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How Does Bitcoin React to Economic Uncertainty Volatility Shocks?

Bachelor's thesis

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Declaration of Authorship

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Prague, August 2, 2022

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Abstract

This thesis explores the volatility connectedness between Bitcoin and economic uncertainty. We aim to model reactions of Bitcoin's volatility to shocks in economic uncertainty to uncover whether Bitcoin can provide protection from an economic unrest. The uncertainty is assessed from the media-based Economic Policy Uncertainty (EPU) Index, the market-based VIX Index and the public-based Economic Queries Related Uncertainty (EURQ) Index. Using the dynamic network connectedness measure, it is possible to track the time evolution of directional volatility spillovers in each time point of our dataset spanning from April 2015 to February 2022. Our results show several significant periods when Bitcoin receives volatility spillovers from economic uncertainty. However, in most cases, the effect is weak. One exception is the COVID-19 crisis, during which Bitcoin forms a substantial volatility connectedness with the VIX Index. We also show that before 2020, Bitcoin reacts to several shocks driven by the EPU Index. Further, amid inflation fears at the end of 2021, the volatility spillovers mainly originate from the EURQ Index.

Keywords	Bitcoin, economic uncertainty, network structure, volatility spillover
Title	How Does Bitcoin React to Economic Uncertainty Volatility Shocks?

Abstrakt

Tato práce zkoumá propojenost volatility Bitcoinu a ekonomické nejistoty. Naším cílem je ukázat jak volatilita Bitcoinu reaguje na šoky do volatility ekonomické nejistoty a zjistit, zda Bitcoin může poskytnout ochranu před ekonomickou nejistotou. Nejistota je popsána indexem nejistoty hospodářské politiky vnímané médii (EPU), tržním indexem VIX a veřejností vnímané nejistoty měřené vyhledáváním ekonomických termínů souvisejících s nejistotou na webové stránce Google (EURQ). Pomocí dynamické síťové propojenosti je možné sledovat časový vývoj směrových přelévání volatility v každém časovém bodě našeho zkoumaného období od dubna 2015 do února 2022. Naše výsledky ukazují několik významných období, kdy Bitcoin přijímá volatilitu z ekonomické nejistoty. Ve většině případů je však tento účinek slabý. Jedna výjimka je krize COVID-19, během níž Bitcoin vytváří významnou vazbu volatility s indexem VIX. Ukazujeme také, že před rokem 2020 Bitcoin reaguje na několik šoků vyvolaných indexem EPU. Dále, uprostřed obav z inflace na konci roku 2021, přelévání volatility pochází především z indexu EURQ.

Klíčová slova Bitcoin, ekonomická nejistota, síťová struktura, přelévání volatility

Název práce Jak Bitcoin reaguje na období zvýšené volatility ekonomické nejistoty?

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Acronyms

API Application Programming Interface

BTC Bitcoin

ECB European Central Bank

EPU Economic Policy Uncertainty Index

ETF Exchange Traded Funds

EURQ Economic Uncertianty Related Queries Index

FED Federal Reserve System

FOMC Federal Open Market Committee

FRF Frequency Response Function

MPU Monetary Policy Uncertainty Index

QBLL Quasi-Bayesian Local-Likelihood

RV Realized Volatility

SPX Standard's & Poors 500 Stock Market Index

STL Seasonal Trend Loess

TVP-VAR Time-Varying Parameter Vector Autoregression

VIX Chicago Board Options Exchnage Volatility Index

VMA Vector Moving Average

Chapter 1

Introduction

Bitcoin whitepaper was released by Nakamoto (2008) during times of great uncertainty. The fall of Lehman Brothers created a large uncertainty shock that propagated throughout the financial sector and led to the Great Recession (Kenourgios & Dimitriou 2015). Bitcoin indirectly reacts to the large contagion effects in the financial world by being able to function independently of governments and banks. Such independence may establish Bitcoin as a financial asset that is not linked to the uncertainty surrounding the standard financial system.

Several studies discuss spillover effects from financial markets, crude oil, gold and currencies to Bitcoin (Guo *et al.* 2021; Ozturk & Cavdar 2021). A large body of literature also exists on the topic, closely related to contagion effects, of Bitcoin possessing hedging or diversifying characteristics against stock market indices (Shahzad *et al.* 2019; Kristoufek 2020). However, very little has been written about the direct effects of economic uncertainty on Bitcoin. This thesis aims to fill this gap by constructing a dynamic volatility network consisting of Bitcoin and three uncertainty indexes.

Diebold & Yilmaz (2012) introduced measurement of volatility spillover by estimating forecast-error variance decompositions, which shows how much of future uncertainty in asset j is caused by shocks in asset k, from the generalized vector autoregressive model (VAR). Barunik & Krehlik (2018) further argue that shocks differ based on different time frequencies, hence extend the Diebold & Yilmaz (2012) framework by adding horizon-specific connectedness, i.e. allowing to differentiate between short-, medium- and long-term connections. Recently, Barunik & Ellington (2020) elaborated on previous methods and defined a frequency-depended dynamic network framework based on a time-varying vector autoregression (TVP-VAR) that allows to estimate connectedness measures at each time point, unlike the traditional approaches that gauge time dynamics by using moving windows. This feature offers to precisely track and identify shocks within an observed period. Further, the (quasi) Bayesian approach to parameters estimation enables to construct confidence intervals of network measures.

Therefore, we employ Barunik & Ellington (2020) framework to explore the volatility connectedness between Bitcoin and economic uncertainty. We select three indexes to describe economic uncertainty. Each addresses the uncertainty from a different point of view – the Economic Policy Uncertainty Index, created by Baker *et al.* (2016), is based on media coverage of economic policy uncertainty-related words. The VIX Index is known to indicate financial market fear that stems from the market participants' expected uncertainty. Lastly, we construct a daily index of the EURQ Index developed by Bontempi *et al.* (2021) to assess the public perception of uncertainty.

Although Bitcoin is still a developing asset[1] its market capitalization reached 1.27 trillion USD in 2021 – putting Bitcoin among the top 20 stocks with the highest market capitalization. Companies mining new Bitcoins are entering the stock market, Tesla and Microstrategy are the most known companies to put Bitcoin on their balance sheets. El Salvador has made Bitcoin its legal tender - the first country in the world to make Bitcoin an official currency (Alvarez *et al.* 2022). Also, the first Bitcoin Exchange Traded Funds (ETF), which can attract broader public interest in investing in Bitcoin, are being issued (Todorov 2021). Hence, Bitcoin's integration into the traditional financial system as well as the real economy is becoming notable and a better understanding of the contagion effects from several uncertainty indexes can help investors in selecting the right investment strategy as well as regulators in issuing new regulations.

This thesis is structured as follows. Chapter 2 provides a description of relevant literature. Chapter 3 describes the data collection process as well as any data transformation that was done. The first part of Chapter 4 explains the motivation behind the selection of the Dynamic Network framework, which is then described and selected parameters for model estimation are presented. Chapter 5 provides results and puts them into context. Chapter 6 then summarizes and concludes the thesis.

[1]The exact definition of Bitcoin is not fully clear, although it was developed with the goal of being a payment system. Its true nature seems to resemble a financial asset (Corbet *et al.* 2018)

Chapter 2

Literature Review

2.1 Bitcoin

Bitcoin is a decentralized payment system created by Nakamoto (2008) that works on a peer-to-peer network. The design of the network allows users to send or accept payments without a need for any overlook by a central authority. The security is maintained through solving computationally demanding puzzles by so-called miners. As a reward for the computational power consumed, miners obtain newly issued Bitcoins (approx. every 10 minutes). The amount is based on the predefined number that halves every four years. The first reward was 50 Bitcoins, currently, it is 6.25 BTC. Next halving is expected to happen at the beginning of 2024. The supply is limited to 21 million coins. To modify certain Bitcoin features require a majority agreement among the network's users.

The literature on Bitcoin is quickly expanding and gaining attention of more scholars, however it still remains relatively unexplored. Härdle *et al.* (2020) provides a comprehensive overview of the main research areas of cryptocurrencies. A lot of attention is drawn to the placement of Bitcoin into the typical financial world (Baur *et al.* 2018). The name of cryptocurrencies might be a bit misleading, as Bitcoin seems to have closer to a financial speculative asset than currency (Corbet *et al.* 2018). A large focus is on the ability of Bitcoin to act as a diversifier during turbulent market times, similarly as Gold (Shahzad *et al.* 2019; Urquhart & Zhang 2019; Gkillas & Longin 2019; Guesmi *et al.* 2019). The parallel between Bitcoin and Gold mainly stem from the fact that Bitcoin, just like gold, has a limited supply and new coins can not be created out of thin air, but has to be mined. Bitcoin is thus sometimes referred to as Digital gold. This idea prevailed until the COVID-19 bear market, when Bitcoin failed to act as a safe-haven (Conlon & McGee 2020; Kristoufek 2020). The contagion effect from financial markets to Bitcoin vary across different time periods and increased significantly during the COVID-19 crisis as documented by Guo *et al.* (2021) and Wang *et al.* (2022) find. Other body of literature also stresses the high volatility of cryptocurrencies (Zhang & Li 2020; Dutta & Bouri 2022), thus to properly account for any movements, we collect high-frequency data for Bitcoin prices in form of 5 minutes intervals. In this thesis, using the dynamic network framework, we explore the risk contagion among Bitcoin and uncertainty in each time point from 2015 to 2022. Hence, each shock bearing a contagion effect can be specifically identified and described.

2.2 EPU Index

Baker, Bloom, & Davis (2016) developed a news-paper-based economic policy index, which observes articles in pre-selected newspapers. An article relevant to EPU Index is recognized as follows: It must contain at least one word related to economy, policy, and uncertainty categories. The number of relevant articles is counted and rescaled to produce a quantifiable index. For most countries, the index is created on a monthly basis. The reason for it, stated by Baker *et al.* (2016), is that usually not enough articles exist to produce a meaningful daily or weekly count. However, the US EPU index is also computed daily, thanks to the Newsbank aggregator covering around 1,500 US newspapers. This amount of daily news offers sufficient quantity to create a daily index. The daily US EPU Index correlates at 0.85 with the monthly US EPU Index. Thus, it is producing relatively similar results to the monthly index. This thesis will use the daily US EPU Index since it allows to conduct a more precise analysis, especially when considering the high volatility of the Bitcoin market.

Since its introduction, EPU Index has drawn considerable academic attention. The quantifiable changes in economic policy uncertainty recorded by the index open the door to numerous analyses. Many studies focus on a linkage between EPU and the stock market. Pástor & Veronesi (2012) analyzed how changes in government policy affected stock prices and concluded that policy changes should increase volatilities and correlation among stocks and stock prices should fall on average with announcements of policy change. Subsequent studies used the EPU index, and the main results are that the EPU index has a negative effect on stock returns, an increase in EPU index leads to increased volatility and that the EPU index poses certain predictability powers. Liu & Zhang (2015) observed that higher economic policy uncertainty leads to an increase in stock price volatility. Further, adding the EPU index into the volatility models can improve its forecasting accuracy. Phan *et al.* (2018) made an extensive evidence study on the predictability of stock market excess returns by the EPU index and found plausible evidence that the EPU index can predict stock excess returns. Another body of literature is focusing on a predicting volatility of stock market by the EPU Index (He *et al.* 2020), global stock market risk (Tsai 2017), stock-bond correlation (Li *et al.* 2015) and probability of US recession based on the EPU Index (Karnizova & Li 2014).

Though most of the studies concern the stock market, the EPU index is also applied to other fields of economy. Shoag & Veuger (2016) state that local policy uncertainty resembles unemployment during the Great Recession. Balcilar *et al.* (2015) controls for economic policy uncertainty to improve forecasts of US inflation. Baker *et al.* (2016) found that sizable effects of economic policy uncertainty exist on stock price volatilities, investment rates, and employment growth.

The EPU index seems to be relevant for many economic and financial variables. It can be helpful for investors, policymakers as well as for regulators. However, to our knowledge, only a scarce literature exists on Bitcoin relationship with the EPU Index. Most studies focus on predicting the price or volatility of Bitcoin by the EPU Index (Demir 2018; Cheng & Yen 2020). Demir (2018) find that the EPU Index can predict Bitcoin returns and a quantile on quantile regression further shows that the relationship is positive during increased time of uncertainty, suggesting that Bitcoin can serve as a diversifier under uncertainty shocks. These results are consistent with (Bouri *et al.* 2017; Wang *et al.* 2020).

Further studies investigate the connection on a local level. For instance, Cheng & Yen (2020) found out that China's EPU index can predict BTC volatility, while the United States', Japan's, and Korea's EPU indexes can not. Shaikh (2020) also worked with countries' EPU indexes and concluded that overall, the USA and Japan EPU indexes have a negative effect on returns, while China's positive. However, as in other studies, the effects are opposite in extreme times of uncertainty. Also, the author includes MPU (Monetary Policy Uncertainty Index), which is estimated to be significant and negative.

2.3 VIX Index

Chicago Board Options Exchange Volatility Index (VIX) represents another index that tries to capture market risk and investor sentiment. This index measures the expectation of volatility of the S&P index in the short term (30 days) based on index options since 1993. As it is believed that more volatility in the market price signalizes higher fear among market participants, the VIX index is also called the "fear index." The higher the index's value, the higher the market volatility and thus more uncertainty in the market.

The calculation of the VIX index includes call and put SPX options within an expiration period between 23 and 37 days and risk-free treasury bill interest rates. A calculation specified in the CBOE (2021) computes the expected average 30-day implied volatility of the S&P index.

Several studies are already focusing on the relationships between Bitcoin and the VIX index. Bouri *et al.* (2017) studied the relationship between VIX and Bitcoin volatility during the 2013 bitcoin crash and found an inverse relationship between Bitcoin and the VIX index. López-Cabarcos *et al.* (2021) found out that Bitcoin volatility behaves differently across time. In periods with higher VIX volatility, Bitcoin can be used as a safe haven, but when VIX is more stable, bitcoin becomes more attractive to speculation. Al-Yahyaee *et al.* (2019) also studied the relationship between bitcoin and the VIX index in time frequency space with wavelet coherence and found that the VIX index can have the power to predict the price of Bitcoin. The same result was also obtained in another study done by Fang *et al.* (2019). Guo *et al.* (2021) explore the contagion effects from VIX Index to Bitcoin and finds that the pre- and post-COVID periods substantially differ – Bitcoin is relatively independent from VIX Index before the COVID-19 shock.

2.4 EURQ Index

Google Trends ability to measure public interest by a search volumes has draw significant attention of a wide range of study fields. Google Trends data appears to possess a decent predictive powers, which motivates scholars to many applications – forcasting stock movements and returns (Bulut 2018; Hamid & Heiden 2015; Hu *et al.* 2018; Salisu *et al.* 2021; Preis *et al.* 2013), predicting a private consumption (Woo & Owen 2019), modeling investor demand around earnings announcements (Drake *et al.* 2012), predicting public desease (Verma *et al.* 2018; Cervellin *et al.* 2017).

Bontempi, Frigeri, Golinelli, & Squadrani (2021) developed the EURQ index that measures a volume of uncertainty-related searches. The authors of the EURQ Index address important problems in gauging uncertainty based on search queries. One of the problems is that the relation of a search of an uncertainty-related term might not always be caused by an increase in uncertainty but only by sole interest in a given term. Bontempi *et al.* (2021) provides the term "European Central Bank" as an example - it can be searched to obtain a view of the ECB on a debt crisis, thus an uncertainty related or because of individual, extemporaneous research interest in ECB that is not uncertainty-related. To mitigate this problem, authors carefully choose 184 word terms in order to reflect changes in perceived uncertainty. For instance, word term such as "tax rate" which is likely to be seasonally affected and searched in a way that is unrelated to uncertainty. Authors of the EURQ Index use a term "tax rate" $-$ "calculator", where the $-$ sign, in a Google trends methodology, means that results contain searches with "tax rate" but exclude searches with "calculator", hence removing a possibility of searching for "tax rate calculator", which is expected to not be related to uncertainty. Moreover, the 184 terms are closely related to the terms used in the media-based EPU Index. Thus, the EURQ should provide information on how the public perceives the uncertainty instead of the media.

Google Trends are known to suffer from a sampling error due to the fact that the Trends is compiled from only unknown fraction of searches (Steegmans 2021). However, Bontempi *et al.* (2021) uses terms that are expected to have a large search volume, thus potentially a lower variance. Furthermore all the 184 terms are summed together, so the effect of sampling error may be averaged out. Consequently, it is not adjusted for the Google Trends sampling error as it is assumed to be only minor.

Kristoufek (2013) was among the first to investigate the relationship between Bitcoin price and an interest in searches of the word Bitcoin. The results indicates that an increase in Bitcoin search volume increases its price. More recent paper from Arratia & López-Barrantes (2021) finds the same patter, however stress that it changes over time.

In this paper, we use Google Trends to gauge the public perception of uncertainty and by measuring volatility spillovers we assess how shocks are transmitted in our network of variables in time.

Chapter 3

Data

This thesis examines the volatility connectedness of Bitcoin, a leading cryptocurrency, the Economic Policy Uncertainty Index, the VIX Index and the EURQ Index. Bitcoin prices, the EPU Index, VIX Index and the EURQ Index dataset spans from April 10th, 2015 to February 23th, 2022.

Table 3.1: Descriptive Statistics

sample size = 1723	BTC	EPU	VIX	EURQ
Min	0.000	0.127	9.140	0.033
Mean	0.002	0.479	17.90	0.107
Median	0.001	0.477	15.84	0.101
Max	0.110	0.953	82.71	0.351

Note: This table displays the mean, median and standard deviation for the volatility of Bitcoin and three uncertainty indexes. The observed time period spans from April 2015 to February 2022.

3.1 Bitcoin

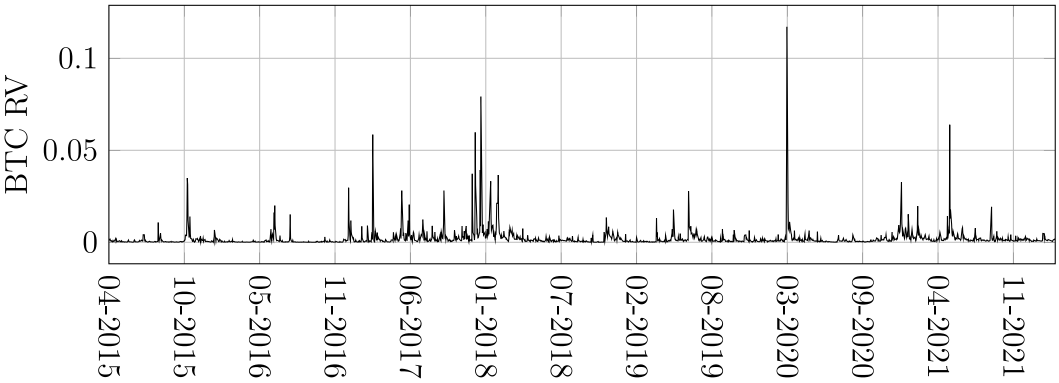
The data on Bitcoin prices in 5 minutes intervals were obtained from `www.tradingview.com` WebSocket[1] API. We transform the Bitcoin price data and the S&P 500 data to daily realized volatility in the following way:

$$RV_t = \sum_{i=1}^{T} \log \left(\frac{P_{t,i}}{P_{t,i-1}} \right)^2$$

[1]We extend on the following GitHub repository `https://github.com/rushic24/tradingview-scraper` on accessing data from www.tradingview.com by allowing to download more than 500 time points.

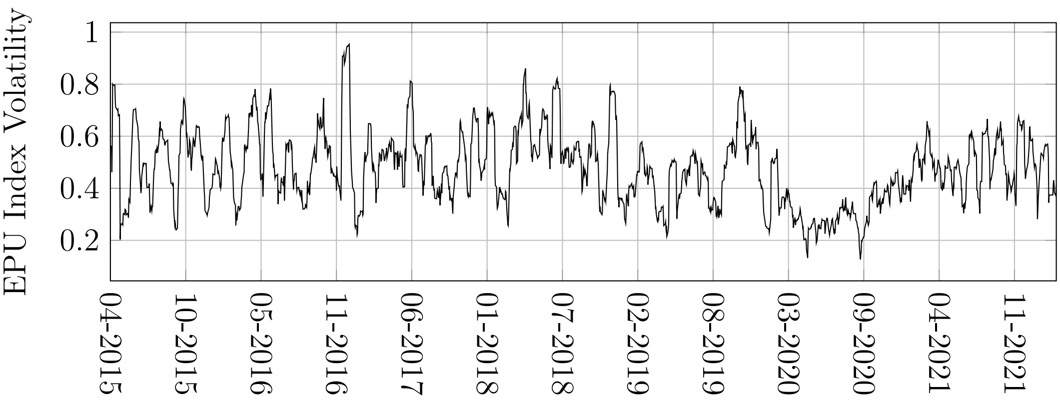
where RV_t is the realized volatility for a given day, T represents the total number of intraday observations and $p_{t,j}$ is the closing price of the jth partition on a day t. As is common in financial literature, we use log returns as they typically follow a normal distribution (see Fergusson & Platen 2006). The day for a Bitcoin price is partitioned into 5 minutes intervals, from 00:00-24:00, following our dataset of 5-minutes Bitcoin prices and the fact that Bitcoin is traded non-stop.

Figure 3.1: Realized Volatility of Bitcoin



Note: The figure shows realized volatility computed from 5 min Bitcoin price data from April 2015 to February 2022.

Figure 3.2: Volatility of the Economic Policy Uncertainty Index



Note: The figure plots the volatility of the EPU Index in the time period April 2015 – February 2022.

As can be seen in Figure 3.1, the volatility of Bitcoin experienced several shocks. A long time of high uncertainty can be noticed at the end of 2017 when Bitcoin reached that all-time high of nearly 20,000$ and subsequently crashed to less than 11,000$. Further, the highest volatility of 0.11 is recorded during the COVID-19 period.

3.2 Uncertainty indexes

In this thesis, three uncertainty indexes are used. First, we use the Economic Policy Uncertainty (EPU) Index, which measures the uncertainty about economic and policy action from the media point of view. Secondly, the CBOE Volatility Index (VIX index) is a measure of market uncertainty stemming from the implied volatility of S&P 500 options. Moreover, Google Trends Uncertainty Index, a search-based index, uncovers how the public perceives uncertainty. The following three subsections provide information on how data for each index were obtained.

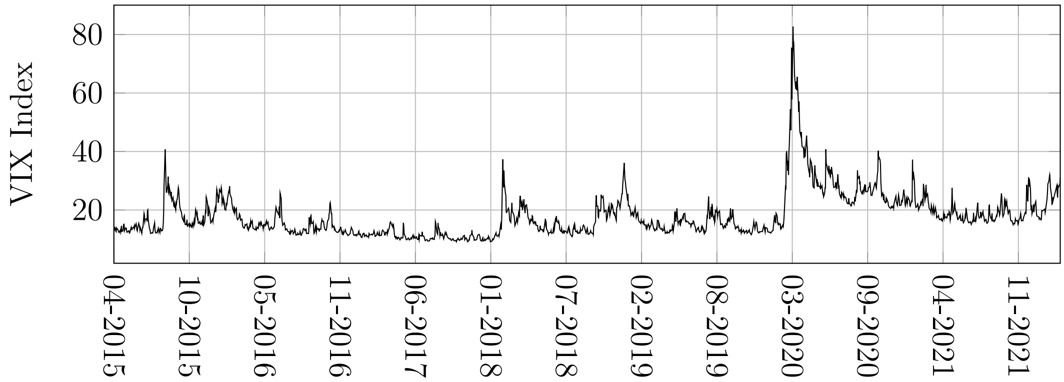
3.2.1 EPU Index

The economic policy uncertainty index is retrieved from https://www.policyuncertainty.com. The website is run by Baker *et al.* (2016). We use the US EPU index, which is computed daily. The global EPU index is only calculated on a monthly scale and thus does not provide the desired frequency for our analysis. The daily EPU Index, however, experiences many fluctuations and sudden drops to low values from day to day with no particular trend. That effect is pervasive in tranquil times. The reasons for it could be attributed to counting words from newspaper articles. When economic policy-related words are not under substantial interest, the word volumes are driven more by randomness or other events unrelated to uncertainty. When the volatility was calculated as the square root of log returns, the results were very misleading. Hence, we estimate volatility as a 14-day rolling standard deviation of log returns.

3.2.2 VIX Index

The VIX index daily values were collected from the Chicago Board Options Exchange website. As for S&P 500, the VIX index is computed on a business day resulting in a total of 1723 observations. The VIX Index itself describes volatility, hence we do not transform it in any way.

Figure 3.3: CBOE Volatility Index (VIX)



Note: In this figure, the VIX Index values are depicted, ranging from April 2015 to February 2022.

3.2.3 Google Trends Uncertainty Index

The EURQ index is computed every month, however, for this thesis analysis, day observations are more suitable. Therefore we use the EURQ Index search terms and compute daily values. Although data from Google trends are easily accessible[2], two characteristics set by Google complicate the creation of a daily index for a long time period.

1st Characterichts The time-frequency of search values is set by Google and is based on the observed time period (Table 3.2).

2nd Characterichts The results are scaled by a maximum number of searches of a given term in an observed time period.

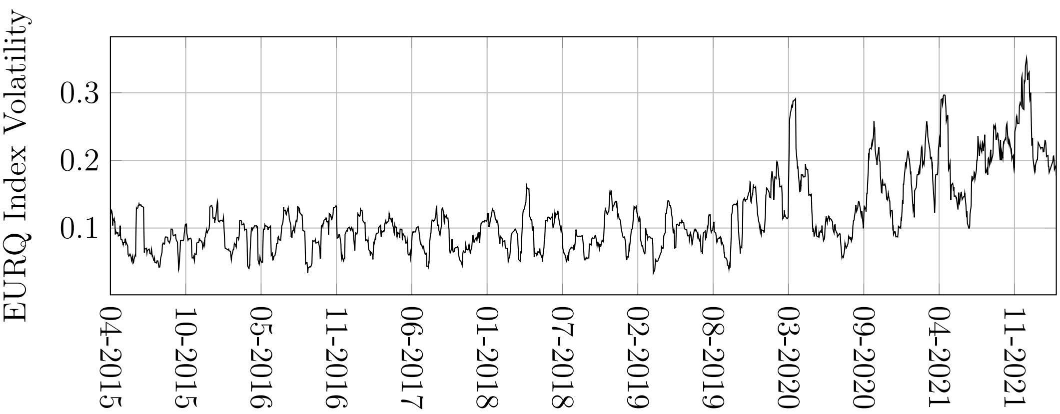
Firstly, following 1st Characteristics it is not possible to obtain daily data for a long-time period in one download[3]. A possible solution would be to connect shorter periods with daily values to obtain values for a 5-year period. However, this method is not viable given the 2nd Characteristics . Changing periods will likely change the scaling factor, as a maximum number of searches in different periods are expected to be different, and thus make the connection of shorter periods unreliable.

Secondly, the 2nd Characteristics prevents to sum results for different word terms. Hacamoyand *et al.* (2011) use a method to make word terms comparable and subsequently applicable to sum. This method uses the feature "compare"

[2]https://trends.google.com/

[3]Google only allows to obtain daily values up to approximately nine months period, then the frequency is weekly.

Figure 3.4: Volatility of the EURQ Index



Note: This figure shows the volatility of the EURQ Index from April 2015 to February 2022.

of Google Trends, which allows to compare up to 5 word terms. The scale is always the maximum number of searches across all word terms. Thus, Hacamoyand *et al.* (2011) proposes to find a term that has, among selected terms, the maximum number of searches and set it as a benchmark, which is used for each iteration of the "compare" feature - 4 terms change, the benchmark remains the same. Since we search for values in many time periods, finding a benchmark for selected word terms for the EURQ index can be quite challenging as we need to have a word with the maximum number of searches among all terms and also in each period. Another challenge in selecting a proper benchmark is that it should not be a word that is searched a lot relative to other terms, as the relative results for the other terms could be 0 or close to 0. Bontempi *et al.* (2021) uses the benchmark method to sum different terms, but do not provide the benchmark term. Hence, in the end, the term "social security" was selected as our benchmark. It satisfies all conditions of a benchmark and has one of the lowest search volumes, so in comparison with less searched terms, words with non-zero values are still obtained. Now, it is possible to aggregate search volumes of different terms and thus create an index representing all search terms. Further, daily values of the index need to be connected to have values for desired 5 years period. As 1st Characteristics and 2nd Characteristics imply the daily values of different periods can not be simply merged together. Hence, we apply algorithm[4] based scaling by overlapped pe-

[4]The algorithm is based on the following GitHub repository: `https://github.com/qztseng/google-trends-daily`

Table 3.2: Google Trends Time Resolution

Time Period	Data Frequency
last 7 days	hourly
36 hours – 269 days	daily
269 days – 5 years	weekly
5 years+	monthly

Note: This table displays an overview of what Google Trends data frequency is provided by Google for a selected time period.

riods. Firstly, the whole time frame of 5 years is divided intervals of maximum length of 9 months (when daily values are obtained from Google Trends) with 100 day overlap for neighborhood intervals. Search volumes for these intervals are then downloaded[5]. The scaling of the intervals is done by a ratio of max values in the overlapped period of two neighborhood intervals.

For example, let's consider an interval $t_1 = [1, 200]$ and $t_2 = [101, 300]$, with overlap period of 100 days $op = [101, 200]$. Then, we define intersections of op with t_1 and t_2 as $z_1 = t_1 \cap ol$ and $z_2 = t_2 \cap ol$ then the rescaling factor is defined in a following way:

$$r = \frac{\max(z_2)}{\max(z_1)}$$

Rescaling is done on the next interval, just note that the process works backward, hence t_2 is obtained and then the rescaling ratio is applied for the latest interval, i.e. t_1. So, in this case, the daily index for time period of $t_2 \cup t_1$ results in $I = (t_2 \setminus z_2) \cup (t_1 \cdot r)$. This algorithm is used on all intervals and in the end, a daily index for the desired time period of more than 9 months is obtained.

As well as the monthly EURQ Index defined by Bontempi *et al.* (2021) suffers from seasonality, our daily version also experiences seasonal effects. We employ Ollech (2018) method that is specifically designed remove seasonallity from daily time series. A Seasonal Trend Loess regression (STL) is applied iteratively to decompose a time series into a trend, seasonal and irregular component. Also, the RegARIMA model is used to correct for calendar and outlier effects. Further, we proceed with the computation of volatility. Given that, during calm times, the search frequencies are lower and variance is higher, sharp jumps between days are very common. So a simple square root of daily

[5]Using Python package `PyTrends` freely available at `https://pypi.org/project/pytrends/`

log return would not appropriately account for the variance as all the jumps would result in high volatility. To eliminate the influence of sharp jumps in calm periods, we estimate volatility as a standard deviation of the previous 14 days log returns (resulting in dropping the first 14 days).

Chapter 4

Methodology

4.1 Dynamic Network Framework

Barunik & Ellington (2020) elaborate on Diebold & Yilmaz (2012) and Barunik & Krehlik (2018) to propose a time-varying parameter vector autoregression (TVP-VAR) to estimate Dynamic Network connectedness through an adjacency matrix defined by a time-varying variance decomposition matrix. The TVP-VAR (p) with assets following a locally stationary process is given by

$$\boldsymbol{X}_{t,T} = \boldsymbol{\Phi_1}(t/T)\boldsymbol{X}_{t-1,T} + \ldots + \boldsymbol{\Phi_p}(t/T)\boldsymbol{X}_{t-p,T} + \boldsymbol{\epsilon}_{t,T} \tag{4.1}$$

where $(\boldsymbol{\Phi}_1(t/T), ..., \boldsymbol{\Phi}_p(t/T))^T$ refers to the time-varying coefficients, $\boldsymbol{X}_{t,T} = (\boldsymbol{X}^1_{t,T}, \ldots, \boldsymbol{X}^N_{t,T})^T$ is a vector of variables, p is the lag order, $\epsilon_{t,T}$ is the residual term, t is the time index and T is the final time observation. The process $\boldsymbol{X_{t,T}}$ can be regarded as weakly locally stationary if it can be, in a neighborhood of a fixed time point, approximated by a stationary process. Additionally, time is rescaled into a continuous time parameter $u = t/T$, for $t \in [1, \ldots, T]$. Furthermore, the TVP-VAR process follows vector moving average VMA(∞) (Dahlhaus & Polonik 2009; Roueff & Sanchez-Perez 2018)

$$\boldsymbol{X}_{t,T} = \sum_{h=-\infty}^{\infty} \boldsymbol{\Psi}_{t,T}(h)\boldsymbol{\epsilon}_{t-H}. \tag{4.2}$$

where $\boldsymbol{\Psi}_{t,T}(h)$ is a stochastically bounded process containing an infinite number of lags and hence has to be approximated with a finite number of horizons.

The connectedness measure stems from a variance decomposition as we can assess how much of a shock in a variable j is transferred to the system of variables. In Barunik & Ellington (2020) setting, the decomposition is done by transforming the information in $\mathbf{\Psi}_{t,T}(h)$. Standard variance decomposition is assessed by Cholesky decomposition, which assumes certain order of variables in which the shock will progress. However, the shocks do not have to appear alone, hence Barunik & Ellington (2020) uses Pesaran & Shin (1998) method of a generalized identification scheme that does not require any ordering and adjusts it to a locally stationary process. To include frequency domain, developed by Barunik & Krehlik (2018), Barunik & Ellington (2020) apply time-varying local frequency response function (FRF) of a shock $\mathbf{\Psi}(u)e^{-i\omega} = \sum_h e^{-i\omega h}\mathbf{\Psi}(u,h)$, where $i = \sqrt{-1}$. The FRF measures how the shock propagates through the system at each time-frequency, i.e. each time horizon (Hanus & Vacha 2018). The following equation then describes the core block in the network construction - the adjacency matrix (Barunik & Ellington 2020):

$$[\boldsymbol{\theta}(u,d)_{j,k}] = \frac{\sigma_{kk}^{-1} \int_a^b \left| \left[\mathbf{\Psi}(u)e^{-i\omega} \sum(u) \right]_{j,k} \right|^2 d\omega}{\int_{-\pi}^{\pi} \left[\left\{ \mathbf{\Psi}(u)e^{-i\omega} \right\} \sum(u) \left\{ \mathbf{\Psi}(u)e^{i\omega} \right\}^T \right]_{j,j} d\omega} \tag{4.3}$$

where $\sum(u)$ represents time-varying covariance matrix.

The adjacency matrix is an important element in the network literature. To follow the correct terminology of network literature – nodes are variables and edges are the connections between nodes. The adjacency matrix then describes interconnections among nodes in a matrix way. Commonly, adjacency matrices values are binary, i.e. a connection exists or not. The frequency-dependent dynamic adjacency matrix defined by Barunik & Ellington (2020) provides weighted edges that reflect the connection's strength. Further, classical network structures have a symmetric adjacency matrix. Such networks are called undirected and do not differentiate between a direction of a connection between two nodes. Barunik & Ellington (2020) allows for a directed connections, i.e. the link of nodes k to j can be different to link between j to k.

Having defined the adjacency matrix with all the necessary network information, useful metrics concerning network characteristics can be derived. The total connectedness measure at a time point u and frequency d is defined as the ratio of the off-diagonal values to the sum of the entire matrix:

$$\mathcal{C}(u,d) = 100 \cdot \frac{\sum_{j,k=1,j\neq k}^{N} [\tilde{\boldsymbol{\theta}}(u,d)]_{j,k}}{\sum_{j,k=1}^{N} [\tilde{\boldsymbol{\theta}}(u,\infty)]_{j,k}} \tag{4.4}$$

where $\tilde{\boldsymbol{\theta}}_j k$ is the normalized adjacency matrix by corresponding row sums since the rows sum of the adjacency matrix does not always sum to one (Barunik & Ellington 2020).

Using the property to measure directional connectedness, so-called to connectedness can be defined as a shock from the system to a variable j by summing all directional edges to a variable j weighted by the sum of the whole matrix (Barunik & Ellington 2020):

$$\mathcal{C}_{j\leftarrow\bullet}(u,d) = 100 \cdot \frac{\sum_{k=1,j\neq k}^{N}[\tilde{\boldsymbol{\theta}}(u,d)]_{j,k}}{\sum_{j,k=1}^{N}[\tilde{\boldsymbol{\theta}}(u,\infty)]_{j,k}} \tag{4.5}$$

Analogically, from connectedness is defined:

$$\mathcal{C}_{j\rightarrow\bullet}(u,d) = \frac{\sum_{k=1,j\neq k}^{N}[\tilde{\boldsymbol{\theta}}(u,d)]_{k,j}}{\sum_{j,k=1}^{N}[\tilde{\boldsymbol{\theta}}(u,\infty)]_{kj}} \tag{4.6}$$

By subtracting the from connectedness from to connectedness for a variable j it can be assessed whether the variable is a net receiver or transmitter of shocks (Barunik & Ellington 2020):

$$\mathcal{C}_j^{\mathrm{NET}}(u,d) = \mathcal{C}_{j\rightarrow\bullet}(u,d) - \mathcal{C}_{j\leftarrow\bullet}(u,d) \tag{4.7}$$

Lastly, we define a ratio that measures how much of the total connectedness is driven by just a subset of variables. An off-diagonal sum of a sub-matrix of variables of interest is divided by the off-diagonal sum of the whole matrix.

$$R(u,d) = 100 \cdot \frac{\sum_{j,k=1,j\neq k}^{N}[\tilde{\boldsymbol{\theta}}(u,d)]_{j,k} \cdot \mathbb{1}_{j\in S}}{\sum_{j,k=1,j\neq k}^{N}[\tilde{\boldsymbol{\theta}}(u,\infty)]_{j,k}} \tag{4.8}$$

where $\mathbb{1}_{j\in S}$ is the indicator function that specifies whether a variable j is part of the selected subset of variables S.

In our case, we use the R ratio to determine how much of the total connectedness is driven solely by the connectedness among economic uncertainty.

4.2 Model Estimation

The model proposed by Barunik & Ellington (2020) is estimated by Quasi-Bayesian Local-Likelihood (QBLL). This estimation applies a Gaussian kernel weighting function that adds more weight to observations that are close to the time point at which the model is being estimated (Petrova 2019). Barunik &

Ellington (2020) further stresses an important feature of the QBLL method: capturing a distribution of a network's measures parameters, which allows for the construction of parameters' confidence intervals.

Regarding assumptions, inputed time-series should follow a locally stationary process. As Barunik & Ellington (2020) explains, a locally stationary process can be understood as a process that can be approximated by stationary ones on small intervals around a fixed time points. To our knowledge, no formal test was found in the existing literature and following other studies using the same methodology, we assume that our selected variables follow a locally stationary process. Furthermore, in classical TVP-VAR models, time-varying parameters have to follow specific distribution, however, thanks to QBLL estimation proposed by Petrova (2019) the time-variation enters in a non-parametric way hence no assumption on the law of motion is required. Finally, the model allows for heteroskedasticity, hence there is no need to adjust for it (Barunik & Ellington 2020).

To estimate the model, several specifications are required. Firstly, a number of lags need to be determined. Commonly, a lag selection is usually based on Information Criterion. However, upon examination of results with a different number of lags $p \in \{2, 5, 10\}$ results for network measures did not change dramatically hence we chose to follow the common practice of $p = 2$. Secondly, a number of horizons have to be specified. That is to approximate the infinite VMA(∞). Barunik & Ellington (2020) use $H = 100$ and report that for different quantities of H (50, 100 and 200) the results are close to identical. Hence, we also set $H = 100$ for the estimation of the TVP-VAR model. Thirdly, the kernel's bandwidth, also known as a smoothing parameter, specifies how smooth are the network measures (Barunik & Ellington 2020). Setting a large bandwidth produces a smoother and more gradual time-evolution of results, while shorter bandwidth results are usually more volatile and experience sharp jumps. As Barunik & Ellington (2020) explains, it is because the larger bandwidth is, the Gaussian kernel weighting function weights the larger number of observations in the neighborhood of an estimated time point. Further, by simulating several processes Barunik & Ellington (2020) find that larger bandwidth values tend to have a lower fit. The length of the kernel's bandwidth is set to $W = 7$. In case of the horizon-decomposition, we set the intervals similarly to Barunik & Ellington (2020) – short-connectedness from 0 to 5 days, medium from 5 to 20 and above 20 is considered as a long-term. Finally, 500 simulations are drawn from the quasi posterior distribution at each time point, similarly to

Barunik & Ellington (2020). And importantly, the estimation is done without correlation, i.e. the covariance matrix $\boldsymbol{\sum(u)}$ is diagonalized, thus, the contemporaneous effects are removed, which results in the network connections with the causal interpretation.

With above specification and $N = 4$ variables, $T = 2533$ and $p = 2$ following TVP-VAR is estimated:

$$\boldsymbol{X_{t,T}} = \boldsymbol{\Phi_0}(t/T) + \boldsymbol{\Phi_1}(t/T)\boldsymbol{X_{t-1,T}} + \boldsymbol{\Phi_2}(t/T)\boldsymbol{X_{t-2,T}} + \boldsymbol{\epsilon_{t,T}}$$

where $\boldsymbol{\Phi_0}(t/T)$ are intercepts, $\boldsymbol{\Phi_1}(t/T)$, $\boldsymbol{\Phi_2}(t/T)$ are the model's parameters and $\boldsymbol{X_{t,T}}$ is

$$\boldsymbol{X_{t,T}} = \begin{pmatrix} BTC_t \\ EPU_t \\ VIX_t \\ EURQ_t \end{pmatrix}$$

and $\boldsymbol{\epsilon_{t,T}}$ is the error term.

Barunik & Ellington (2020) distribute package in programming language `JULIA` that estimates the TVP VAR model and computes above model defined measures. Further, it is possible to obtain adjacency matrices values for each time observation, simplifying an additional individual analysis of the network.

Chapter 5

Results and discussion

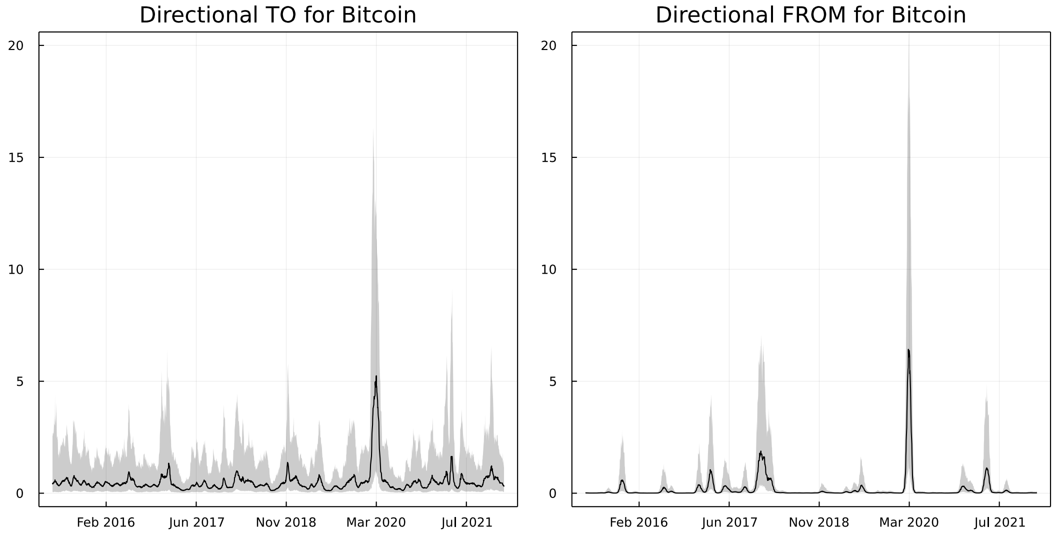
The main results show that Bitcoin is mainly a net-receiver of volatility from uncertainty indexes throughout our observed period. However, as Figure 5.1 displays, only a few periods show a significant volatility spillover. Furthermore, the contagion effect during most events is very subtle. One exception was the COVID-19 crisis when Bitcoin received substantially more than in the other periods. The main uncertainty transmitter to Bitcoin changed over time. In the pre-COVID-19 period, a lot of contagion originated from the EPU Index, as is seen in the Figure 5.5. The VIX Index was the strongest transmitter of uncertainty during the COVID-19 period and the spillover from VIX Index to the Bitcoin market remained even after the initial COVID-19 shock. During the period of inflation fears at the end of 2021, contagion toward Bitcoin was driven by the EURQ Index, describing the public perception of uncertainty.

The Figure 5.1 exhibits that Bitcoin also contributed to the network. Notably, during the burst of the Bitcoin bubble at the end of 2017, Bitcoin was transmitting volatility shocks to the uncertainty indexes. Even more intense spillover from Bitcoin to economic uncertainty emerged during the COVID-19 crisis. Implying that Bitcoin can possess some information that transfers to the economic uncertainty.

The Figure 5.2 presents the total connectedness of our network together with a line showing how much of the total connectedness is driven by the connectedness among uncertainty indexes. Further, the Figure 5.3 shows the decomposition of the total connectedness into short-, medium- and long-term connectedness. Note that the horizon specific connections sum to the total connectedness.

The most significant connection within the system is formed at the beg-

Figure 5.1: Directional TO and FROM Connectedness for Bitcoin

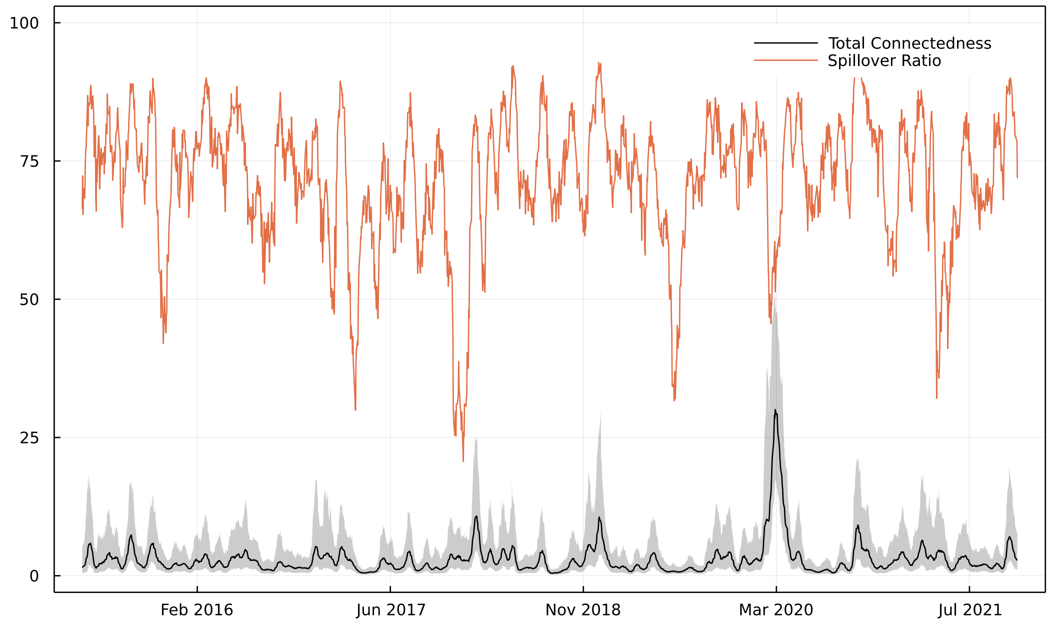


Note: The figure on the left shows directional to connectedness $\mathcal{C}_{j\leftarrow\bullet}(u,d)$ stemming from Equation 4.5 for Bitcoin. The figure on the right then plots from connectedness $\mathcal{C}_{j\rightarrow\bullet}(u,d)$ defined in Equation 4.6 for Bitcoin. The grey areas depict, in both figures, 95 % confidence bands.

ging of the COVID-19 outbreak. In Figure 5.3 it can be noticed that long-term connectedness surpasses short- and medium-term connectedness during the COVID-19 shock. Such occurrence is also present in Barunik & Ellington (2020) measure of connectedness within S&P 500 sectors, where as well during turbulent times, long-term connectedness passes short-term connectedness. At the end of 2022, long-term connection rose above the short-term one but never above both of the shorter horizons as it did during the COVID-19 period. As Barunik & Krehlik (2018) explains, fundamental changes in investors' expectations may have a long-term impact on the system of variables. In the case of the COVID-19 connectedness, the long-term connectedness was very likely driven by the exogenous nature of the shock and little knowledge surrounding the virus at that time. Both of these reasons might led to a challenging assessment of the COVID-19-induced uncertainty, resulting in long-term connectedness of uncertainty. Further, as Figure A.1 displays, most of the uncertainty was driven by the VIX Index, while Bitcoin, the EPU Index and the EURQ Index were mainly receivers. The Figure 5.4 then shows the state of the network during its highest total connectedness on March 11, 2020, which is around the period of the highest stock market falls during COVID-19 bear market.

A short-term connectedness is mainly formed when agents process information rapidly, so a shock to a variable causes only short-term cyclical behavior (Barunik & Krehlik 2018). The short-term connectedness seems to prevail in our observed period. In quiet times or after a shock, e.g. COVID-19, the dominance of a short-term connectedness emerges as faster processing of uncertainty shocks results in shocks being only short-lived. Short-term connectedness also seems to lead even during a mild shock. Although the total connectedness pro-

Figure 5.2: Total Dynamic Network Connectedness

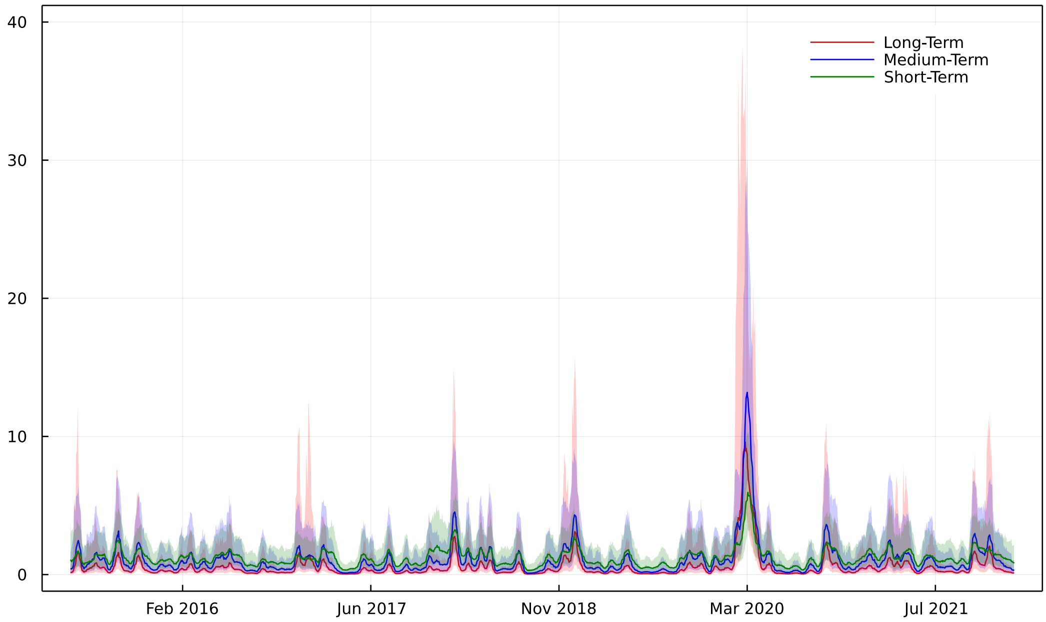


Note: This figure plots the total connectedness of our system of variables $C(u, d)$ from Equation 4.4 on y-axis. Grey areas represent 95 % confidence intervals of the total network connectedness. The red line is the ratio describing how much of the connectedness is driven by connectedness among uncertainty indexes described in Equation 4.8.

vides valuable insights into the network as a whole, we are more interested in the connectedness of Bitcoin with the uncertainty indexes and mainly with the EPU Index. To investigate this connectedness, we plot TO, FROM connectedness in the Figure 5.1 and NET connectedness in the Figure 5.6 for Bitcoin. Generally, Bitcoin can be considered a net receiver of shocks of uncertainty. The most intensive shock to Bitcoin was transferred during the COVID-19 bear market and around 80% of that shock came from the VIX Index. The EPU Index accounted only for less than 10%. During the 2017 Bitcoin Crash, when the total connectedness was mainly dominated by the connectedness between Bitcoin and uncertainty indexes, Bitcoin was a net transmitter of uncertainty. The highest values of that directional connectedness from Bitcoin to the system appeared around 22.12.2017, a day when Bitcoin fell by 45%. In figure

Figure A.5 it can be seen how the shock was evenly distributed among all three uncertainty indexes on that day.

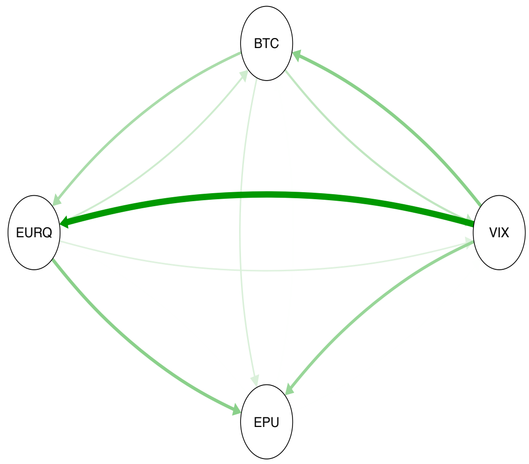
Figure 5.3: Horizon Specific Decomposition of Total Connectedness



Note: The total connectedness decomposition into short-, medium- and long-term connectedness is depicted in the above figure. The red line describes the long-term connectedness, the blue line the medium-term and the green the short-term. Shaded areas in corresponding colors to lines represent 95 % confidence intervals.

Bitcoin is a net receiver during an increased connectedness amid inflation fears and reports about reducing asset purchases. In December, the Federal Open Market Committee (FOMC) reported a further decrease in asset purchases and several possible increases in interest rates in 2022. Thus, giving a signal of tightening the USA's monetary policy and turning the focus from pandemic recovery to fighting inflation. In this period, uncertainty was mainly transmitted from the public-based EURQ Index. We hypothesis that most of the public fear was influenced by the rising inflation that is easy to detect for a person and has a direct impact on lowering a person's budget constraint. Such influences conceivably drove public uncertainty , estimated by the EURQ Index during that time. Our results show that this uncertainty was mainly transferred to the media-based EPU Index, i.e. the opposite direction of influence is noticed as the EPU Index is usually a transmitter of shocks to the EURQ Index (Figure A.2, Figure A.3). Also, Bitcoin was a substantial receiver of that shock from the EURQ Index, while the VIX Index remained largely intact. Suggesting that the Bitcoin market was more sensible to the increased uncertainty

Figure 5.4: Snapshot of the Network on March 11, 2020



Note: This figure shows the directional connectedness among the network on March 11, 2020.

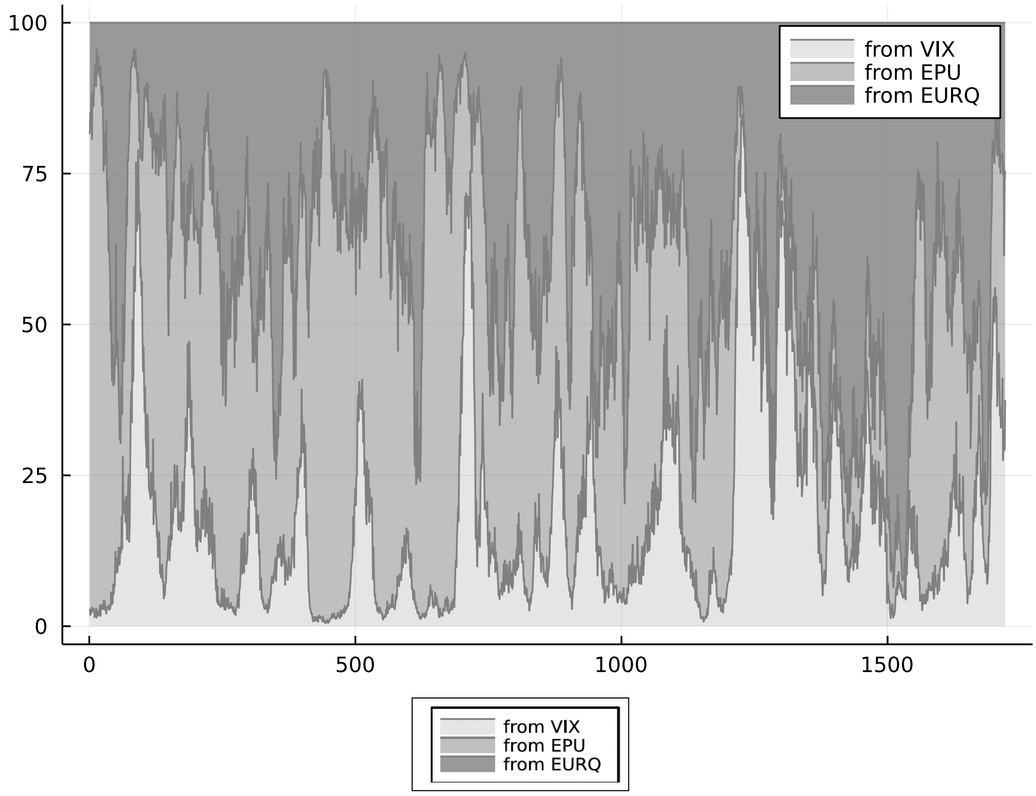
likely driven by public inflation fears than the VIX Index representing financial market uncertainty.

Before the COVID-19 outbreak, five significant shocks can be noticed – in three cases, Bitcoin was a net-receiver (May 2015, December 2016, October 2018) and in the other two a net-transmitter (February 2017, November – January 2017). Chronologically, in May 2015, most of the uncertainty to Bitcoin was coming from the EURQ Index, the EPU Index attributed by about relatively 40 % from the three uncertainty indexes (Figure 5.5). In December 2016, Bitcoin was a net-receiver until February 2017, when Bitcoin started to transmit uncertainty to the system of variables. During that period, the EPU Index rose dramatically in two days, when FED announced a raise in interest rates for the second time since 2008. This action likely led to an increase in the EPU Index volatility and Bitcoin seems to receive some of this shock.

From November to January 2017, Bitcoin was a strong net-transmitter of uncertainty. It is the longest Bitcoin's transmission of shock to the system of variables in our time period. Also, as can be seen in Figure 5.2, during that time, the relative connectedness of Bitcoin with the three uncertainty indexes was at its top. The background in this period is that Bitcoin's price surged to nearly 20,000$ and then fell below 11,000$. The shock was quite uniformly distributed among all three uncertainty indexes.

The shock in October 2018, when Bitcoin was a net-receiver, was intense but

Figure 5.5: Decomposition of TO Connectedness to Bitcoin

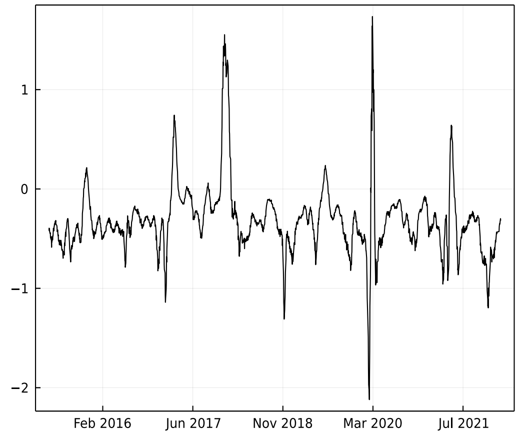


Note: This figure describes the relative distribution of TO connectedness to Bitcoin from the three uncertainty indexes.

short-lived. Although, more extended periods of mild net-receiving for Bitcoin preceded and followed the October 2018 shock, which was likely mainly caused by the stock market turmoil. The announcement of a rate increase by the FED on 25th September 2018 did not lead to any dramatic shock this time. The shock started in late October and culminated in November when Bitcoin fell from around 6,500$ to 3,500$.

In quiet time, however, the connectedness weakens and the transmission of uncertainty is deficient. These results appear to be in line with Bouri *et al.* (2017) and Wang *et al.* (2019) that stated that the relationship between the EPU Index and Bitcoin is mainly negligible but becomes significant during increased time of uncertainty. In the case of the VIX Index, we can confirm the increased contagion during the COVID-19 period, as stated by Guo *et al.* (2021). Further, we provide more evidence on the pre-COVID-19 period, when we identify several significant spillover periods and their background. Also, we capture the contagion effect from the EURQ Index to the whole system.

Figure 5.6: NET Directional Connectedness for Bitcoin



Note: The net connectedness for Bitcoin defined as the difference between to connectedness and from connectedness (Equation 4.7) is plotted in this figure.

The interpretation of results should take into consideration the sensitivity of our measure to the type of volatility, especially in the case of the EPU Index, which exhibits sharp day-day jumps, which does not necessarily have to correspond to changes in uncertainty. These jumps can create large jumps in volatility and, consequently, a false connectedness. While we tried to control for it by computing volatility as a 14-day rolling standard deviation, some inaccuracy might still be present. Also, the jumps may be caused by counting words related to uncertainty in a newspaper. Firstly, it can not always be determined whether the increase in word count truly reflects an increase in uncertainty. Secondly, certain uncertainty unrelated events can take up media space, thus lowering uncertainty word count and the EPU Index, while there was no real decrease in uncertainty.

Chapter 6

Conclusion

This thesis investigates the volatility connectedness between Bitcoin and three uncertainty indexes – the Economic Policy Uncertainty Index, the VIX Index and the EURQ index derived from Google Trends – that asses uncertainty from different points of view. Our findings show several significant volatility spillover effects during an increased time of uncertainty. Most notable is the uncertainty spillover effect in the course of the COVID-19 crisis, when Bitcoin received most of the risk from the VIX Index. Also, we show that Bitcoin acted as a receiver of EURQ index induced shock in uncertainty amid inflation fears at the end of 2021.

Further, we identify 3 significant shocks before 2020 – May 2015, December 2016 and October 2018 – when Bitcoin received risk spillover from uncertainty indexes and primely from the EPU Index. It is hard to asses the true motives behind the EPU Index shocks, however in both December 2016 and October 2018, the beginning of risk spillover was marked by the FED interest rate rise. Spillover effects from Bitcoin to economic uncertainty emerged during the 2017 Bitcoin crash and the COVID-19 period, hinting that Bitcoin is not irrelevant to economic uncertainty.

Nonetheless, apart from the COVID-19 crisis, the contagion effects are vastly bland, suggesting that Bitcoin is independent of uncertainty indexes during calm times, embrace a subtle contagion during mild periods of increased uncertainty, but fails to protect against a widespread and an intensive economic uncertainty.

Following research could incorporate more cryptocurrencies to extend the analysis on the cryptocurrency market. Further, a good and bad volatility could be distinguished to see which type of volatility shocks drive the connectedness.

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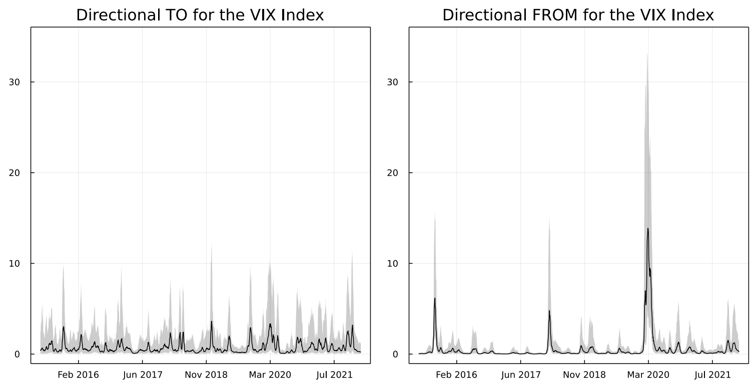
Appendix A

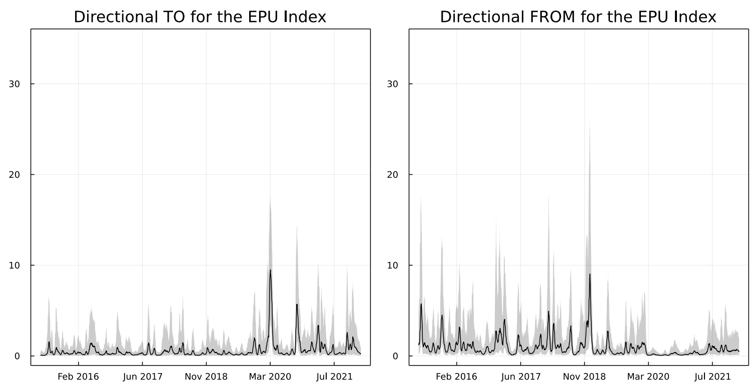
Figures

Figure A.1: Directional TO and FROM Connectedness for the VIX Index



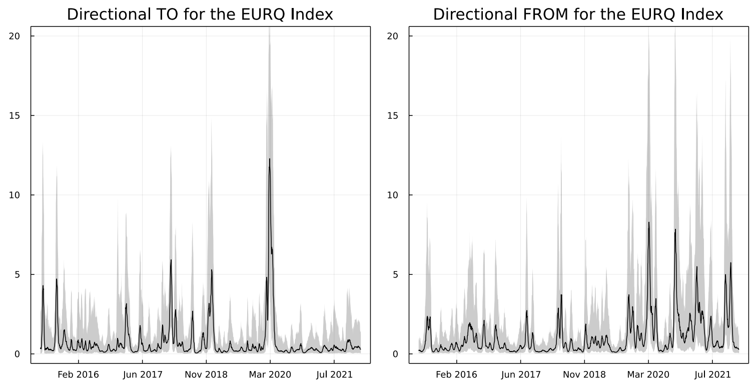
Note: The figure on the left shows directional to connectedness $\mathcal{C}_{j\leftarrow\bullet}(u,d)$ for the VIX Index. The grey areas depict 95 % confidence bands.

Figure A.2: Directional TO and FROM Connectedness for the EPU Index



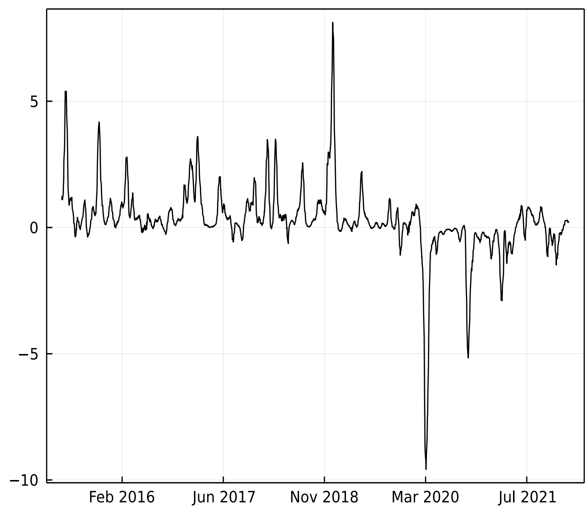
Note: The figure on the left shows directional to connectedness $\mathcal{C}_{j\leftarrow\bullet}(u,d)$ for the EPU Index. The grey areas depict 95 % confidence bands.

Figure A.3: Directional TO and FROM Connectedness for the EURQ Index



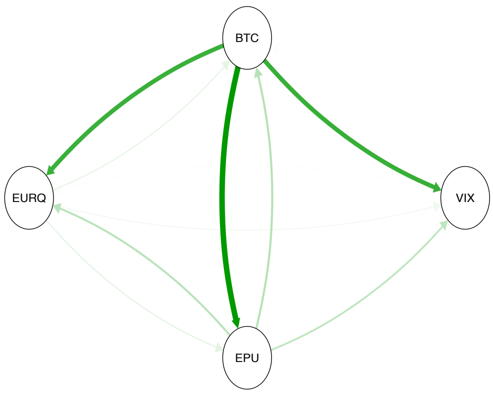
Note: The figure on the left shows directional to connectedness $\mathcal{C}_{j\leftarrow\bullet}(u,d)$ for the EURQ Index. The grey areas depict 95 % confidence bands.

Figure A.4: NET Directional Connectedness for the EPU Index



Note: The net connectedness for the EPU Index is plotted in this figure.

Figure A.5: Snapshot of the Network on December 22, 2017



Note: This figure shows the directional connectedness among the network on December 22, 2017.