EOS	P-value	0.035**	EOS	CBDC Uncertainty Index	P-value	0.652
		lag	1			lag	1
CBDC Uncertainty Index	XMR	P-value	0.128	XMR	CBDC Uncertainty Index	P-value	0.513
		lag	1			lag	1
CBDC Uncertainty Index	XLM	P-value	0.078*	XLM	CBDC Uncertainty Index	P-value	0.107
		lag	1			lag	1
CBDC Uncertainty Index	DASH	P-value	0.006***	DASH	CBDC Uncertainty Index	P-value	0.324
		lag	1			lag	1
CBDC Uncertainty Index	ETC	P-value	0.001***	ETC	CBDC Uncertainty Index	P-value	0.522
		lag	1			lag	1

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 54: The effects of during crisis period weekly data of the Central Bank Digital Currency Uncertainty Index (CBDCUI) on Cryptocurrencies returns with lag = 6, and the effects of Cryptocurrencies returns on the Weekly data of the Central Bank Digital Currency Uncertainty Index (CBDCUI) with lag = 6.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
CBDC Uncertainty Index	BTC	P-value	0.058*	BTC	CBDC Uncertainty Index	P-value	0.066*
		lag	6			lag	6
CBDC Uncertainty Index	ETH	P-value	0.131	ETH	CBDC Uncertainty Index	P-value	0.023**
		lag	6			lag	6
CBDC Uncertainty Index	XRP	P-value	0.002***	XRP	CBDC Uncertainty Index	P-value	0.202
		lag	6			lag	6
CBDC Uncertainty Index	LTC	P-value	0.003***	LTC	CBDC Uncertainty Index	P-value	0.008***
		lag	6			lag	6
CBDC Uncertainty Index	BCH	P-value	0.000***	BCH	CBDC Uncertainty Index	P-value	0.011**
		lag	6			lag	6
CBDC Uncertainty Index	EOS	P-value	0.000***	EOS	CBDC Uncertainty Index	P-value	0.025**
		lag	6			lag	6
CBDC Uncertainty Index	XMR	P-value	0.000***	XMR	CBDC Uncertainty Index	P-value	0.000***
		lag	6			lag	6
CBDC Uncertainty Index	XLM	P-value	0.191	XLM	CBDC Uncertainty Index	P-value	0.026**
		lag	6			lag	6
CBDC Uncertainty Index	DASH	P-value	0.000***	DASH	CBDC Uncertainty Index	P-value	0.013**
		lag	6			lag	6
CBDC Uncertainty Index	ETC	P-value	0.000***	ETC	CBDC Uncertainty Index	P-value	0.017**
		lag	6			lag	6

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 55: The effects of during crisis period weekly data of the Central Bank Digital Currency Attention Index on Cryptocurrencies returns with lag = 1, and the effects of Cryptocurrencies returns on the Weekly data of the Central Bank Digital Currency Attention Index with lag = 1.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
CBDC Attention Index	BTC	P-value	0.335	BTC	CBDC Attention Index	P-value	0.041**
		lag	1			lag	1
CBDC Attention Index	ETH	P-value	0.131	ETH	CBDC Attention Index	P-value	0.316
		lag	1			lag	1
CBDC Attention Index	XRP	P-value	0.001***	XRP	CBDC Attention Index	P-value	0.597
		lag	1			lag	1
CBDC Attention Index	LTC	P-value	0.092*	LTC	CBDC Attention Index	P-value	0.137
		lag	1			lag	1
CBDC Attention Index	BCH	P-value	0.033**	BCH	CBDC Attention Index	P-value	0.315
		lag	1			lag	1
CBDC Attention Index	EOS	P-value	0.015**	EOS	CBDC Attention Index	P-value	0.357
		lag	1			lag	1
CBDC Attention Index	XMR	P-value	0.149	XMR	CBDC Attention Index	P-value	0.310
		lag	1			lag	1
CBDC Attention Index	XLM	P-value	0.035**	XLM	CBDC Attention Index	P-value	0.076*
		lag	1			lag	1
CBDC Attention Index	DASH	P-value	0.013**	DASH	CBDC Attention Index	P-value	0.188
		lag	1			lag	1
CBDC Attention Index	ETC	P-value	0.000***	ETC	CBDC Attention Index	P-value	0.805
		lag	1			lag	1

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 56: The effects of during crisis period weekly data of the Central Bank Digital Currency Attention Index on Cryptocurrencies returns with lag = 6, and the effects of Cryptocurrencies returns on the Weekly data of the Central Bank Digital Currency Attention Index with lag = 6.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
CBDC Attention Index	BTC	P-value	0.002***	BTC	CBDC Attention Index	P-value	0.057*
		lag	6			lag	6
CBDC Attention Index	ETH	P-value	0.079*	ETH	CBDC Attention Index	P-value	0.148
		lag	6			lag	6
CBDC Attention Index	XRP	P-value	0.003***	XRP	CBDC Attention Index	P-value	0.005***
		lag	6			lag	6
CBDC Attention Index	LTC	P-value	0.006***	LTC	CBDC Attention Index	P-value	0.012**
		lag	6			lag	6
CBDC Attention Index	BCH	P-value	0.002***	BCH	CBDC Attention Index	P-value	0.003***
		lag	6			lag	6
CBDC Attention Index	EOS	P-value	0.000***	EOS	CBDC Attention Index	P-value	0.009***
		lag	6			lag	6
CBDC Attention Index	XMR	P-value	0.000***	XMR	CBDC Attention Index	P-value	0.004***
		lag	6			lag	6
CBDC Attention Index	XLM	P-value	0.108	XLM	CBDC Attention Index	P-value	0.098*
		lag	6			lag	6
CBDC Attention Index	DASH	P-value	0.000***	DASH	CBDC Attention Index	P-value	0.076*
		lag	6			lag	6
CBDC Attention Index	ETC	P-value	0.000***	ETC	CBDC Attention Index	P-value	0.000***
		lag	6			lag	6

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 57: The effects of during crisis period weekly data of the Cryptocurrency Environmental Attention (ICEA) index on Cryptocurrencies returns with lag = 1, and the effects of Cryptocurrencies returns on the Weekly data of the Cryptocurrency Environmental Attention index with lag = 1.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
Cryptocurrency Environmental Attention index	BTC	P-value	0.478	BTC	Cryptocurrency Environmental Attention index	P-value	0.091
		lag	1			lag	1
Cryptocurrency Environmental Attention index	ETH	P-value	0.041	ETH	Cryptocurrency Environmental Attention index	P-value	0.257
		lag	1			lag	1
Cryptocurrency Environmental Attention index	XRP	P-value	0.156	XRP	Cryptocurrency Environmental Attention index	P-value	0.523
		lag	1			lag	1
Cryptocurrency Environmental Attention index	LTC	P-value	0.047	LTC	Cryptocurrency Environmental Attention index	P-value	0.099
		lag	1			lag	1
Cryptocurrency Environmental Attention index	BCH	P-value	0.025	BCH	Cryptocurrency Environmental Attention index	P-value	0.214
		lag	1			lag	1
Cryptocurrency Environmental Attention index	EOS	P-value	0.003	EOS	Cryptocurrency Environmental Attention index	P-value	0.275
		lag	1			lag	1
Cryptocurrency Environmental Attention index	XMR	P-value	0.078	XMR	Cryptocurrency Environmental Attention index	P-value	0.247
		lag	1			lag	1
Cryptocurrency Environmental Attention index	XLM	P-value	0.182	XLM	Cryptocurrency Environmental Attention index	P-value	0.045
		lag	1			lag	1
Cryptocurrency Environmental Attention index	DASH	P-value	0.020	DASH	Cryptocurrency Environmental Attention index	P-value	0.174
		lag	1			lag	1
Cryptocurrency Environmental Attention index	ETC	P-value	0.000	ETC	Cryptocurrency Environmental Attention index	P-value	0.988
		lag	1			lag	1

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 58: The effects of during crisis period weekly data of the Cryptocurrency Environmental Attention (ICEA) index on Cryptocurrencies returns with lag = 6, and the Effects of Cryptocurrencies returns on the Weekly data of the Cryptocurrency Environmental Attention index with lag = 6.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
Cryptocurrency Environmental Attention index	BTC	P-value	0.001***	BTC	Cryptocurrency Environmental Attention index	P-value	0.276
		lag	6			lag	6
Cryptocurrency Environmental Attention index	ETH	P-value	0.007***	ETH	Cryptocurrency Environmental Attention index	P-value	0.109
		lag	6			lag	6
Cryptocurrency Environmental Attention index	XRP	P-value	0.001***	XRP	Cryptocurrency Environmental Attention index	P-value	0.120
		lag	6			lag	6
Cryptocurrency Environmental Attention index	LTC	P-value	0.001***	LTC	Cryptocurrency Environmental Attention index	P-value	0.114
		lag	6			lag	6
Cryptocurrency Environmental Attention index	BCH	P-value	0.000***	BCH	Cryptocurrency Environmental Attention index	P-value	0.391
		lag	6			lag	6
Cryptocurrency Environmental Attention index	EOS	P-value	0.000***	EOS	Cryptocurrency Environmental Attention index	P-value	0.174
		lag	6			lag	6
Cryptocurrency Environmental Attention index	XMR	P-value	0.000***	XMR	Cryptocurrency Environmental Attention index	P-value	0.024**
		lag	6			lag	6
Cryptocurrency Environmental Attention index	XLM	P-value	0.118	XLM	Cryptocurrency Environmental Attention index	P-value	0.123
		lag	6			lag	6
Cryptocurrency Environmental Attention index	DASH	P-value	0.000***	DASH	Cryptocurrency Environmental Attention index	P-value	0.626
		lag	6			lag	6
Cryptocurrency Environmental Attention index	ETC	P-value	0.000***	ETC	Cryptocurrency Environmental Attention index	P-value	0.480
		lag	6			lag	6

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 59: The effects of during crisis period weekly data of the Cryptocurrency Environmental Attention (ICEA) index on Cryptocurrencies returns with lag = 7, and the Effects of Cryptocurrencies returns on the Weekly data of the Cryptocurrency Environmental Attention index with lag = 7.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
Cryptocurrency Environmental Attention index	BTC	P-value	0.001***	BTC	Cryptocurrency Environmental Attention index	P-value	0.291
		lag	7			lag	7
Cryptocurrency Environmental Attention index	ETH	P-value	0.012**	ETH	Cryptocurrency Environmental Attention index	P-value	0.212
		lag	7			lag	7
Cryptocurrency Environmental Attention index	XRP	P-value	0.000***	XRP	Cryptocurrency Environmental Attention index	P-value	0.057*
		lag	7			lag	7
Cryptocurrency Environmental Attention index	LTC	P-value	0.001***	LTC	Cryptocurrency Environmental Attention index	P-value	0.171
		lag	7			lag	7
Cryptocurrency Environmental Attention index	BCH	P-value	0.000***	BCH	Cryptocurrency Environmental Attention index	P-value	0.265
		lag	7			lag	7
Cryptocurrency Environmental Attention index	EOS	P-value	0.000***	EOS	Cryptocurrency Environmental Attention index	P-value	0.224
		lag	7			lag	7
Cryptocurrency Environmental Attention index	XMR	P-value	0.000***	XMR	Cryptocurrency Environmental Attention index	P-value	0.002***
		lag	7			lag	7
Cryptocurrency Environmental Attention index	XLM	P-value	0.153	XLM	Cryptocurrency Environmental Attention index	P-value	0.156
		lag	7			lag	7
Cryptocurrency Environmental Attention index	DASH	P-value	0.000***	DASH	Cryptocurrency Environmental Attention index	P-value	0.488
		lag	7			lag	7
Cryptocurrency Environmental Attention index	ETC	P-value	0.000***	ETC	Cryptocurrency Environmental Attention index	P-value	0.225
		lag	7			lag	7

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 60: The effects of during crisis period Monthly data of the Economic Policy Uncertainty Index for Europe index on Cryptocurrencies returns with lag = 1, and the effects of Cryptocurrencies returns on the Monthly data of the Economic Policy Uncertainty Index for Europe index with lag = 1.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
EUROEPU Index	BTC	P-value	0.507	BTC	EUROEPU Index	P-value	0.201
		lag	1			lag	1
EUROEPU Index	ETH	P-value	0.636	ETH	EUROEPU Index	P-value	0.014**
		lag	1			lag	1
EUROEPU Index	XRP	P-value	0.588	XRP	EUROEPU Index	P-value	0.044**
		lag	1			lag	1
EUROEPU Index	LTC	P-value	0.596	LTC	EUROEPU Index	P-value	0.038**
		lag	1			lag	1
EUROEPU Index	BCH	P-value	0.765	BCH	EUROEPU Index	P-value	0.011**
		lag	1			lag	1
EUROEPU Index	EOS	P-value	0.892	EOS	EUROEPU Index	P-value	0.013**
		lag	1			lag	1
EUROEPU Index	XMR	P-value	0.993	XMR	EUROEPU Index	P-value	0.085*
		lag	1			lag	1
EUROEPU Index	XLM	P-value	0.917	XLM	EUROEPU Index	P-value	0.166
		lag	1			lag	1
EUROEPU Index	DASH	P-value	0.919	DASH	EUROEPU Index	P-value	0.019**
		lag	1			lag	1
EUROEPU Index	ETC	P-value	0.524	ETC	EUROEPU Index	P-value	0.002***
		lag	1			lag	1

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.

Table 61: The effects of during crisis period Monthly data of the Economic Policy Uncertainty Index for Europe index on Cryptocurrencies returns with lag = 6, and the effects of Cryptocurrencies returns on the Monthly data of the Economic Policy Uncertainty Index for Europe index with lag = 6.

Index	Cryptocurrency	Estimates		Cryptocurrency	Index	Estimates	
EUROEPU Index	BTC	P-value	0.029**	BTC	EUROEPU Index	P-value	0.000***
		lag	6			lag	6
EUROEPU Index	ETH	P-value	0.022**	ETH	EUROEPU Index	P-value	0.002***
		lag	6			lag	6
EUROEPU Index	XRP	P-value	0.000***	XRP	EUROEPU Index	P-value	0.000***
		lag	6			lag	6
EUROEPU Index	LTC	P-value	0.000***	LTC	EUROEPU Index	P-value	0.003***
		lag	6			lag	6
EUROEPU Index	BCH	P-value	0.062*	BCH	EUROEPU Index	P-value	0.007***
		lag	6			lag	6
EUROEPU Index	EOS	P-value	0.007***	EOS	EUROEPU Index	P-value	0.028**
		lag	6			lag	6
EUROEPU Index	XMR	P-value	0.002***	XMR	EUROEPU Index	P-value	0.090*
		lag	6			lag	6
EUROEPU Index	XLM	P-value	0.023**	XLM	EUROEPU Index	P-value	0.000***
		lag	6			lag	6
EUROEPU Index	DASH	P-value	0.129	DASH	EUROEPU Index	P-value	0.000***
		lag	6			lag	6
EUROEPU Index	ETC	P-value	0.498	ETC	EUROEPU Index	P-value	0.000***
		lag	6			lag	6

Note: the table contains the lag order and p-value estimate, and the ***, **, and * denote the 1 %, 5%, and 10 % significance levels, respectively.