Bitcoin, Uncertainty, and Internet Searches

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ABSTRACT

This thesis examines the predictive power of the Macroeconomic Uncertainty Index (MUI) with a horizon of one month and the volume of uncertainty-related online searches measured by Economic Uncertainty Related Queries (EURQ) on the Bitcoin returns. The sample includes 118 observations with monthly frequency and ranges from September 2010 to June 2020. In addition to the conventional methods, due to the presence of outliers and the departure from Gaussian assumptions; the quantile analysis framework was used to study the persistency of the shocks, the long-run relationships, and Granger causality among the variables. For this purpose, the quantile unit root test of Galvao (2009), the quantile cointegration test of Xiao (2009), and the Granger causality test in quantiles (Troster, 2016) were applied.

The empirical findings highlight several vital points that lead to important policy implications. First, the variables display asymmetric behavior in response to the shocks along different conditional quantiles. Second, the Bitcoin-EURQ indicates different adjustment mechanisms towards long-run equilibrium in different quantiles. Third, the long-run and causal relationships between the series might be significantly different throughout the conditional distributions of the variables. Fourth, of particular interest, the findings provide evidence for the significant predictive power of the fluctuations in MUI and EURQ on Bitcoin returns, mostly in low and high quantiles. Implications of these findings for empirical researchers and Bitcoin investors are discussed in the conclusion section in detail.

Keywords: Cryptocurrency, Bitcoin, Macroeconomic uncertainty, Internet search volumes, Economic uncertainty-related queries, Granger causality in quantiles.

ÖZ

Bu tez, bir aylık bir ufukla Makroekonomik Belirsizlik Endeksinin (MUI) tahmin gücünü ve Bitcoin getirileri üzerinde Ekonomik Belirsizlikle İlgili Sorgular (EURQ) tarafından ölçülen belirsizlikle ilgili çevrimiçi aramaların hacmini incelemektedir. Örneklem, Eylül 2010'dan Haziran 2020'ye kadar aylık frekans ve aralıklarda 118 gözlem içermektedir. Geleneksel yöntemlere ek olarak, aykırı değerlerin varlığı ve Gauss varsayımlarından sapma nedeniyle; şokların kalıcılığını, uzun dönemli ilişkileri ve değişkenler arasındaki Granger nedenselliğini incelemek için kantil analiz çerçevesi kullanıldı. Bu amaçla Galvao'nun (2009) kantil birim kök testi, Xiao'nun (2009) kantil eşbütünleşme testi ve kantillerde Granger nedensellik testi (Troster, 2016) uygulanmıştır.

Ampirik bulgular, önemli politika çıkarımlarına yol açan birkaç hayati noktayı vurgulamaktadır. İlk olarak, değişkenler, farklı koşullu nicelikler boyunca şoklara yanıt olarak asimetrik davranış sergiler. İkincisi, Bitcoin-EURQ, farklı niceliklerde uzun vadeli dengeye yönelik farklı ayarlama mekanizmalarını gösterir. Üçüncüsü, seriler arasındaki uzun dönemli ve nedensel ilişkiler, değişkenlerin koşullu dağılımları boyunca önemli ölçüde farklı olabilir. Dördüncüsü, özellikle ilgi çekici olan bulgular, MUI ve EURQ'daki dalgalanmaların Bitcoin getirileri üzerindeki, çoğunlukla düşük ve yüksek niceliklerdeki önemli tahmin gücüne dair kanıt sağlıyor. Bu bulguların ampirik araştırmacılar ve Bitcoin yatırımcıları için etkileri sonuç bölümünde ayrıntılı olarak tartışılmaktadır.

Anahtar Kelimeler: Kripto para, Bitcoin, Makroekonomik belirsizlik, İnternet arama hacimleri, Ekonomik belirsizlikle ilgili sorgular, Kuantillerde Granger nedenselliği.

To My Mother, Maryam Asadi, and My Brother, Armin

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1

INTRODUCTION

The popularity of Bitcoin has been substantially increasing in recent years. The rising attention to Bitcoin, particularly from investors, highlights the importance of studies on Bitcoin's price behavior. Poyser (2017) categorizes Bitcoin price determinants into internal and external factors. Hash rate, coin circulation, supply and demand, and transaction costs are some examples of internal factors. External factors are categorized into three general categories: political factors, cryptocurrency market factors, and macro-financial factors. Bitcoin attractiveness, speculations, stock markets, interest rate, legalization, and restrictions are the examples of the external factors. This research investigates the predictive power of the fluctuations in the Macroeconomic Uncertainty Index (MUI) and Economic Uncertainty Related Queries (EURQ) on Bitcoin price. Hence, this research considers different dimensions of the uncertainty by addressing both the aggregate uncertainty shocks in the economy and the uncertainty conveyed to the economic agents. Furthermore, using several methods based on quantiles, a more comprehensive perspective regarding the relationship of the variables under investigation is provided. Thus, I examine the impact of both uncertainty and the economic agents' perception on Bitcoin prices from a new perspective and provide important empirical findings.

The Bitcoin developer(s) under the pseudonym Satoshi Nakamoto introduced Bitcoin in a white paper as "*a peer-to-peer electronic cash system*" (Nakamoto, 2008, P. 1) for online payments. Bitcoin facilitates direct online transactions between two parties by the elimination of the trusted third party. Hence, instead of trust, the Bitcoin system performs based on cryptographic proof. To this end, the Bitcoin ecosystem utilizes a Distributed Ledger Technology (DLT) called Blockchain. Blockchain acts as a giant and global digital ledger that records transactions with a cryptographic signature called Hash or Digest. The details of the recorded transactions on Blockchain are publicly accessible on the network; nonetheless, the real-life identity of the parties involved in the transactions remains anonymous. Generally speaking, each Bitcoin transaction includes two stages: transaction creation and transaction verification. In the creation stage, the transactions are created and digitally signed. The digital signature is a function of the private key and the transaction itself to prevent forgery. The private key is a secret piece of data analogous to a password, proving the Bitcoin ownership and enabling the owner to spend Bitcoin to other parties. The created transaction is broadcasted across the peer-to-peer network for validation. In the second stage, the transaction is authenticated under the mining process by solving computational problems. To be more specific, this process involves guessing procedures and somewhat resembles a lottery for the miners. When the miners solve the computational puzzles, the verified transactions are added to the existing Blockchain in the form of the new blocks of data and updates the information on the Blockchain.

Internet and e-commerce have become integral elements of numerous businesses throughout the world. The emergence of e-commerce highlighted the necessity of more efficient economic structures than traditional systems. Consequently, the interactions between e-commerce and Bitcoin as a novel and effective payment system have been increasing. Bitcoin was primarily introduced as a cash system, providing a more transparent, faster, and cost-efficient medium than traditional payment systems (Walch, 2015). Furthermore, global access to Bitcoin (Grinberg, 2012), robustness against common frauds (Androulaki et al., 2013, Simser, 2015), and decentralization are some of the Bitcoin features. Such properties and mainly the potential of Bitcoin to help alter supply-chain networks in almost all business sectors (Fosso Wamba et al., 2019) can explain several aspects of the rising tendency towards Bitcoin utilization. However, Bitcoin does not exclusively act as a medium of exchange, and it also functions as an investment alternative (Baur et al., 2018, Glaser et al., 2014, Platanakis and Urquhart, 2020, Polasik et al., 2015).

The Bitcoin network was launched in January 2009, and Bitcoin gained monetary value against conventional currencies in 2010. The first official application of Bitcoin as a means of payment occurred in May 2010 to buy two pizzas valued at $25 for 10000 Bitcoins. Since then, Bitcoin has experienced immense price growth. For the first time, Bitcoin price reached a value higher than $1 in February 2011, and it passed the $28000 threshold in December 2020. The Bitcoin price growth and an upward long-run trend in its return have led to more Bitcoin's popularity with investors as an investment alternative. In addition, bitcoin price has also demonstrated episodes of high volatility. The relatively high volatility of Bitcoin has provided a valuable opportunity for speculators and noise traders to act in the Bitcoin market. Even though Bitcoin's high return and volatility have attracted various investors' attention, compared with the conventional financial assets, commodities, and currencies, Bitcoin is still unknown territory. This fact places emphasis on the significance of the studies on Bitcoin price formation to provide more theoretical and practical information for the Bitcoin market participants.

Risk and return, as two cornerstones of investment theory, play a critical role in investment decisions. The return and volatility characteristics of Bitcoin have attracted the attention of researchers, and extensive literature has emerged. Several studies suggest the impact of sentiment and emotions on Bitcoin prices (Bartolucci et al., 2020; Makrichoriti et al., 2016). The sentiment is generally defined as the investors' beliefs about risk and future cash flows that available information and fundamentals cannot fully justify (Baker and Wurgler, 2007). Besides, sentiment and uncertainty are closely related. The importance of uncertainty has been documented by the previous literature (Awasthi et al., 2020). The presence of uncertainty helps increase the effect of sentiment on asset prices (Birru and Young, 2020). Consequently, uncertainty might influence Bitcoin prices through the channel of sentiment. Furthermore, given that some studies confirmed the linkage between Bitcoin and economic factors (Li and Wang, 2017), the uncertainty about economic fundamentals can potentially affect the Bitcoin market.

A part of the literature about Bitcoin focuses on addressing the impact of uncertainty on Bitcoin price/returns through various uncertainty proxies (Bouri et al., 2017; Demir et al., 2018; Fang et al., 2020; Gozgor et al., 2019; Shaikh, 2020). Even though these proxies capture significant aspects of economic-related uncertainty, they have some shortcomings to the best of my knowledge. First, they might not represent the uncertainty in the whole economy comprehensively enough. Second, they may not only be driven by uncertainty, and other factors might largely influence them. Third, they might not capture the association between uncertainty and real economic activities adequately. Accordingly, I employ the MUI of Jurado et al. (2015) based on the forecast errors for a vast number of economic series to capture the aggregate uncertainty in the whole economy. Due to its characteristics, MUI avoids the mentioned shortcomings as much as possible.

The connectedness of Bitcoin and the internet is so much that Bitcoin is sometimes considered as the internet currency. Online platforms, mainly social media, serve as the primary sources of information for Bitcoin investors (Kraaijeveld and De Smedt, 2020). Online platforms also play a nontrivial role in the formation or alteration of the investors' sentiment. Such platforms can help quantify the effect of investors' sentiment on the Bitcoin market. Additionally, various studies have substantiated the predictive role of online resources, such as Twitter, forums, and Google, for Bitcoin returns (Kraaijeveld and De Smedt, 2020, Phillips and Gorse, 2018, Mai et al., 2015). On the other side, from the psychological perspective, uncertainty and the lack of information usually lead to searching for more information. Thus, I expect a positive association between the current level of the revealed uncertainty and the online search volume about uncertainty-related topics proxied by EURQ.

This research investigates Bitcoin's price behavior by applying traditional and quantile time series analysis, and extends the existing literature in two ways: First, the proxies employed can provide us a new perspective about Bitcoin, uncertainty, and internet searches. Unlike most of the literature, I employed a proxy that directly estimates the uncertainty in the economy considering a broad range of uncertainty sources. Furthermore, different from most existing studies about the impact of the internet on Bitcoin price, I considered a proxy regarding the online queries about uncertainty. The second contribution is the adopted econometric methodology. The quantile unit root test of Galvao (2009) and the quantile cointegration test of Xiao (2009) were applied. Besides, to investigate the Granger causality in quantiles, the parametric test of Troster

(2016) was employed. Despite the traditional time-series analysis in which generally one or/and two moments of distributions are considered, using quantile analysis enables us to investigate a broad range of quantiles to gain more detailed information about Bitcoin's price behavior. The power of the quantile analysis is not limited to accounting for the changes in the location, and it can also help us address the changes in scale and shape of the conditional distributions. Besides, the quantile analysis provides a more robust framework for ill-behaved data.

The rest of this study is organized as follows. In the next section, a literature review on Bitcoin price is presented, and in section 3, I describe the methodology. Then, section 4 reports and discusses the empirical results, and finally, section 5 includes the conclusion and final remarks.

Chapter 2

LITERATURE REVIEW

After its official introduction in 2008 as a decentralized cryptographic currency with a pseudo-anonymous nature, Bitcoin encountered a surge of concerns regarding its misuse. Describing cryptocurrencies as the currency for criminals (Mihm, 2013) is a case in point. Such concerns and the complexity of Bitcoin's nature caused Bitcoin to be treated cautiously at its early stage. However, the situation quickly changed, and the trust in Bitcoin increased. In the same vein, Bitcoin received growing attention from scholars.

Given the extraordinary price increase and increased attention, many different aspects of Bitcoin have been examined by the researcher for the last several years. For example, the potential speculative properties of Bitcoin have been addressed in the literature extensively and still a debate has been going on whether Bitcoin shares common properties with the standard or speculative financial assets (Kristoufek, 2015; Yermack, 2015; Klein et al., 2018; Aharon and Qadan, 2019). Also, the presence of price bubbles has been investigated extensively by the researchers (Cheah and Fry, 2015; Li et al., 2018; Cretarola and Figà-Talamanca, 2019; Chaim and Laurini, 2019). As one of the fundamental concept of financial theory, the degree of the cryptocurrency market efficiency has also been among the subjects on which researchers have focused (Urquhart, 2016; Bariviera, 2017; Brauneis and Mestel, 2018; Karalevicius et al., 2018; Kristoufek, 2018; Khuntia and Pattanayak, 2018;

Tiwari et al., 2018; Vidal-Tomás and Ibañez, 2018; Bundi and Wildi, 2019; Mensi et al., 2019; Sensoy, 2019; Resta et al., 2020; Manahov and Urquhart, 2021).

Although the research topics related to Bitcoin are spread over a wide area, I will be selective and focus on the areas that directly concern my research topic. In the expanding literature about Bitcoin, it is often debated what the price drivers are and how they contribute to Bitcoin price formation. Literature offers many factors, such as cryptomarket-based, macro-based, and technical factors, as potential drivers of Bitcoin prices. In their relatively early study, Ciaian et al. (2015) considered cryptomarket-specific factors and traditional currencies price determinants to investigate Bitcoin price formation. They supported the time-varying impact of Bitcoin attractiveness on the price and confirmed the impact of Bitcoin market forces on its price formation. Georgoula et al. (2015), using time-series analysis, indicated the negative effect of the USD/EUR exchange rate and the positive effect of the hash rate on the price. Li and Wang (2017) examined the influence of specific economic and technology factors on Bitcoin price and detected that the price was more sensitive to the economic factors in the long run. Balcilar et al. (2017), using a non-parametric Granger causality approach, indicated the Granger causality from Bitcoin trading volume to the mid-quantiles of Bitcoin returns. Koutmos (2018a) found a bidirectional interaction between Bitcoin transaction activity and return. However, the impact of the return shocks on transaction activity was larger in magnitude. Nguyen and Thaver (2018) addressed both transactional and speculative demands as drivers of Bitcoin price. They indicated that factors such as the supply of Bitcoin, the size of the Bitcoin economy, media attention, and the price of another cryptocurrency could affect the Bitcoin price formation.

Sovbetov (2018), using ARDL methodology, found that trading volume, volatility, S&P 500 index and the attractiveness of cryptocurrencies influence the crypto-prices.

Recently, researchers have intensified their efforts to reveal the determinants of Bitcoin prices by using wide variety of econometric methods and potential determinants. There are many studies recently contributed to the literature. İçellioğlu and Öner (2019), considering a daily sample from August 2016 to April 2019, applied the heterogeneous panel data analysis (HPDA) to investigate the interactions between several cryptocurrencies and the selected macro-financial variables. The authors found that the rise in S&P 500 index, oil price, and gold price causes the Bitcoin price to increase. Conversely, the rise in the two-year benchmark US Bond interest rate and US Dollar index leads to a fall in the Bitcoin prices. Alaoui et al. (2019) applied the multifractal detrended fluctuation analysis (MF-DFA) and the multifractal detrended cross-correlations analysis method (MF-DCCA) to a sample from July 2010 to May 2018. The authors found a non-linear interaction between Bitcoin price movement and trading volume and concluded the presence of multifractality. Koutmos (2019) found that the returns on the aggregate market portfolio proxied by the US total market price index (CSRP) do not have explanatory power for Bitcoin return. However, the interest rates and the implied volatilities in the US stock and foreign exchange market are among the factors explaining Bitcoin return.

Jareño et al. (2020) documented the negative effect of the US ten-year nominal interest rates on Bitcoin return in the highest quantile. Kapar and Olmo (2020), considering the sample from July 2010 to January 2018, found the positive impact of the S&P 500 index and negative impact of fear sentiment (proxied by the FED Financial Stress Index) on the Bitcoin price. Xiao and Sun (2020) suggested the impact of gold prices, the Forex market, and the volatility of major financial markets on most cryptocurrencies' returns. Huynh et al. (2020) showed the predictive power of the ratio of the gold price to platinum price on Bitcoin returns. Huynh et al. (2020) also corroborated the volatility transmission from the gold and platinum market to the Bitcoin market. Most recently, Virk (2021) investigated the correlation between Bitcoin and several fiat currencies, namely the Canadian dollar (CAD), Swiss Franc (CHF), Japanese Yen (JPY), British Pound (GBP), and Euro (EUR). Using the DCC model, the author couldn't find any correlation between Bitcoin and the selected currencies' returns.

The elements of uncertainty and risk play a crucial role in financial markets. These elements could affect the price movements of financial products by influencing market participants' perception and their investment decisions. Accordingly, several studies have investigated the interaction between Bitcoin, uncertainty, and risk. Such studies potentially propose significant implications about Bitcoin's hedging ability and its role as a portfolio diversifier. Demir et al. (2018) supported the predictive role of the Economic Policy Uncertainty (EPU) on Bitcoin's daily returns with negative responses from bitcoin returns to the positive changes in the EPU. Koumba et al. (2019) employed the D-Vine pair-copula methodology and substantiated the dependence between US-EPU and Bitcoin, Ripple, and Ethereum prices. Balli et al. (2019) documented the hedging ability of cryptocurrencies against uncertainty because of the negative association between EPU and the connectedness of the cryptocurrencies. Mokni (2021) confirmed that the EPU could help predict both Bitcoin's return and volatility. Shaikh (2020), using the Markov regime-switching model, documented the impact of EPU, global EPU, and global Monetary Policy

Uncertainty (MPU) on cryptomarket behavior. Shaikh (2020) also suggested the negative relationship between the Bitcoin market and each uncertainty in the Federal Open Market Committee (FOMC) and the uncertainty in the equity market. Wang et al. (2020) employed the Dynamic Conditional Correlation (DCC)-GARCH model to examine the dynamic correlation between EPU and Bitcoin price. The authors found that the impact of US EPU on BTC/USD was more significant than the impact of the United Kingdom (UK) EPU on the BTC/GBP.

Wu et al. (2019) documented that Bitcoin could not be a safe-haven against the EPU at normal market conditions. However, Bitcoin could serve as a weak safe-haven during the highly bullish and bearish market condition. Dyhrberg (2016), using the asymmetric GARCH methodology, concluded the potential of Bitcoin as a hedging tool against the stocks in the Financial Times Stock Exchange Index, and only in the short-run, against USD. Guesmi et al. (2019) concluded that taking a short position in Bitcoin could be a hedging remedy against the investment risk of the different financial assets. The authors also suggested that the strategy of adding Bitcoin to a portfolio containing oil, emerging stocks, and gold significantly reduces the portfolio's risk. Giudici and Abu-Hashish (2019) also advocated the role of Bitcoin as a beneficial portfolio diversifier. Kliber et al. (2019), considering the leading local stock market indices, found Bitcoin as a diversifier in China and Japan, a weak hedge in Sweden and Estonia, and a safe haven for the case of Venezuela. Dimpfl and Odelli (2020) considered two bitcoin markets (Bitfinex and Kraken) to investigate the level of price risk using an autoregressive conditional duration model. The authors found that the price risk reaches the highest level when the US and European investors are sleeping and do not trade.

Contrary to the studies that documented the interactions between EPU and Bitcoin, Al Mamun et al. (2020) found the insignificant role of US EPU. However, Al Mamun et al. (2020) confirmed the significant role of Global EPU (GEPU) and geopolitical risk in explaining Bitcoin risk premia. Qin et al. (2021) employed bootstrap full- and sub-sample rolling-window Granger causality tests and supported the presence of bidirectional causality between GEPU and Bitcoin returns. Aysan et al. (2019) documented the predictive power of the geopolitical risk for Bitcoin return and volatility. The authors also identified Bitcoin as a hedging alternative against geopolitical risk. In contrast, Colon et al. (2021) did not support the potential of the cryptocurrency market as a safe haven against geopolitical risks in most cases. However, Colon et al. (2021) supported the potential of the cryptocurrency market to function as a strong hedge against GEPU during a bull market. Fang et al. (2019) posited the positive impact of GEPU on Bitcoin-equities and Bitcoin-commodities correlation and the negative effect of GEPU on Bitcoin-bonds correlation. Cheng and Yen (2020) rejected the predictive power of EPU for Bitcoin monthly returns in the US, Japan, and Korea. Cheng and Yen (2020) nonetheless confirmed the predictive power of EPU in China. In line with Cheng and Yen (2020), Yen and Cheng (2021) investigated the predictive power of EPU in the US, China, Korea, and Japan on Bitcoin volatility and found similar results.

Furthermore, Al-Yahyaee et al. (2019) employed Multiple Wavelet Coherence (MWC), Cross Wavelet Transform (CWT), Wavelet Coherence (WC), and Power Wavelet Coherence (PWC) methods to investigate the interactions between several uncertainty indices and Bitcoin price. The authors used the Geopolitical Risk Index, the US EPU index, the Volatility Uncertainty Index (VIX), and the Crude Oil Volatility

Index (OVX) as the uncertainty measures. Al-Yahyaee et al. (2019) found that the correlation between Bitcoin and the uncertainty proxies depends on the horizon under investigation and that the Bitcoin-VIX nexus is affected by the US EPU, Geopolitical Risk, and OVX across different frequencies. The results also indicated the predictive power of VIX on Bitcoin return at different frequencies. Kyriazis (2020) also confirmed the positive impact of VIX and the negative effect of Geopolitical risk on Bitcoin return. Jareño et al. (2020) indicated that VIX and the Saint Louis financial stress index (STLFSI) negatively affect Bitcoin return in most quantiles; however, the VIX has more explanatory power. Bouri et al. (2017) used wavelet-based quantile-in-quantile regression to investigate the World VIX (WVIX) interactions as a proxy for the global uncertainty with Bitcoin returns. Bouri et al. (2017) confirmed the negative relationship between uncertainty and Bitcoin returns and suggested the potential of Bitcoin as a hedging alternative against the uncertainty.

Moreover, Kalyvas et al. (2020) employed uncertainty and behavioral factors to explore their potential effect on the Bitcoin price crash risk. The uncertainty factors consisted of the US implied volatility index (VIX) and EPU, and the behavioral factors included Buzz and a sentiment measure. The results indicated that the higher level of uncertainty is associated with the lower level of Bitcoin price crash risk and, therefore, Bitcoin can hedge the uncertainty. The authors also found a weaker association between the behavioral factors and the crash risk. Koutmos (2018b) addressed the liquidity uncertainty in the Bitcoin market using a Markov regime-switching model. Koutmos (2018b) indicated that the power of the relationship among the uncertainty and several microstructure variables deteriorated during the high uncertainty regime. Ghabri et al. (2021) used a family of multivariate GARCH-type models to scrutinize the potential effect of Bitcoin on liquidity risk. The empirical results showed that adding Bitcoin to a traditional assets portfolio reduces the downside liquidity risk and improves the Sharpe ratio. In addition, this study also documented the efficient role of Bitcoin for hedging purposes. Gozgor et al. (2019) found a positive correlation between Trade Policy Uncertainty Index (TPI) and Bitcoin returns. Gozgor et al. (2019) also supported the change in the sign of the correlation during the regime changes. French (2021) used Bayesian Vector Auto-Regression Analysis (BVAR) to examine Bitcoin return and Twitter-based Market Uncertainty index (TMU). The empirical results suggested the impact of TMU on Bitcoin return with a more potent effect during the Covid-19 pandemic. Jiang et al. (2020) indicated the presence of predictive power of US equity uncertainty for Bitcoin returns in the short term.

The degree to which the prices in financial markets react to news and sentiment could vary from one market to another. However, almost in all financial markets, prices are affected by news and the sentiment factor directly or indirectly. Thus, studies that scrutinize the role of sentiment and news in financial markets gain significance due to their potential for revealing more information about price formation in the respective markets. Bitcoin price has appeared to be highly responsive to the sentiments. Hence, the investigation of the sentiment and news impact on Bitcoin price has formed another strand in the literature. Goczek and Skliarov (2019) claimed that supply and demand as one of the market forces do not similarly affect the Bitcoin price as the traditional currencies are affected. However, the authors suggested Bitcoin's popularity as the key driver of Bitcoin price. Makrichoriti et al. (2016), using Vector Auto-Regressive (VAR) methodology, concluded that the investors' sentiment was one of the Bitcoin price determinants. They also suggested that idiosyncratic factors mainly affect

Bitcoin price. Polasik et al. (2015) employed Ordinary Least Squares (OLS) and Tobit estimations and found the sentiment expressed in newspaper reports and the number of total Bitcoin transactions as the drivers of Bitcoin returns. Corbet et al. (2017) suggested that the news associated with GDP and Consumer Price Index (CPI) do not affect the Bitcoin returns, while the news related to durable goods and the unemployment rate had a significant relationship with Bitcoin return. Karalevicius et al. (2018) supported the relationship between media sentiment and Bitcoin price. The authors concluded that semi-short-run Bitcoin price movements could be predicted with the assist of the expert media. Ahn and Kim (2019), using different Textual sentiment analyses, showed that disagreement in investors' sentiment leads to a high level of Bitcoin volatility and price jump. Pyo and Lee (2020) explored the potential effect of the Federal Open Market Committee (FOMC), the employment rate, CPI, and producer price index (PPI) announcements on Bitcoin price. The authors found the impact of FOMC announcements on Bitcoin price. In contrast, they did not support the significant effect of the employment rate, CPI, and PPI announcements on Bitcoin price. Rognone et al. (2020), using high-frequency data, indicated that intra-day positive and negative news about Bitcoin positively affected Bitcoin returns and, based on that, concluded the presence of enthusiasm among Bitcoin users. However, the authors found that cryptocurrency cyber-attack news decreased the enthusiasm and negatively affected the Bitcoin return.

It is well-documented in the literature that Bitcoin can be influenced through the channel of the internet platform. Polasik et al. (2015) and Kapar and Olmo (2020) postulated the impact of Google search volume on Bitcoin. Panagiotidis et al. (2018) underscored Google search intensity as an important Bitcoin's price driver using

LASSO methodologies. Baig et al. (2019) revealed that Google searches for the keyword “Bitcoin” and Bitcoin price clustering have a positive association. Ibikunle et al. (2020) showed that the level of Google searches for the keyword “Bitcoin” is a crucial driver of the noise component in Bitcoin price. Katsiampa et al. (2019) used Google search volume regarding the name of several cryptocurrencies (including Bitcoin) as a proxy for information demand. The authors found that Bitcoin return on the previous day does not affect the information demand flow; however, the Bitcoin volume on the previous day influences the information demand. Nasir et al. (2019) found a positive and short-run relationship between Google trends and Bitcoin return. Subramaniam et al. (2019) also confirmed that the rise in the Google search volume index would lead to the higher Bitcoin return at an expansionary state. Dastgir et al. (2019) applied a Copula-based Granger causality test to examine the causality between Bitcoin return and Google searches for Bitcoin (Bitcoin attention). The authors mainly found a bidirectional Granger causality between variables in the right and left tails. Chen et al. (2020) constructed a new proxy, based on Google, to capture the impact of the fear sentiment associated with the Covid-19 on Bitcoin. The authors suggested that fear negatively impacts Bitcoin return, while it positively influences trading volume. Oad Rajput et al. (2020) constructed a new Bitcoin-related sentiment index (BSI) based on the Google search volume and investigated the BSI impact on Bitcoin return, volume, and volatility. The empirical findings revealed a negative association between BSI and Bitcoin volatility and a positive association between BSI and other variables.

Additionally, Sabalionis et al. (2020) indicated that, compared to the number of tweets and Google search interest regarding Bitcoin, the number of active addresses on the Blockchain is the most significant factor impacting Bitcoin price. Phillips and Gorse

(2018) derived several factors from Reddit (Posts per day, new authors, and subscriber growth) and showed their predictive power on Bitcoin in the long run. Ciaian et al. (2015) found that search volumes on Wikipedia about Bitcoin had no impact on its price in the long term. Besides the predictive role of online forums in the Bitcoin market (Mai et al., 2015), and the impact of Twitter has also been uncovered in the literature. Mai et al. (2015) suggested that the bullish and bearish Tweets of Twitter users with a high number of followers affect Bitcoin returns in the next hour. The authors of Garcia et al. (2014) also included online sources in their study. Using VAR model, the authors found two positive feedback loops: social cycle and user adoption cycle. The former involves feedback between Bitcoin search volume, price, and word of mouth, while the latter indicates the feedback between Bitcoin price, search volume, and the number of new Bitcoin users. Kraaijeveld and De Smedt (2020) also concluded that Twitter sentiment could help predict Bitcoin returns, while Tweet volume did not have predictive power for Bitcoin returns. Bouri and Gupta (2021) employed EURQ based on Google trends and EPU. After standardizing the logarithm transformation of both EURQ and EPU to have unit variance, the authors applied the EGARCH model and found the relatively more robust power of EURQ than EPU in predicting Bitcoin returns.

This research investigates the relationship between Bitcoin, EURQ, and MUI at different levels. Even though the relationship between Bitcoin and uncertainty has been investigated through different proxies, most of these proxies are not uniquely driven by uncertainty (Jurado et al., 2015) and fail to measure the pure uncertainty shocks properly. Furthermore, to the best of my knowledge, the existing uncertainty measures in the Bitcoin literature mainly capture political aspects of uncertainty or do not differentiate between the concept of uncertainty and volatility. By selecting MUI as an uncertainty proxy, I aim to avoid mentioned deficiencies and capture pure uncertainty shocks in the whole economy as much as possible. In terms of selecting EURQ as a proxy, Bouri and Gupta (2021) is the closest to this study. In Bouri and Gupta (2021), the EGARCH model was applied to investigate the relationship between Bitcoin returns, EPU, and EURQ. However, in this research a quantile-based analyses were conducted. This method provides a broader view of the variables' dynamics and interactions, hence this research extends Bouri and Gupta (2021). In summary, the current study in terms of proxy selection and econometric methodology is different from the previous studies in the literature.

Chapter 3

METHODOLOGY

This section briefly describes the methodology used in the present study. This section is categorized into three general parts: Unit root tests, Cointegration tests, and Granger causality tests.

3.1 Unit root tests

To examine the presence of unit root in the series, I begin the analysis with well-known tests of Augmented Dickey-Fuller (ADF) (Dickey-Fuller,1979), Augmented Dickey-Fuller Generalized Least Squares (ADF-GLS) (Elliott et al., 1996), and Zivot-Andrews (ZA) (Zivot and Andrews, 1992). Subsequently, the quantile unit root test proposed by Koenker and Xiao (2004) was applied to further the investigation of unit root behavior. The quantile unit root test is an extension of the ADF test but it is based on quantile autoregression (QAR). In contrast with the conventional unit root tests, which generally build on conditional mean, the quantile unit root test enables us to investigate process persistence within different ranges of conditional quantiles. QAR framework can address the systematic alteration in shape, scale, and location of conditional distributions caused by conditioning variables and provides robust inference. Galvao (2009) extended Koenker and Xiao (2004) by including stationary covariates and a linear deterministic trend. Following Galvao (2009), I add a linear time trend to Koenker and Xiao's (2004) model and explore the mean-reverting patterns through different quantiles. Let us consider the following ADF representation with a drift term and deterministic trend:

$$y_t = \beta_0 + \beta_1 t + \alpha_1 y_{t-1} + \sum_{j=1}^{q} \alpha_{j+1} \Delta y_{t-j} + u_t \quad (1)$$

The $\tau\ th$ quantile of y_t given its past information set $\mathcal{F}_{t-1}^{Y} \in \mathbb{R}^m$ can be written as :

$$Q_{y_t}(\tau|\mathcal{F}_{t-1}^{Y}) = \beta_0(\tau) + F^{-1}(\tau) + \beta_1(\tau)\, t + \alpha_1(\tau)\, y_{t-1} + \sum_{j=1}^{q} \alpha_{j+1}(\tau)\, \Delta y_{t-j} \quad (2)$$

Where $\mathcal{F}_{t-1}^{Y} := (y_{t-1}, y_{t-2}, \dots \dots \dots . y_{t-m})', \alpha_j(\tau)$ and $\beta_i(\tau)$ are unknown deterministic functions mapping $\tau \in [0,1] \to R$, and $F(.)$ denotes c.d.f of $\{u_t\}$.

To save space, it is possible to rewrite Eq. (2) as follows:

$$Q_{y_t}(\tau|\mathcal{F}_{t-1}^{Y}) = z_t'\, \delta(\tau) \quad (3)$$

Where

$z_t = \left(1, t, y_{t-1}, \Delta y_{t-1}, \dots, \Delta y_{t-q}\right)', \delta(\tau) = \left(\mu_0(\tau), \beta_1(\tau), \alpha_1(\tau), \dots ., \alpha_{q+1}(\tau)\right)'$, and considering that $\mu_0(\tau) = F^{-1}(\tau) + \beta_0(\tau)$. To estimate eq. (3) the following minimization problem should be solved:

$$\widehat{\delta(\tau)} = argmin_{\,\delta \in R^{q+3}} \sum_1^n \rho_\tau(y_t - z_t' \delta(\tau)) \quad (4)$$

Where $\rho_\tau(k) = k \times (\tau - I(k < 0))$ is an asymmetrically weighted loss function (check function) as in Koenker and Besset (1978), and $I(.)$ is an indicator function. I am interested in the value of the persistence parameter $\alpha_1(\tau)$ to test the null hypothesis of unit root $H_0: \alpha_1(\tau) = 1$ at respective conditional quantiles where under the alternative hypothesis, y_t exhibits trend stationary characteristics. Consequently, I estimate the value of $\alpha_1(\tau)$ in $\tau\ th$ conditional quantiles where $\tau \in \{0.05, 0.10, \dots, 0.95\}$. Following Koenker and Xiao (2004) and Galvao (2009), I employ t-ratio $t_n(\tau)$ as test statistic; $t_n(\tau)$ has a non-standard limiting distribution, and calculate the critical values using the resampling procedure.

$$t_n(\tau) = \frac{f(\widehat{F^{-1}(\tau)})}{\sqrt{\tau(1-\tau)}} \left(\lambda_{-1}' P_\Delta\, \lambda_{-1}\right)^{1/2} \left(\widehat{\alpha_1(\tau)} - 1\right) \quad (5)$$

Where $F(.)$ and $f\ (.)$ denote c.d.f and p.d.f of $\{u_t\}$ respectively, λ_{-1} is the vector of lagged dependent variables (y_{t-1}) and P_Δ is a projection matrix onto the space orthogonal to $\phi = \left(1, t, \Delta y_{t-1}, \dots, \Delta y_{t-q}\right)$.

3.2 Cointegration tests

If the linear combination of integrated time series with the same orders of c has an integration order of $c^* < c$, the time series are cointegrated. The cointegration test of Johansen (1991, 1995) is applied to the following Vector Error Correction Model (VECM):

$$y_t = \alpha + \beta\, x_t + \sum_{j=1}^{g} \Pi_j\, y_{t-j} + \sum_{j=1}^{h} \gamma_j\, x_{t-j} + u_t \tag{6}$$

Xiao (2009) introduced quantile cointegration based on the intuition behind Engle and Granger's (1978) residual-based cointegration model. The quantile cointegration accounts for conditional heteroskedasticity, and cointegrating vector(s) may be time-varying. That is, quantiles of shocks in each period can influence the value of cointegrating coefficients. Xiao's (2009) quantile cointegration analysis was performed to verify the long-run co-movement of processes within conditional quantiles. Also the stability test of Xiao (2009) was conducted to verify the constancy of cointegrating coefficients over a sequence of quantiles (τ). The importance of the test is in that it allows us to unveil the state-dependency of the model. The null hypothesis is H_0: $\theta(\tau) = \theta$, where $\theta(\tau)$ is the variable cointegrating vector, and θ is a vector of unknown constants. Following Xiao (2009), the least squares estimator of $\theta\ (\hat{\theta}\ )$ was applied; thus it is possible to utilize Kolmogoroff-Smirnoff test statistic $SUP_\tau\, |\widehat{V_n}(\tau)|$ where SUP_τ denotes supremum norm and $\widehat{V_n}(\tau) = n\ (\hat{\theta}\ (\tau) - \hat{\theta}\ )$. Asymptotic distribution of $SUP_\tau\, |\widehat{V_n}(\tau)|$ is non-standard, and the critical values for the test statistic was calculated by conducting 1000 Monte Carlo iterations.

The preliminary cointegration regression is specified as:

$$y_t = \alpha + \beta_t' x_t + u_t \tag{7}$$

Where $x_t \in R^v$ is a vector of integrated regressors. If x_t is not weakly exogenous due to the potential correlation between regressors and u_t, quantile regression estimator will suffer from second-order bias. Xiao followed the idea of Saikkonen (1991) and included lags and leads of the regressors' first difference as one of the available solutions to rule out the potential endogeneity in the model. The model with lags and leads is described as:

$$y_t = \alpha + \beta_t' x_t + \sum_{j=-k}^{k} \Delta x_{t-j}' \Pi_j + \varepsilon_t \tag{8}$$

And the $\tau\, th$ quantile of y_t conditional on $\phi_t = \sigma\{x_t, \Delta x_{t-j}, \forall j\}$ is:

$$Q_{y_t}(\tau|\phi_t) = \alpha(\tau) + \beta'(\tau)\, x_t + \sum_{j=-k}^{k} \Delta x_{t-j}' \Pi_j + F^{-1}(\tau) \tag{9}$$

Then, quadratic terms of regressors are included. Hence, the final quantile cointegration model is given by:

$$Q_{y_t}(\tau|\phi_t) = \alpha(\tau) + \beta'(\tau) x_t + \gamma'(\tau) x_t^2 + \sum_{j=-k}^{k} \Delta x_{t-j}' \Pi_j + \sum_{j=-k}^{k} \Delta x_t^{2'} \Gamma_j + F^{-1}(\tau) \tag{10}$$

3.3 Granger causality test

I denote the vectors containing accumulated information generated by series $y_t, x_t, and\ both$ up to period $t-1$ as $\mathcal{F}_{t-1}^{Y} \in \mathbb{R}^m$, $\mathcal{F}_{t-1}^{X} \in \mathbb{R}^n$, $and\ \mathcal{F}_{t-1} = (\mathcal{F}_{t-1}^{Y}{}', \mathcal{F}_{t-1}^{X}{}')' \in \mathbb{R}^{m+n}$, respectively. Following Granger (1969, 1980), the null hypothesis of Granger non-causality from x_t to y_t is defined as follows:

$$H_0: F(y_t|\mathcal{F}_{t-1}) = F(y_t|\mathcal{F}_{t-1}^{Y}) \tag{11}$$

Or equivalently:

$$H_0: Q_{y_t}(\tau|\mathcal{F}_{t-1}) = Q_{y_t}(\tau|\mathcal{F}_{t-1}^{Y}), \text{ a.s. } \forall \tau \in \wp \subset [0,1] \tag{12}$$

Where $F(y_t|.)$ and $Q_{y_t}(\tau|.)$ represent the conditional distribution and $\tau\, th$ conditional quantile of y_t. Put differently; Granger non-causality indicates that the past information of x_t does not affect the conditional distribution of y_t given $\mathcal{F}_{t-1}^{Y}$, thus,

$F(y_t|\mathcal{F}_{t-1}^{Y})$ does not depend on $\mathcal{F}_{t-1}^{X}$. Granger causality can demonstrate time-precedence such that under Granger causality, one can states that lagged value(s) of x_t can help predict the future of y_t. In empirical practices, one might observe Granger causality in some quantiles, while it might not hold in the whole distribution. Hence, exploring Granger causality in quantiles could be more informative about the degree of the non-causality. This section briefly describes the quantile Granger causality test of Troster (2016).

Using the definition of quantiles and properties of indicator functions, I express the implication of Eq. (11) in the form of the following mean restriction problem:

$$\mathbb{E}\left\{I\left(y_t \leq Q_{y_t}(\tau|\mathcal{F}_{t-1})\right) \middle| \mathcal{F}_{t-1} \right\} = \mathbb{E}\left\{I\left(y_t \leq Q_{y_t}(\tau|\mathcal{F}_{t-1}^{Y}) \right) \middle| \mathcal{F}_{t-1} \right\} = \tau\,,$$

$$a.s\ \forall\tau \in \wp \subset [0,1] \tag{13}$$

And we have:

$$H_0:\ \mathbb{E}\left\{I\left(y_t \leq Q_{y_t}(\tau|\mathcal{F}_{t-1}^{Y}) \right) \middle| \mathcal{F}_{t-1} \right\} = \tau \tag{14}$$

Troster (2016) assumes that the parametric model $M\left(\mathcal{F}_{t-1}^{Y}, \theta_0(\tau)\right) \in \mathcal{M} = \left\{M\left(.,\theta(\tau)\right)\middle|\ \theta(.): \tau \to \theta(\tau) \in \Theta \subset \mathbb{R}^p, \forall\tau \in \wp\right\}$ determines $Q_{y_t}(\tau|\mathcal{F}_{t-1}^{Y})$ for all $\tau \in \wp$ correctly. To be more specific, the three following models are specified:

$$M_1\left(\mathcal{F}_{t-1}^{Y}, \theta_0(\tau)\right) = \rho_0(\tau) + \rho_1(\tau)\, y_{t-1} + F^{-1}(\tau)$$

$$M_2\left(\mathcal{F}_{t-1}^{Y}, \theta_0(\tau)\right) = \rho_0(\tau) + \rho_1(\tau)\, y_{t-1} + \rho_2(\tau)\, y_{t-2} + F^{-1}(\tau)$$

$$M_3\left(\mathcal{F}_{t-1}^{Y}, \theta_0(\tau)\right) = \rho_0(\tau) + \rho_1(\tau)\, y_{t-1} + \rho_2(\tau)\, y_{t-2} + \rho_3(\tau)\, y_{t-3} + F^{-1}(\tau)$$

By applying Lemma 1 in Escanciano (2006) and considering the model M, Troster (2016) developed Eq. (14) into the following null hypothesis:

$$H_0:\ \mathbb{E}\left\{ \left[I\left(y_t \leq M\left(\mathcal{F}_{t-1}^{Y}, \theta_0(\tau)\right)\right) - \tau \right] \exp(i\,\omega'\,\mathcal{F}_{t-1}) \right\} = 0$$

With: $\exp(i\,\omega'\,\mathcal{F}_{t-1}) = \exp\left(i\,[\omega_1(y_{t-1}, x_{t-1})', \ldots, \omega_s(y_{t-s}, x_{t-s})']\right)$ (15)

Where $i^2 = -1$, and $\omega \in \mathbb{R}^z$ with $z \leq m + n$ belongs to a standard normal distribution.

Based on (14) and some regulating conditions as in Troster (2016), the test statistic is derived as:

$$s_t = \int_{\wp} \int_{\mathcal{W}} |v_T(\omega, \tau)|^{\,2} \, dF(\omega) \, dF(\tau) \tag{16}$$

$v_T(\omega, \tau) := T^{-1/2} \sum_{t=1}^{T} \{ \, [\, I \left(\, y_t \, \leq \, M \, \left(\mathcal{F}_{t-1}^{Y}, \hat{\theta}_0(\tau) \right) \right) - \, \tau \,] \, \exp(i \, \omega' \, \mathcal{F}_{t-1} \,) \, \}$ with $\hat{\theta}_0(\tau)$ as $\sqrt{T}$- consistent estimator of $\theta_0(\tau)$. Furthermore, $F(\omega)$ and $F(\tau)$ indicate the distributions of ω and the quantiles, respectively.

The test statistic distribution is asymptotically non-pivotal, and the critical values are generated by applying the subsampling procedure. Troster (2016) follows Sakov and Bickel (2000) and selects $b = \left[kT^{2/5} \right]$ as subsample size for each of $B = T - b + 1$ subsamples, where k is a constant parameter and [.] denotes the floor function.

Chapter 4

DATA AND EMPIRICAL FINDINGS

In this section, the data is introduced, and after that, the empirical findings are presented. For the empirical investigation, in this research MATLAB, Stata, EViews, and R programs were utilized.

4.1 Data

This research considers Bitcoin Price (BTC) (quoted in USD), the Macroeconomic Uncertainty Index (MUI), and Economic Uncertainty Related Queries (EURQ) in their logarithmic form. The sample period covers from September 2010 to June 2020. The ending date is due to the data availability for MUI, and the frequency of data is monthly, with 118 observations for each variable. The monthly frequency was selected due to the data availability for MUI.

Nakamoto (2008) proposed Bitcoin as decentralized virtual money which benefits from an open-source, peer-to-peer network. New Bitcoins are created under the "mining" process by miners; however, there is a limited number of 21 million Bitcoins accessible. Even though there are more than 4500 cryptocurrencies as of February 2021 (Coinmarketcap, 2021), I turn my focus on Bitcoin as the leading cryptocurrency with the highest market capitalization as of April 2021 (Coinmarketcap, 2021). The historical prices of Bitcoin were collected from Quandl (https://www.quandl.com).

MUI provides an econometric estimate of uncertainty based on the methodology used in Jurado et al. (2015). The procedure is based on the proposition that, in the process of decision-making, the predictability of the economy outweighs the variability of an economic indicator per se. Accordingly, it suggests eliminating the predictable components in the quantification of the uncertainty in the macroeconomic series. Hence, the MUI strives to distinguish between predictable components and unpredictable shocks. MUI is a forecast-based measure of uncertainty with different time horizons (one month, three months, and twelve months). Since Bitcoin price is highly subject to short-term uncertainties, the shortest time horizon available for MUI (one month) were employed to investigate the impacts of macroeconomic uncertainty. The data for MUI were downloaded from Sydneyludvigson (https://www.sydneyludvigson.com).

Bontempi et al. (2021) proposed EURQ, which builds on Google trends to measure internet search volume about the topics associated with uncertainty. In contrast with media-based measures of uncertainty, EURQ mainly concentrates on the uncertainty perceived by economic agents by tracking their reactions to uncertainty through online searches. Hence, this variable provides an indicator of change in people's sentiment about uncertainty. Such sentiment changes are usually driven by financial, political, macro-real, or normative factors. EURQ also traces the economic 'agents' need for more information. As a search-based measure, it holds the potential to reveal more personal information than surveys, especially when the rate of the insincere or/and no-responses in the surveys are high (Da et al., 2015). For the case of the USA, Bontempi et al. (2021) selected 184 queries closely related to 210 search keywords used in the news-based EPU of the Baker et al. (2016) and developed the EURQ based on the individuals' queries perspective. The data of EURQ for the US was obtained from the Policyuncertainty website (https://www.policyuncertainty .com). Furthermore, given the seasonal patterns in EURQ, the series were adjusted for seasonality.

As the final part of the current sub-section, I consider the graphs of each time series to gain preliminary knowledge about the dynamics and behavior of the variables.

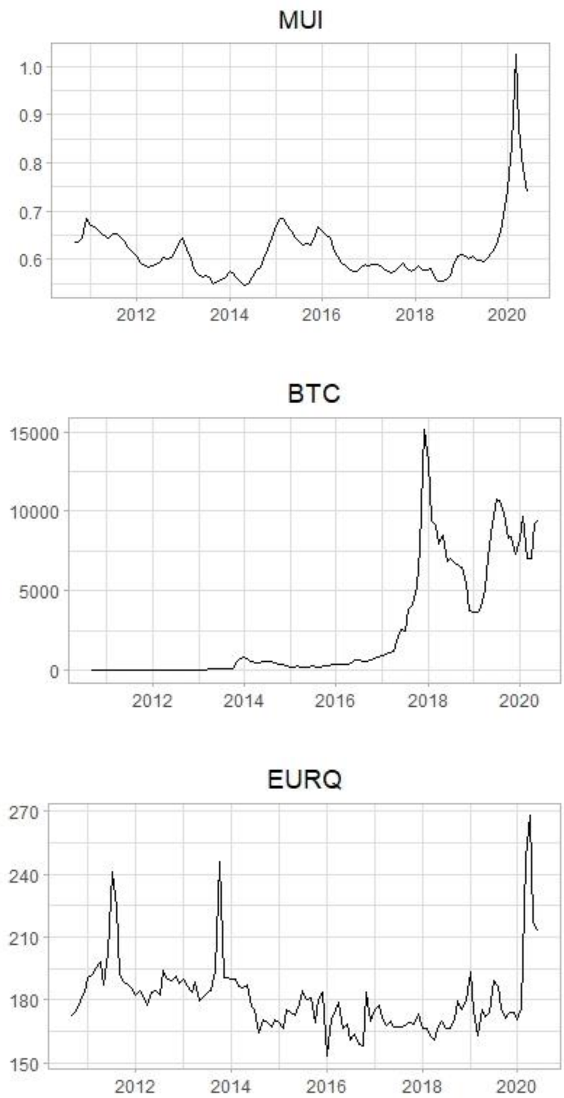

Figure 1a: The plot of each time series at the level.

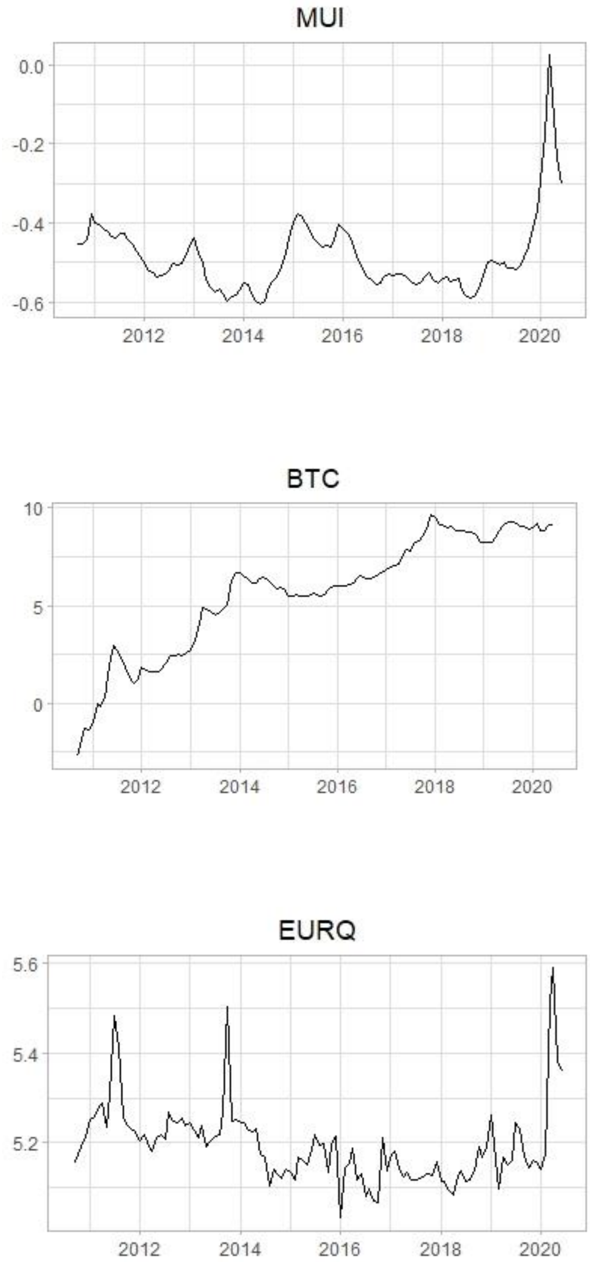

Figure 1b: The plot of the logarithmic transformation of each variable.

According to Figure 1b, BTC exhibits an upward trend. Furthermore, a considerable rise in EURQ and MUI starting from December 2019 is evident. This increase could be associated with the rising uncertainty during the early pandemic period. However, as we reach the last months in the sampled period, both uncertainty measures decrease. Also, several outliers are discernible for variables. The existence of outliers might undermine the estimation and inference power in the traditional time series analysis.

The quantile analysis framework alleviates this problem since it offers a more robust framework.

Table 1 presents the descriptive statistics for all variables in logarithmic form. The Pearson product-moment correlation coefficient (Pearson,1948) is also included in Table 1 to measure the strength of the potential linear association between variables. Pearson's correlation framework reports an insignificant correlation between BTC and MUI, a negative correlation between BTC and EURQ, and a positive linear relationship between EURQ and MUI. The positive association between EURQ and MUI aligns with my initial expectation about the positive relationship between uncertainty and search for information. However, the negative correlation between BTC and EURQ is unexpected. This finding might be related to a violation of Pearson's correlation test assumptions. According to Table 1, the variables are skewed, and the excess kurtosis is not zero in any of the three cases. The test of Jarque and Bera (1980) examines the normality of data where the joint null hypothesis assumes that excess kurtosis and skewness are statistically zero. The Jarque-Bera test results in Table 1 display the rejection of normality for all three variables at the 5% significance level.

Table 1. The descriptive statistics and pairwise correlations results

	MUI	***BTC***	***EURQ***
Mean	-0.487	5.657	5.195
Median	-0.508	6.130	5.183
STD	0.094	3.009	0.089
Skewness	2.304	-0.751	1.833
Kurtosis	11.148	2.780	8.018
MAX	0.024	9.623	5.590
MIN	-0.607	-2.713	5.032
Jarque-Bera	430.771^{***}	11.332^{**}	189.836^{***}
Correlations			
MUI	1.000		
BTC	-0.056	1.000	
EURQ	0.451^{**}	-0.251^{**}	1.000

- (***) and (**) denote rejection of the null hypothesis at the 1% and 5% significance level, respectively.

The departure from Gaussian distribution in the variables highlights the need for a robust framework such as the quantile regression framework. Besides, the Pearson correlation coefficient is sensitive to outliers and might not perform accurately in the presence of the outliers. Consequently, the Copula method to investigate the dependency of variables is applied further. The Maximum-Likelihood methodology is used to fit various families of Copulas, and the Copula with the lowest Akaike Information Criterion (AIC) (Akaike, 1973) is selected. For BTC vs. MUI, I fit rotated Tawn type 1 (90 degrees) as an extension of Gumbel Copula and a rotated BB8 (90 degrees) for BTC vs. EURQ.

Finally, a Joe Copula for the case of EURQ vs. MUI is fitted. Subsequently, 1000 samples from each Copula is simulated to calculate Kendall's tau and Spearman's rank correlation coefficients. Table 2 indicates consistent results with the Pearson correlation coefficient for BTC vs. EURQ and EURQ vs. MUI at the 5% significant level. For BTC and MUI, Table 2 reports a significant negative relationship at the 5% level, which corroborates the theoretical expectations.

Table 2. Kendall's tau and Spearman rank correlations results

	BTC vs. MUI	***BTC vs. EURQ***	***EURQ vs. MUI***
Kendall’s tau	-0.182**	-0.277**	0.192**
Spearman	-0.266**	-0.410**	0.283**

- (**) denotes rejection of the null hypothesis at the 5% significance level.

4.2 Empirical findings

Table 3 demonstrates the test statistic for traditional unit root tests. The null hypothesis for all three tests is that the series contains a unit root. ADF and ADF-GLS test results support the presence of unit root in BTC and MUI at the level. However, for EURQ, the null hypothesis is rejected at the level. A maximum lag length of 13 was allowed for the endogenous variable in both tests and the best model was selected according to Schwarz Information Criterion (SIC) (Schwarz, 1978). I also observe that both tests reject the presence of unit root in the first difference of the variables. Hence, I conclude the stationarity of the variables at their first difference. Zivot-Andrews (ZA) test examines the null hypothesis allowing for a potential endogenous structural break in the series. As seen in table 3, the ZA test suggests consistent results with ADF and ADF-GLS tests for all variables.

Table 3. Standard unit root tests results

	ADF	*ADF-GLS*	*ZA*
MUI (Level)	-2.952	-2.898	-4.352
MUI (The first difference)	-7.177**	-7.016**	-6.419**
BTC (Level)	-3.337	-1.445	-3.956
BTC (The first difference)	-7.131**	-6.501**	-7.824**
EURQ (Level)	-4.301**	-4.046**	-6.179**
EURQ (The first difference)	-10.876**	-10.707**	-11.184**

- (**) denotes rejection of the null hypothesis at the 5% significance level.
- Both intercept and deterministic trends for all three tests are considered.
- A maximum lag length of 13 was allowed for the endogenous variable.

Unit root was further analyzed by employing the quantile unit root test. Under the non-normality of data, the test is efficient and more robust than traditional least square-based unit root tests (Koenker and Xiao, 2004). Table 4 exhibits the quantile unit root test results considering nineteen evenly spaced conditional quantiles of each variable. For each variable in Table 4, there are three elements: Alpha, t-stat, and CV. Alpha represents the estimated values of $\alpha_1(\tau)$ at respective quantiles (τ), t-stat displays the test statistic $t_n(\tau)$ and CV is the critical value at the 5% significance level. For MUI, the null hypothesis of a unit root is rejected in $\tau = 95\%$ and the quantiles lower than the median (except for τ =5%). BTC in higher and lower quantiles exhibits high persistency. Finally, EURQ shows unit root behavior only in a few quantiles, and it has mean-reverting properties in other quantiles. Also, in comparison with the other variables, the dynamic behavior of EURQ is less asymmetric. Furthermore, considering the tails of the conditional distributions, all variables contain unit root in the lowest (5%) and the highest quantiles (95%) except for MUI, for which the presence of unit root at τ =95% is rejected.

Table 4. Quantile unit root test results

	MUI			*BTC*			*EURQ*		
τ	**Alpha**	**t-stat**	**CV**	**Alpha**	**t-stat**	**CV**	**Alpha**	**t-stat**	**CV**
0.05	0.764	3.823	-2.310	0.932	1.236	-2.936	0.342	5.029	-2.310
0.1	0.790	-5.3923**	-2.564	0.955	-0.898	-2.806	0.393	-6.7324**	-2.512
0.15	0.777	-5.9883**	-2.779	0.946	-1.175	-2.717	0.519	-5.4901**	-2.628
0.2	0.826	-4.6445**	-2.977	0.928	-2.556	-2.907	0.533	-6.0636**	-2.617
0.25	0.828	-5.8953**	-3.098	0.919	-3.0165**	-2.874	0.617	-5.8206**	-2.767
0.3	0.856	-5.0286**	-3.268	0.934	-2.722	-3.018	0.602	-6.2223**	-2.708
0.35	0.882	-4.3162**	-3.315	0.923	-3.5611**	-3.098	0.589	-7.1657**	-2.854
0.4	0.891	-3.7974**	-3.364	0.899	-4.4749**	-3.178	0.628	-6.5568**	-2.968
0.45	0.882	-4.6076**	-3.410	0.896	-4.8449**	-3.142	0.658	-7.1806**	-3.003
0.5	0.893	-3.338	-3.410	0.888	-4.8690**	-3.195	0.706	-5.8050**	-2.850
0.55	0.897	-3.138	-3.410	0.897	-3.7417**	-3.259	0.706	-6.1382**	-2.975
0.6	0.927	-1.916	-3.410	0.895	-3.3366**	-3.212	0.746	-5.2540**	-2.849
0.65	0.951	-1.177	-3.410	0.917	-2.387	-3.271	0.747	-3.9239**	-2.928
0.7	0.986	-0.305	-3.410	0.921	-1.834	-3.327	0.739	-3.2016**	-3.011
0.75	1.050	0.952	-3.410	0.903	-1.801	-3.285	0.790	-2.590	-2.935
0.8	1.102	1.697	-3.410	0.877	-2.085	-3.329	0.790	-1.931	-3.093
0.85	1.162	2.256	-3.137	0.901	-1.554	-3.356	0.836	-0.551	-2.937
0.9	1.203	3.353	-2.848	0.930	-0.655	-3.159	1.004	0.009	-2.659
0.95	1.323	-4.3177**	-2.346	0.928	1.069	-2.916	0.981	0.149	-2.856

- (**) denotes rejection of the null hypothesis at the 5% significance level.

Table 5 includes the result of Johansen's (1991, 1995) cointegration test. The test can estimate the number of linear long-run relationship(s) among variables. According to Table 3, EURQ does not show unit root behavior. Hence, Johansen's test results for EURQ is not reported. Based on both Trace and Eigenvalue statistics, there is no evidence of a cointegrating relationship between BTC and MUI.

Table 5. Johansen's cointegration test results

	Trace Statistic ***(CV=15.41)***	***Max eigenvalue statistic*** ***(CV=14.07)***
BTC vs. MUI	14.128	9.682

- CV represents the critical value for the test at the 5% significance level.

I continue the analysis with the quantile cointegration framework. The quantile cointegration approach allows for different adjustment mechanisms towards the long-run equilibrium; thus, cointegration coefficients could vary over the quantiles. In particular, if one supposes the dependency of cointegrating coefficients on the innovation term, the coefficients can vary over the quantiles of the innovation term. Hence, depending upon the magnitude of the shocks, the coefficients could be different. Table 6 indicates the test statistic and critical values for the constancy test of Xiao (2009), in which the null hypothesis assumes the stability of cointegration coefficients over the sequence of the quantiles under investigation. For BTC vs. EURQ, the null hypothesis for both coefficients is rejected. For BTC vs. MUI, the results suggest rejecting the null hypothesis for β at 10%, while the constancy of γ is rejected at the 5% significance level. In contrast, there is no evidence against the coefficients' stability for EURQ vs. MUI.

Table 6. Xiao's constancy test results

Model	*Coefficient*	$SUP_{\tau}\,|\widehat{V_n}(\tau)|$	*CV 1%*	*CV 5%*	*CV 10%*
BTC vs. EURQ	β	111509.880***	34260.734	23407.750	18246.635
	γ	10507.449***	2761.888	1622.677	1032.323
BTC vs. MUI	β	7565.196*	15133.713	8168.906	6231.802
	γ	9101.327**	16173.382	8803.967	6498.592
EURQ vs. MUI	β	162.423	732.368	440.003	343.495
	γ	158.346	742.238	466.232	348.173

- (***), (**) and (*) denote rejection of the null hypothesis at 1%, 5%, and 10% significance levels, respectively.
- $\mathrm{SUP}_{\tau}\,|\widehat{\mathrm{V}_{\mathrm{n}}}(\tau)|$ is the test statistic, and CV N% denotes the test critical value at the N% significance level.

Table 7 reports the estimated values of β and γ in the cointegration model for different quantiles. Most of the estimated coefficients for BTC vs. EURQ are significant if I set the significance level as 10%. The long-run relationship of the BTC and EURQ in the extreme quantiles ($\tau = 5\%, 95\%$) is significant at 1% or higher, and there exists a quadratic long-run relationship between these two variables. The results also imply that when the shocks' magnitude is extremely high or low, the cointegration between BTC and EURQ is more powerful. For BTC vs. MUI, the estimated βs are not generally significant at 5%, which is consistent with the results of Table 5. However, the model reveals a significant non-linear relationship at $\tau = 5\%, 90\%$. Even though the coefficients' stability for EURQ vs. MUI cannot be rejected, the estimated coefficients are reported. Apart from EURQ vs. MUI, the sign of the estimated coefficients does not change over the quantiles.

Table 7. Quantile cointegration model results

	BTC vs. EURQ		BTC vs. MUI		EURQ vs. MUI	
τ	***β***	***γ***	***β***	***γ***	***β***	***γ***
0.05	-1227.790***	115.329***	104.772***	141.722***	1.793**	1.517*
0.1	-	-	-	-	-	-
0.15	-	-	-	-	-	-
0.2	-	-	-	-	-	-
0.25	-	-	-	-	-	-
0.3	-	-	-	-	-	-
0.35	-	-	-	-	-	-
0.4	-	-	-	-	-	-
0.45	-	-	-	-	-	-
0.5	-	-	-	-	-	-
0.55	-	-	-	-	-	-
0.6	-	-	-	-	-	-
0.65	-	-	25.166	42.138*	-	-
0.7	-	-	25.672	42.587*	-	-
0.75	-884.647*	83.018*	21.055	38.566*	0.029	-0.084
0.8	-783.477*	73.657*	19.922	37.526*	-0.015	-0.056
0.85	-712.782*	66.760*	19.835	39.951**	-0.205	-0.335
0.9	-361.215	33.629	26.322*	48.554***	-0.337	-0.520
0.95	-384.700***	35.962***	-	-	-	-

- (***), (**) and (*) denote rejection of the null hypothesis at 1%, 5%, and 10% significance level, respectively.

I initiate the examination of Granger causality with the traditional linear test of Granger causality in mean. Table 8 presents the F-statistic for the test, and the null hypothesis is Granger non-causality. According to the results, there is a bidirectional causality between the rate of change in MUI and EURQ at the 1% significance level. In contrast, the test does not suggest Granger causal relationship for other cases.

Table 8. Granger causality in mean (F-test) results

	$\Delta MUI \nRightarrow \Delta BTC$	$\Delta EURQ \nRightarrow \Delta BTC$	$\Delta BTC \nRightarrow \Delta MUI$	$\Delta EURQ \nRightarrow \Delta MUI$	$\Delta BTC \nRightarrow \Delta EURQ$	$\Delta MUI \nRightarrow \Delta EURQ$
F-stat	0.72716	2.6396	1.6818	11.211***	2.0421	17.858***

- (***) denotes rejection of the null hypothesis at the 1% significance level.
- The maximum lag length of 13 is allowed.

It should be noted that Granger causality in the mean, as one of the quantiles, does not necessarily imply the causality in the whole distribution. In addition, although the rejection of causality in the mean provides a sufficient condition for the rejection of causality in the entire distribution, it is possible to find Granger causality in some quantiles. Therefore, the Granger causality tests in quantiles can provide more comprehensive information about the causal relationship among variables. Thus, the quantile Granger causality test of Troster (2016) is employed. Tables 9, 10, and 11 indicate the subsampling p-values for the Granger causality test. A linear specification of conditional quantiles with different lags of the dependent variables is considered.

Table 9 displays that when the first lag or both first and second lags of Bitcoin returns (ΔBTC) are included in the model, the variations in the Macroeconomic Uncertainty Index (ΔMUI) and Economic Uncertainty Related Queries (ΔEURQ) Granger cause Bitcoin returns in higher and lower quantiles. Nevertheless, when I include up to three lags of ΔBTC, the number of quantiles at which the rate of change for MUI and EURQ Granger cause the Bitcoin fluctuations diminish. Table 9 shows no Granger causality running from ΔMUI and ΔEURQ to ΔBTC in the median and close neighborhood.

Moreover, I observe that the null hypothesis of Granger non-causality across all quantiles is rejected when I consider the lag=1, 2 and that there is no causality in the higher tail of the distributions (τ = 95%).

Table 9. P-values for the quantile Granger causality test

	$\Delta MUI \nRightarrow \Delta BTC$			$\Delta EURQ \nRightarrow \Delta BTC$		
	Lag					
τ	***1***	***2***	***3***	***1***	***2***	***3***
[0.05: 0.95]	0.011**	0.011**	0.079	0.011**	0.011**	0.079
0.05	0.011**	0.045**	0.056	0.011**	0.045**	0.056
0.1	0.090	0.090	0.011**	0.090	0.090	0.011**
0.15	0.011**	0.011**	0.247	0.011**	0.011**	0.247
0.2	0.011**	0.011**	0.067	0.011**	0.011**	0.067
0.25	0.023**	0.124	0.258	0.023**	0.124	0.258
0.3	0.112	0.618	0.258	0.112	0.618	0.247
0.35	0.629	0.180	0.393	0.629	0.180	0.393
0.4	0.730	0.090	0.708	0.708	0.090	0.708
0.45	0.899	0.820	0.820	0.888	0.787	0.798
0.5	0.483	0.663	1.000	0.494	0.652	0.955
0.55	0.191	0.169	0.292	0.191	0.191	0.292
0.6	0.011**	0.202	0.258	0.011**	0.236	0.258
0.65	0.011**	0.011**	0.225	0.011**	0.011**	0.225
0.7	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
0.75	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
0.8	0.090	0.011**	0.090	0.090	0.011**	0.090
0.85	0.112	0.101	0.124	0.112	0.101	0.124
0.9	0.270	0.202	0.303	0.281	0.202	0.315
0.95	0.067	0.517	0.079	0.067	0.584	0.079

- The figures represent the estimated p-values for the Granger causality test where no Granger causality from ΔX to ΔY is denoted as (ΔX ⇏ ΔY).

- (**) denotes rejection of no Granger causality (null hypothesis) at the 5% significance level.

Excluding $\tau \in \{45\%, 50\%, 95\%, \text{and } 55\% \text{ for lag=2}\}$, Table 10 provides evidence of Granger causality. Hence, suggesting the general predictive power of Bitcoin returns and the growth rate of EURQ for MUI fluctuations.

Table 10. P-values for the quantile Granger causality test

	$\Delta BTC \nRightarrow \Delta MUI$			$\Delta EURQ \nRightarrow \Delta MUI$		
	Lag					
τ	***1***	***2***	***3***	***1***	***2***	***3***
[0.05: 0.95]	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
0.05	0.011**	0.011**	0.023**	0.011**	0.011**	0.023**
0.1	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
0.15	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
0.2	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
0.25	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
0.3	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
0.35	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
0.4	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
0.45	0.787	0.832	0.303	0.854	0.820	0.506
0.5	0.933	0.416	0.461	0.854	0.405	0.449
0.55	0.045**	0.101	0.011**	0.034**	0.101	0.011**
0.6	0.034**	0.023**	0.011**	0.034**	0.023**	0.011**
0.65	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
0.7	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
0.75	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
0.8	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
0.85	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
0.9	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**

0.95	0.348	0.449	0.258	0.348	0.449	0.258

- The figures represent the estimated p-values for the Granger causality test where no Granger causality from ΔX to ΔY is denoted as (ΔX ⇏ ΔY).
- (**) denotes rejection of no Granger causality (the null hypothesis) at the 5% significance level.

Eventually, the p-values in Table 11 characterize the Granger causation of ΔBTC and ΔMUI for ΔEURQ in higher and lower quantiles. On the contrary, when it comes to the largest quantile, no causality to ΔEURQ exists.

Table 11. P-values for the quantile Granger causality test

	ΔBTC⇏ ΔEURQ			***ΔMUI ⇏ ΔEURQ***		
	Lag					
τ	***1***	***2***	***3***	***1***	***2***	***3***
[0.05: 0.95]	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
0.05	0.169	0.180	0.011**	0.146	0.180	0.011**
0.1	0.011	0.056	0.011**	0.011**	0.056	0.011**
0.15	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
0.2	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
0.25	0.011**	0.023**	0.011**	0.011**	0.023**	0.011**
0.3	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
0.35	0.011**	0.079	0.056	0.011**	0.011**	0.056
0.4	0.202	0.596	0.629	0.202	0.517	0.584
0.45	0.596	0.876	0.517	0.629	0.899	0.562
0.5	0.214	0.169	0.169	0.258	0.202	0.326
0.55	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
0.6	0.011**	0.011**	0.011**	0.011**	0.034**	0.034**
0.65	0.011**	0.011**	0.011**	0.034**	0.056	0.045**
0.7	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
0.75	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**

0.8	0.011^{**}	0.011^{**}	0.011^{**}	0.011^{**}	0.011^{**}	0.011^{**}
0.85	0.011^{**}	0.011^{**}	0.011^{**}	0.011^{**}	0.011^{**}	0.011^{**}
0.9	0.011^{**}	0.011^{**}	0.011^{**}	0.011^{**}	0.023^{**}	0.011^{**}
0.95	0.360	0.371	0.292	0.236	0.360	0.281

- The figures represent the estimated p-values for the Granger causality test where no Granger causality from ΔX to ΔY is denoted as ($\Delta X \nRightarrow \Delta Y$).
- (**) denotes rejection of no Granger causality (the null hypothesis) at the 5% significance level.

To compare the obtained empirical results with other existing studies in the literature, it should be noted that MUI considers the simultaneous uncertainty in 132 indicators as in Ludvigson and Ng (2010) to account for the uncertainty in the whole economy. Hence, even if it might share some common factors with other uncertainty measures, it will be intrinsically different from other proxies used in the literature. This research is among the studies investigating the predictive power of the economy-related uncertainty proxies regarding the Bitcoin return. Demir et al. (2018) and Koumba et al. (2019) corroborated the predictive role of the US Economic Uncertainty Policy (EPU) on Bitcoin return, while Cheng and Yen (2020) did not reinforce the predictive role of the US EPU. I employed a different economy-related uncertainty proxy (MUI) and found the predictive power of the rate of change in MUI on some quantiles of the Bitcoin return. In the sense that the findings also indicate that the economy-related uncertainty proxies can help predict Bitcoin return, the results are in line with Demir et al. (2018) and Koumba et al. (2019).

Bouri and Gupta (2021) applied the EGARCH model to investigate the relationship between EURQ, EPU, and Bitcoin return as the response variable. The estimations suggested a positive and significant coefficient for the first lag of EURQ's standardized log-transformation in the mean equation. However, using the quantile cointegration analysis, I found a statistically significant non-linear relationship between EURQ and BTC only in the extreme quantiles with a negative sign for the coefficient of the linear component (β) and a positive sign for the coefficient of the non-linear component (γ). Besides, the findings reveal another dimension of the BTC-EURQ relationship by supporting the predictive role of the ΔEURQ for the extremely low and upper quantiles of the ΔBTC.

Chapter 5

CONCLUSION

This thesis investigated the relationship between Bitcoin monthly returns, variations in online searches for uncertainty-related topics, and the fluctuations in macroeconomic uncertainty. To this end, both conventional and quantile-based econometrics methods were applied. The empirical findings indicate that the quantile-based unit root, cointegration, and Granger causality tests provide more detailed and somewhat different results from conventional ones. The quantile unit root test shows that, except for the 95% quantile of MUI, all variables are nonstationary in the tails of the conditional distribution. I found evidence against the stable cointegration coefficient of the conventional cointegration test. The quantile cointegration test results suggest quadratic and non-linear relationships for some quantiles of the distributions. To be more specific, the extremely low and high quantile of Bitcoin price demonstrated a long-run non-linear relationship with EURQ. The quantile Granger causality test shows that the changes in MUI and EURQ Granger cause Bitcoin returns (ΔBTC) for the lower tails of the distribution. Granger causality is also running from ΔBTC and ΔEURQ to ΔMUI and the Granger causality running from ΔBTC and ΔMUI to ΔEURQ in several of the low and high quantiles.

The empirical findings reported in this thesis serve several implications, particularly for Bitcoin investors. Mainly, the empirical results suggest that, under some market conditions, the rate of changes for both uncertainty shocks in the economy and the volume of online searches about uncertainty-related topics can be listed as the predictors of the Bitcoin monthly returns in the investment analyses. Of the main interest, when the expectations from the Bitcoin market signify a highly bearish condition, the fluctuations in MUI and EURQ contain information for financial analysis and risk management. Besides, the empirical results imply the long-run co-movement between Bitcoin prices and each of two other variables in the period of highly bearish cryptocurrency market conditions. Specifically, the sign of the cointegration relationship between Bitcoin and macroeconomic uncertainty suggests that the value investors can benefit from the rise in uncertainty in their long-term investments when the prices are too low. Furthermore, in the highly bearish or bullish market, the shocks to Bitcoin price have a permanent effect. In contrast, the shocks have a transitory impact in a more normal market condition and disappear over time. This fact should be considered for designing investment strategies such as pair trading strategy. As many of the portfolio and risk managers are interested in the tails risk, the information unveiled about the dynamic and stochastic properties of the distributions' tails can also help improve Bitcoin's risk modeling.

The impact of Covid-19 on the interactions between uncertainty and the cryptocurrency markets can be of great significance for the investment decision-making process. In this study, I managed to include some aspects of such impact. However, the thorough investigations call for more data belonging to the pandemic and the ex-post period, which is not available at this time. Furthermore, this study can be extended by considering Bitcoin price volatility to provide more information about the interactions between Bitcoin's risk and different dimensions of the uncertainty. One can also include one-month and twelve-month time horizons for the MUI to capture other aspects of the Bitcoin-uncertainty relationship. A similar framework can also be applied to examine the Granger causality in quantiles of other cryptocurrencies with MUI and EURQ.

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